AutoCaddie

An AI-Driven Smart Coach

Louis Deal (EE), Rylan Simpson (CpE), Jarett Artman (CpE), Joshua Glaspey (CpE)
Department of Electrical and Computer Engineering

Table of Contents

Chapter 1: Executive Summary

Technology is reshaping every facet of our lives, and the domain of sports and physical training remains ripe for innovation. Addressing this gap, a project led by Group 22, stands as a transformative solution aimed at revolutionizing the way athletes and fitness enthusiasts train, improve, and excel.

AutoCaddie leverages cutting-edge Artificial Intelligence algorithms to serve as a smart coach, offering real-time, individualized feedback for enhancing performance. Unlike traditional coaching methodologies that may be subject to human biases and limitations, AutoCaddie employs data analytics and sensor technologies to provide precise and actionable insights.

The project encapsulates a comprehensive development framework that spans across multiple hardware integrations, software engineering, and user interface design. Modern sensors collect a wealth of performance metrics, which are then processed through optimized algorithms alongside machine learning models sequencing live camera data to generate tailored coaching feedback. This represents a leap in technological capability, converging multiple disciplines to deliver a product that not only stands on its own merit but sets new standards for smart coaching solutions.

This document serves as an exhaustive guide detailing every aspect of the AutoCaddie project—from initial research and design constraints to testing protocols and final implementation. It incorporates an in-depth examination of relevant existing technologies, meticulous part selection based on empirical research, and a discussion of design standards to ensure compliance with industry norms.

The AutoCaddie project is not merely a technological advancement; it is a paradigm shift. It promises to elevate the quality of training and performance optimization to unprecedented levels, offering tangible benefits to athletes, coaches, and sports organizations alike. Therefore, it is poised to make a significant impact in bridging the technology gap in today's sports training landscape.

For those who wish to delve deeper into the technical and administrative facets of the project, the document includes extensive appendices and references, providing a wealth of information for further study and research.

Chapter 2: Project Description

2.1 Project Background and Motivation

2.1.1 Introduction

One of the most challenging aspects of sports training and physical fitness is the lack of personalized, real-time feedback. Whether you're a professional athlete or a casual fitness enthusiast, the absence of immediate and accurate coaching can hinder performance and lead to a plateau in improvement. To address this problem, we introduce AutoCaddie, a cutting-edge AI-driven smart coaching system that aims to redefine the way individuals train and improve in their respective sports or fitness regimes.

AutoCaddie employs a comprehensive suite of sensors and data analytics tools to capture a wide range of performance metrics. These metrics are processed through a sophisticated machine learning algorithm, alongside other optimized computations, which then provide real-time personalized coaching feedback directly to the user. This system is designed to be integrated into existing training and can also function independently, offering a versatile solution adaptable to various sports and physical activities.

In addition to real-time feedback, AutoCaddie features an interface that provides a more in-depth analysis of the collected data. This includes the information of the current swing performed by the player and other data we collected from our camera footage. This feedback will be immensely valuable to the player.

Moreover, all the data captured by AutoCaddie can be securely stored and accessed remotely, serving multiple purposes. It can be used for further analysis, for more nuanced feedback, or even utilized for research and development in sports science.

By delivering a highly adaptable, precise, and user-friendly smart coaching solution, AutoCaddie aims to bridge the existing gap in personalized sports training. The system promises not only to enhance individual performance but also to contribute to the broader field of sports technology and analytics.

2.1.2 Motivation

As engineers with a passion for golf, we understand firsthand the challenges and limitations of traditional training methods in the sport. The existing systems often lack real-time, personalized feedback essential for meaningful improvement. AutoCaddie emerged from our desire to integrate our engineering skills with our hobbies, aiming to address these gaps. By leveraging cutting-edge AI and sensor technology, we aspire to enhance not only our own golfing experience but also to make advanced, data-driven coaching accessible to golfers at all levels. Through AutoCaddie, we aim to elevate the standards of training, making the sport more engaging and rewarding for everyone involved.

2.1.3 Function of Project

The function of the AutoCaddie project is to capture and analyze the biomechanics of a golfer's swing using a combination of cameras and sensors. The system processes this data in real-time through machine learning algorithms to identify areas for improvement. The analyzed information is then immediately displayed on a computer screen in a user-friendly format, providing golfers with actionable tips to enhance their swing. This enables golfers to make instant corrections, fostering more effective practice sessions and accelerating skill development.

2.2 Project Goals and Objectives

2.2.1 General Goals

- Develop an artificial intelligence program utilizing machine learning to provide multiple modes of feedback for a user's golf swing (using primarily a driver).
- Design a printed circuit board (PCB) capable of performing wireless transmission of simple numeric data to a central computer.
- Interface kinematic and video data into a central data processor computer.
- Measurably improve the user's golf swing through the usage of the system.

2.2.2 Software

2.2.2.a Main Goal:

Develop an ML-driven AI to provide feedback to a user's swing that integrates both sensor and video data.

2.2.2.b Objectives:

- Find a database to train the AI.

GolfDB [1] is a repository of golf videos from a set number of camera perspectives and is freely available to the public. These videos will be utilized to train the machine learning program to evaluate a swing from two different camera angles, one from the side and one from behind.

- Integrate video feed data to AI program.

Two cameras (listed under budget) will be utilized to send video data to the laptop for AI analysis via a wired connection.

- Effectively train the AI to recognize swings and make comparisons.

The AI program will receive video data via a cable and will compare the active video feed to the videos gathered from GolfDB, returning audio and visual feedback based on that comparison.

- Program the AI to effectively provide feedback based on comparisons.

The machine learning program will be programmed such that it returns audio feedback (via a buzzer either on the player or the laptop to indicate proper arm straightness) and visual feedback via a graphical user interface (GUI) displayed on a screen.

- Integrate IMU sensor data with AI.

Absolute position and calculated arm straightness (IMU orientation vectors will be included in a vector calculation to determine the overall angle from shoulder to wrist across the arc of the swing and will be compared to a threshold of acceptable arm angles) will be fed to the AI program to assist it in providing feedback.

- Design and integrate visual and audio feedback queues.

An on-screen GUI designed by the machine learning team will be utilized to provide visual feedback based on the IMU data and analyzed active video feeds, while a buzzer will be used to indicate proper position of the arm.

2.2.3 Hardware

2.2.3.a Main Goal:

Design a system to measure the kinematics of the user's arm, and wirelessly relay the data via a transceiver to a central computer for processing.

2.2.3.b Objectives:

- Select and acquire hardware components.

The included hardware system of the AutoCaddie project should integrate IMU systems that interface with a wireless communication circuit utilizing wireless transceiver modules for communication with a computer. Furthermore, cameras that meet the requirements of an implementation of machine learning artificial intelligence should be chosen.

- Integrate I2C or UART communication of IMUs with MCU chip.

I2C or UART, communication protocols for technology, will be used to extract the measurements provided by the IMUs and send them to the MCU.

- Integrate wireless communication between MCU and main processor computer.

UART, another serial communication mode, will be utilized to send the calculations from the MCU chip to the wireless transceiver on the PCB, and will be used to extract the received data on the laptop to the AI analysis program.

- Design mounting system for IMU sensors on user.

The IMUs will be integrated into a flexible sport compression sleeve, set into the surface of it at the wrist, elbow, and shoulder. The wires connecting the IMUs to the MCU will be fed through flexible tubing which will prevent the wires from inhibiting the ergonomics of the wearable system.

- Design IMU housing components for mounting system

The IMUs will be mounted into a compression sleeve using an adhesion method (likely Velcro) and a compression method to prevent their motion (likely elastic bands which can be tightened from a central knot).

- Design data collector/data transmission PCB

A system model has already been developed, but a lower-level model of the PCB will not be completed for some time.

- Design PCB housing for mounting system

The PCB will be housed within a 3d-printed, filament-based plastic housing designed to the specific shape of the PCB board. The battery will be contained within and will be activated with a switch to ensure that power can be conserved. The design will be such that it does not impede the motion of the player.

- Integrate video camera feed into main processor computer.

2.2.4 Hyperparameters for AI Analysis

2.2.4.a Main Goal:

Accurately define and quantify the essential components of a golf swing for the AI to assess and provide feedback.

2.2.4.b Objectives:

- Analyze the arm position.

Monitor the relative positioning of the arms throughout the swing.
Instruct the AI to detect and highlight any variations from the ideal arm posture.

- Analyze the hip position.

Evaluate the alignment and movement of the hips during various phases of the swing.
Program the AI to compare the user's hip positioning with reference videos from GolfDB.

- Analyze the head straightness.

Ensure the golfer's head remains steady and doesn't tilt excessively during the swing.
Train the AI to notify if there's too much head movement that might affect the swing's accuracy.

- Analyze the shoulder rotation.

Quantify the degree and fluidity of the shoulder rotation during the swing.
Guide the AI to assess shoulder mobility and compare it against ideal benchmarks.

- Analyze the hip rotation.

Measure the rotation of the hips and their synchronization with the rest of the body.
Enable the AI to determine if the hip rotation is optimal or requires adjustment.

- Analyze the swing arc.

Analyze the trajectory and curve of the club as it moves through the swing.
Empower the AI to provide feedback on the swing arc's efficiency and effectiveness.

2.3 Overview of Planned System Design

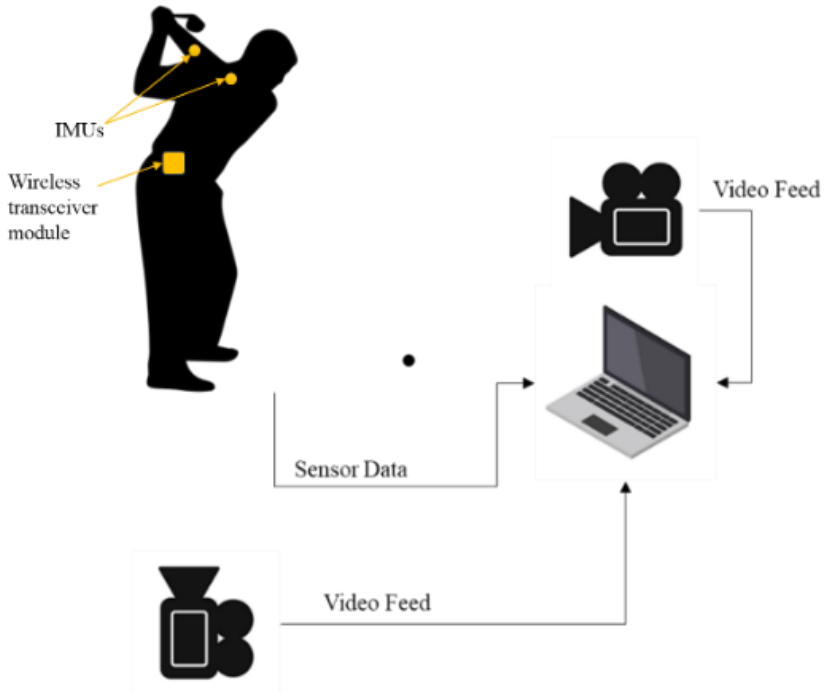


Figure 1: Graphic representation of physical system setup.

As seen by the above figure, the AutoCaddie system involves three separate streams of data. The system integrates two video camera feeds and a sensor data feed from IMU sensors on the user. The data is fed to a computer or laptop that can be placed in view of the user for visible and audible feedback. As each data feed source is portable, the devices that produce the data can be placed within the environment as necessary, while maintaining given requirements. The sensor data on the user should maintain consistent data streaming to the computer and should be both secure on the user and should be calibrated as necessary. The first of the two cameras should be placed at the front of the user, in order to record the full posture and swing arc of the club, as well as the straightness of the user's arm. The second camera should be placed on the side of the user, to record the swing plane of the club as well and the swing pathing in relation to the ball. Finally, the computer where feedback is given can be placed by preference of the user.

2.3.1 Block Diagram

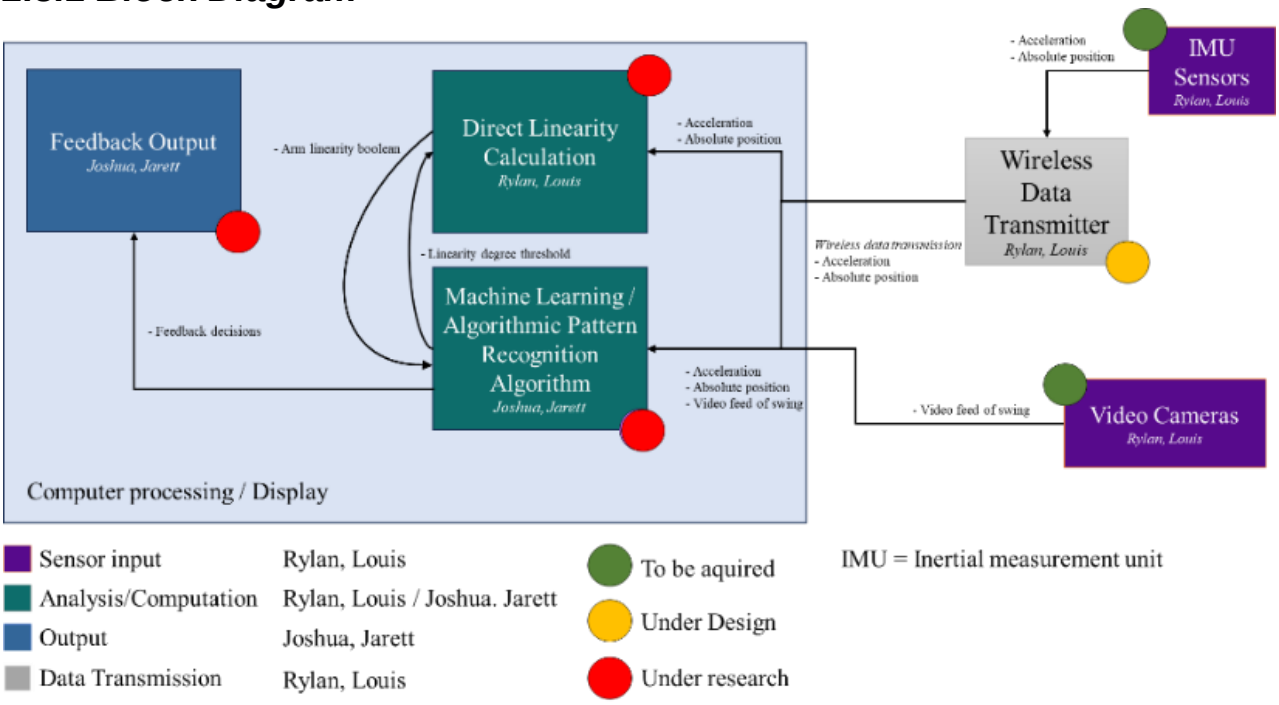


Figure 2: Block diagram showcasing the system overview and datapath of the AutoCaddie system.

The related block diagram figure demonstrates the high-level overview of the AutoCaddie system and the flow of the data within the system during its function. Outside of the data processing subsystem, there are two channels in which external data is collected and is sent for processing. These two channels are the IMU sensor channel and the video camera channel. The IMU sensors collect orientational and acceleration data on the user's driving arm. This data is then sent to a wireless transceiver module so that the sensor data can be sent to a processor for analysis wirelessly, so as not to impede user movement with wires. This sensor data can be cleaned and post-processed by artificial intelligence as necessary. The video cameras record video footage of the user, particularly during swing action. This video footage is transmitted to the central computer where the artificial intelligence analyses the footage against a database by which it was previously trained on. Finally, once the artificial intelligence's analysis and direct calculations are completed, the program generates an output sequence, where audiovisual feedback is provided to the user.

2.3.2 Software Flow Diagram

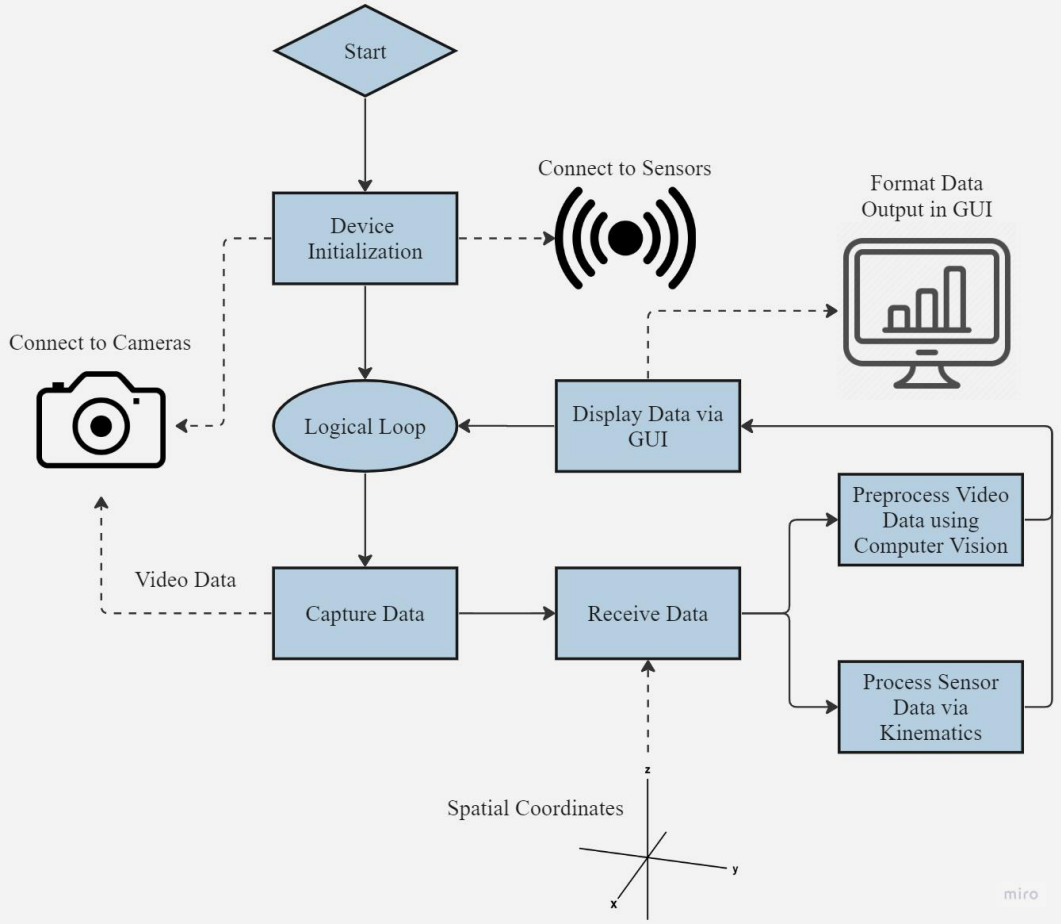


Figure 3: Block diagram showcasing a high-level overview of the software control within AutoCaddie.

This block diagram gives a high-level overview of the flow of the software system within AutoCaddie. The system begins by initializing the connected peripherals including the IMU sensors and two video cameras. Once all of these systems have been connected, the primary loop begins. First, the user is recorded taking a golf swing by both the physical data recording devices. The data from the IMUs are packaged and transmitted via wireless communication, and the cameras export the entire video broadcast to the computing device via a wired connection. Once the data has been collected, it is analyzed using two separate analysis systems. The first system extracts frames from the video data, preprocesses them, and sends them through AutoCaddie's deep neural network. The second system takes the IMU data and, through matrix operations, performs kinematic equations to deconstruct the data. At this point, the results are formatted and displayed to the user through a GUI, and the system can loop back to the data capturing state. All of these internal software systems combine to provide AutoCaddie's comprehensive AI feedback.

2.4 Engineering Requirements and Constraints

2.4.1 Engineering Requirements Overview

The AutoCaddie project is an interdisciplinary initiative that converges the fields of mechanical engineering, computer science, and data analytics to construct a sophisticated, real-time golf swing analyzer. This senior design project aims to solve a specific problem in the realm of sports technology: providing immediate, actionable feedback to golfers to improve their swing.

The hardware setup involves a strategically positioned high-resolution frontal camera along with additional sensors. These devices are meticulously engineered to capture crucial metrics of a golfer's swing, such as speed, angle, and body posture. One unique feature of this system is the incorporation of a buzzer mechanism. This buzzer sounds at the appropriate moment, signaling the golfer to start their swing and thereby ensuring a standardized initiation point for all swing data collected.

The raw sensor and IMU data will be processed by a dedicated computing unit located near the golfer. This unit is equipped with both machine learning algorithms and hyper-specific algorithms designed to analyze the biomechanical aspects of a golf swing in real time. The algorithms will offer immediate coaching advice based on the analyzed data displayed on a nearby computer screen.

The screen's user interface is designed for simplicity and ease of use, ensuring that golfers can effortlessly understand and apply the real-time feedback provided. The feedback is tailored to highlight areas requiring immediate attention, allowing for quick adjustments and improved swings in subsequent attempts.

An essential hardware requirement for the project is the creation of a 3D-printed housing unit that attaches to the golfer's arm. This housing will serve as a secure mount for the circuitry and sensors. Additionally, a sleeve will be designed to house the sensors in a manner that allows for accurate data capture while maintaining comfort and freedom of movement for the golfer.

The AutoCaddie system is built to be adaptable, capable of functioning both as an integrated part of existing training setups and as a standalone unit. While the system does not allow for adjustments based on the training environment, it is engineered to be reliable and effective in a variety of standard golf training settings.

In essence, the AutoCaddie project embodies a harmonious blend of hardware and software engineering components. The project serves not only as a practical, real-world application for immediate, data-driven golf swing improvement but also as an invaluable educational experience for the team. It equips team members with the hands-on experience necessary for multidisciplinary engineering roles in their future professional endeavors.

2.4.2 Engineering Requirements Table

Requirement	Description	Reasoning
Cost	Total costs less than $500	System must be affordable for market entry and accessible for all players
Responsiveness	(Expected) Feedback within 10 seconds	Prevents long waiting time for feedback, including connection feedback systems for IMUs
Connection range	Stable connection from at least 20 meters of signal source	Requirements align with wireless data communication restrictions to send valid data for accurate feedback.
Accuracy	Feedback is accurate at least 90% of the time	Requirement sets standard for AI generated feedback, requiring reliable and desirable feedback.
Battery Life	2 hours battery life minimum of wireless transceiver	Requirements establish usability standards, enabling users to practice with the system for a meaningful duration.
Ergonomic	Wearable system is nonrestrictive and mountable in less than 5 minutes	Requirement establishes a usability standard for user-friendly system mounting.
Mounted Dimensions	Wireless transmission PCB designed in less than a 10cm-by-10cm frame	Requirement facilitates ergonomic design, following non-obstructing sizing for placement on user.
Weight	Wearable system weighs at most 5 pounds	Requirement facilitates ergonomic design, avoiding user fatigue of a weightier system.

Table 1: Engineering requirements table that outlines the relevant requirements set for the engineering design of the AutoCaddie System.

2.4.3 Engineering Constraints

The design of AutoCaddie seeks to involve both direct-conditional and user-resultant AI-driven feedback. To achieve this design endpoint, the system is required to integrate both a senor system to measure and analyze user kinematics, and a video feed of the user for a machine learning algorithm to analyze the user's motions. The primary driving force behind the AutoCaddie system is the machine-learning based AI. This machine-learning based AI system must have some form of existing data to extrapolate off, and due to time constraints, a pre-existing database will be used. For these purposes, GolfDB shall be utilized. For accurate and consistent comparison of live data to the database, a video feed of the user must support at least a 30 frame-per-second video stream of at least a 420-pixel resolution. Furthermore, since the user should practice their golf swings in a proper outdoor environment, the software environment must be constrained to a portable computer system, such as a laptop, which must be plugged in or have some form of steady charge available, as to not overly limit a user's use time.

Regarding the hardware, there are several constraints that should be put in place. First of all, to promote potential accessibility for users in-market, the total costs of the device should remain under 500 dollars. Equally as important, the design of the hardware sensor systems must be designed so as not to impede the movement of the user while being as accurate as possible. The IMU sensors must be secured on the user and must be immobile with respect to the user's arm. Additionally, IMU sensors are subject to drift, so the IMU sensor system must be periodically calibrated, or else data inaccuracies may accumulate and produce incorrect results. With regards to the physical setup of the IMU sensor system, direct cable connections to the computer for data processing can interfere with user swings, so the data communications must be constrained to wireless communications that can be received by the laptop or other data processor's technology. These communications must also be constrained to a given data transmission speed floor (chosen to be ≥100kbps), so that the AI can utilize a sufficient amount of data within the period of a user's swing action. Finally, in parallel to how the software's computer environment must be portable, the cameras for a video stream of a user must also be portable, as to allow a user to take the system to a desired location for training. The full list of constraints is as follows.

Software:

- Existing database as training reference.
- Video quality of ≥420p at ≥30fps.
- AI must be containable in a portable computer unit.
- Computer must have a constant energy source.

Hardware:

- Total costs must be < $500.
- IMUs must be secured on user and immobile with respect to user arm.
- User-mounted sensor system cannot restrict user swings.
- Wireless communication standards must be used and are receivable by computer.
- Video cameras must be portable and can directly connect to a computer.

2.5 Quality Analysis

2.5.1 User / Marketing Specifications

Affordability	< $500 price point
Battery Life	2 Hour Lifespan
Feedback speed	< 10 response generation time
Weight	< 5 pounds (On user)
Accuracy	> 90% feedback accuracy

Table 2: User/Marketing specifications of the AutoCaddie system that can be used to endorse the AutoCaddie system.

2.5.2 House of Quality

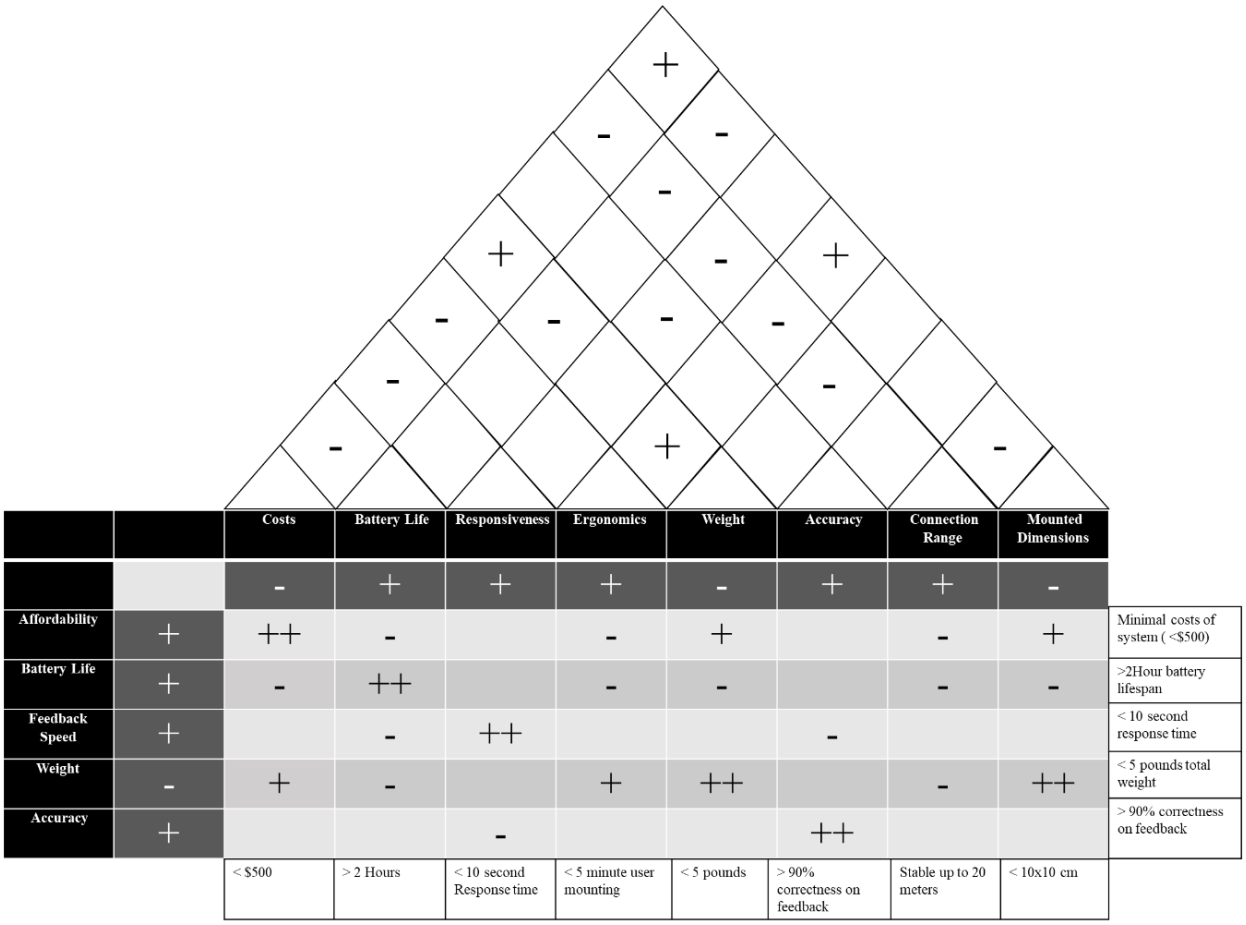


Figure 4: The house of quality analysis figure, demonstrating the relationships and overlaps between the engineering and user requirements and specifications.

As seen by the house of quality diagram, both the user/market specifications share some conditions, including that of battery life, weight, and accuracy. Regarding individual conditions of both user/market specifications and engineering requirements, both battery life and weight are the most influential. Increasing battery life requires either less powerful systems that draw less power, or requires the integration of a larger battery, thus increasing conditions such as weight and costs. Furthermore, reducing the weight of the system restricts the selection of both parts and overall design, possibly requiring the integration of more costly condensed application parts. Overall, most of the requirements or specifications are influenced by the hardware design.

Chapter 3: Project-Related Research

AutoCaddie is a project that demands knowledge of data acquisition's technical and physical aspects. Now that the goals, constraints, and high-level analysis are determined, it is possible to move forward with research toward the technology to be utilized by this product.

Before diving into specific research, it paints a stronger basis to reference previous examples of similar projects. By observing the methods and implementations of previous endeavors, we can shed light on some of the problems that may arise throughout the development process. Not to mention, it can help give a bit of creativity by introducing new perspectives to a similar topic.

As an overview, there are a few areas of interest that are worth exploring. AutoCaddie's primary selling point is automating the coaching process of golf and allowing the process to be more convenient. For the purpose of general information, it is worth investigating existing AI golf coach programs to determine different methods of implementation. For example, it is necessary to investigate if other products rely exclusively on software or introduce other physical means of recording data. Additionally, it is necessary to investigate technology that utilizes IMU data via physical body tracking to determine linearity or other gyroscopic data. Other useful examples of projects that can help gain primarily fall into the realm of neural networks, which will be explored later.

3.1 Existing Similar Projects and Topic Research

This project is not the first of its kind. There are other existing AI golf coaches that provide user feedback to help improve technique. Many of these products are sold at high prices, which takes away from the convenience of the system's design. To explore this topic in general, it is important to reference previous examples that have investigated similar topics.

3.1.1 Smart Coaching

Coaching is the method of providing feedback to a user for improvement in various tasks. This can be done with verbal instruction, replication, or, effectively, statistical analysis. The high-level explanation of AutoCaddie is having a virtual AI coach that provides useful feedback to the user in the form of processed data from a live video feed.

Generally speaking, a program, controlled by some governing method, is trained on data that is directly related to an area of improvement that a user is requesting. For golf, this can relate to driving down a field. For tennis, this can relate to an initial service motion. There are infinitely many examples of where it is applicable, but some of these products in action are as follows.

One example, coach2vec, [2] uses AI to understand the style of play for professional coaches in soccer. Its design gathers data from ball possessions, or periods where the ball is being controlled by the observed team and gathers a list of statistics collectively from the players to map similarities to specific coaches. For example, observing the

duration of possessions, on average, might signify a specific context of coaching style. The impressive aspect of this design is the usage of “k-Means” similarity to map soccer attributes to a matrix table and query specific details from coaches. In AutoCaddie, we need to establish a direct mapping between a specific training database to a live video feed. However, this process will not directly call for matrix decomposition due to the nature of the parameters. We can observe the behavior in a linear fashion and do 1-to-1 comparisons rather than query for related areas of interest.

Another example, Singlearity-PA, [3] utilizes a large database of baseball games to enhance predictive modeling. The use of neural networks, trained on extensive pitch-by-pitch Statcast data from several years, allows for a more accurate and versatile approach to predicting plate appearance outcomes. The purpose of this program is to counter the limitations of previous calculation-based models by accounting for large amounts of history data that can be overlooked by mere equations. As a result, it ends up outperforming previous result-guessing techniques. The purpose of AutoCaddie does not stray far from this concept. It utilizes a neural network to produce more accurate data than a linear algorithm could produce by a frame-by-frame analysis. Due to the sheer amount of training data, it has access to a broader range of references to classify input data, as well as has stronger predictive capabilities towards the input actions of a swing.

Taking topics from both of these projects, it is important to utilize a neural network to achieve fast and accurate analysis of a video feed. Where algorithms can be limited by an absence of edge-case factors in a specific equation, neural networks shine by referencing large quantities of training data to predict results. Having the GolfDB database of videos allows for accurate coaching in golf that would be limited by normal analysis alone.

3.1.2 AI Golf Coaching

There are many existing smart golf coaching products, mostly composed of software-based assessments. Some examples of well-established products are ALFA Swing, [4] 18birdies, [5] and Sportsbox, [6] which are all mobile app golf coaches. Additionally, there are many examples of research papers pertaining to the topics of computer vision, data analysis, and neural networks which are used throughout these programs. Of the three listed, notably all of them utilize solely video capture to produce feedback. Many of these products rely on the convenience of recording and advising through the same app. Although mobile app development is a consideration, for the sake of the neural network in question, AutoCaddie is planned to connect to a computer program with stronger cameras positioned around the user for precise data acquisition. Something that is lacking in these mobile programs is the reliability of the data, as different cameras present different framerates and image quality. ALFA Swing requires an iPhone X [7] or better to get accurate information, whereas AutoCaddie does not require anything outside of itself.

However, AI Golf [8] is unique in its research on self-training. As mentioned earlier, coaching can be executed in a variety of ways, replication being one of the primary methods. AI Golf establishes this connection and expands by directly comparing the user’s swing to a professional’s swing. The main difference between it and AutoCaddie

is that it establishes its training data by combining a professional input motion sequence with output human poses to map to the user for specific feedback. AutoCaddie will preprocess incoming data into a specific form to match the training data for a direct comparison and provide predictive output based on the comparisons made to the database. However, an important topic worth referencing is discrepancy detection, or the ability of a program to identify differences between two separate feeds. In AutoCaddie, the preprocessing step needs to be capable of not producing discrepancies, but if so, it needs to be capable of recognizing that the video is of a different style rather than observed values being incorrect. Otherwise, false negatives can be generated.

In terms of hardware-based golf coaching, not as many products exist. SMARTGOLF AI Coach [9] is an AI golf coaching system that creates feedback by observation of data through sensors attached to the head of a golf club. It simulates a swing through the use of an interactive video game and provides personalized feedback in real time in terms of ball trajectory, club face, and advice for specific swings such as slices and hooks. Although this technology is useful for coaching with spin and club face, we believe that this is accomplishable with a rear-facing camera and computer vision analysis. Therefore, this type of hardware is unnecessary to the finished product.

3.1.3 Real-Time AI Analysis

On another note, it is necessary to utilize the correct neural network model in order to provide proper real-time analysis. There are multiple ways to train a system such that it is hyper-specific to recognizing select parameters, which is necessary to create a smart golf coach AI.

One example of this is the usage of “Reservoir computing” [10] with image pattern recognition, but it is useful in its property of short-term memory. Projects have been instigated under this concept, such as experimentation with low voltage dynamic memristors, which naturally responds to low-voltage electrical pulses to exhibit short-term memory effects. However, due to the nature of AutoCaddie, exhibiting a short-term memory system is not something that is necessary, since it will be observing all aspects of the data acquisition process and comparing it to a database. Nevertheless, understanding appropriate models and examples as to why specific use cases may yield unwanted results is important for the aspect of this project.

An application of real-time neural network processing is the Guitar Amplifier Emulation with Deep Learning. [11] This product explores the development and evaluation of deep neural network models for simulating audio distortion within guitar amplifiers. Notably, it explores two different models of interest, one being the recurrent neural network that was introduced in the last paragraph. The benefit of using this model is its boost in processing speed. However, a version of “WaveNet” was also utilized, which is a deep generative neural network used specifically for waveforms - which was developed by DeepMind. [12] It is designed to optimize hyper-parameters such as layer depth and activation functions. This model worked well when a large layer version was implemented. AutoCaddie aims to follow a similar model structure as WaveNet in that it can focus on specific hyper-parameters of a golf drive and provide convincing feedback. However, generative AI is a

stretch of a topic since it generates new data given input feeds, whereas the goal of this project is to evaluate the given data.

Closer related, another project introduces a deep convolutional neural network for profile analysis of big powder diffraction data - known as the Parameter Quantification Network (PQ-Net). [13] It can analyze live data from powder X-ray diffraction patterns from multi-phase systems and create predictions for relevant information such as scale factors, lattice parameters, among others. Most notably, the system's performance was evaluated across different test datasets, and it was concluded that the PQ-Net provides faster and more accurate analyses than previous algorithmic methods. The network itself is designed as a deep convolutional neural network, which is designed well for image-related tasks. AutoCaddie mirrors this concept very closely with analyzing live image data and providing insightful feedback, so this architecture is one that can be referenced during the design of the AI. Specifically, PQ-Net is trained via patterns with known parameters and learns to predict the expected behavior. Then, when given live data, the same process is used to create conclusions about the data. Many other low-level concepts from this project, such as minimizing the mean absolute error (MAE) loss function when training, incorporating dropout layers to prevent overfitting, and implementing deep ensembles are all important characteristics of improving performance in an algorithm as large as AutoCaddie's algorithm aims to be.

Overall, understanding differences between neural network models and their applications can help narrow down similar concepts to be used within generating the design. There is no correct method of creating a deep neural network, so long as it is trained correctly. That is where models such as PQ-Net shine, in that they are designed to optimize hyperparameters, and the mathematical methods can be reused within the AutoCaddie project.

3.1.4 Inertial Measurement Unit Joint Kinematics Modeling

Regarding the use of IMUs for the modeling of joint kinematics and angles between limbs as a supplement to AutoCaddie's artificial intelligence, there are several existing research articles and applications that exist, which highlight the benefits and existing methodologies for such practices. In the article by Versteyhe et al., [14] the focus lies on the utility of quaternions in biomechanics, offering a four-variable representation of orientation that avoids singularities and simplifies numerical procedures. The article outlines the background of the development of quaternions, which found themselves in use due to their improvements over Euler orientation vectors. Particularly applied in modern biomechanics, quaternions aid advancements in computer technology and motion capture by providing more robust means of calculations.

Versteyhe et al. sets the stage for the article by Challis et al. [15] where the development of a method using IMUs for knee joint kinematics is discussed. IMUs provide a portable and user-friendly alternative to traditional motion analysis methodologies. The method involves sensor calibration, placement on limb, and the application of quaternion math. Overall, Challis et al. showcases the practicality of IMUs in capturing joint kinematics

accurately. The validation experiments demonstrate the method's potential for clinical and scientific evaluations.

Adding to this narrative, Rahman et al. [16] introduces a wireless wearable sensor system utilizing IMUs and the Madgwick filter-based algorithm for joint angle measurement, focusing on the arms. The algorithm proves effective in trials, outperforming other systems and showcasing resilience to external acceleration. The study acknowledges limitations and points towards future directions, including real-world assessments and the development of a comprehensive wearable system for total body joint monitoring.

Together, these papers paint a comprehensive picture of the intersection between quaternions and IMUs in biomechanics. Quaternions, as highlighted by Versteyhe et al., provide a robust way to represent orientation, addressing challenges posed by other methods. IMUs, as discussed in the work by Challis et al. and Rahman et al., offer a practical solution for capturing joint kinematics, making these technologies a powerful combination.

The existence of these methods and technologies using IMUs to measure joint angles is driven by the need for accuracy, portability, and user-friendliness, crucial factors in applications such as rehabilitation or other applications requiring kinematic analysis. The advantages of quaternions, as mentioned by Versteyhe et al., align with the need for clear and unambiguous orientation representation. The IMUs, showcased by Challis et al. and Rahman et al., address the limitations of traditional motion analysis labs, providing a solution that can be easily applied in clinical settings.

The promising results from the wireless wearable sensor system designed by Rahman et al. further affirm the potential of these technologies for joint angle measurement in rehabilitation scenarios. The convergence of these advancements underscores the continuous evolution of methods and technologies, offering innovative solutions for precise and practical biomechanical measurements with applications ranging from rehabilitation to scientific research. Overall, the articles provide a good foundation for the intention in using IMU kinematics analysis using quaternions for measuring user movements of the arm.

3.1.5 Effects of Distractions and Stimuli During Swing Action

The research conducted by Leo Roberts et al. [17] on skilled golfers in this study sheds light on the impact of distraction and off-task thoughts on golf performance. While expert athletes have been shown to manage irrelevant thoughts during motor actions, this study focused on how such distractions during the preparation phase affect later performance. The results indicated that, generally, the golfers were able to maintain their performance levels. However, a notable finding was the control of distance for the shortest shots deteriorated when preparation was disrupted by secondary tasks. The analysis revealed that this interference led to both cognitive mistakes, such as poor decision-making, and execution mistakes, like poor timing. This suggests that off-task thoughts during the preparatory phase can lead to a range of errors by disrupting the organization of thought processes essential for effective action. Overall, this study uncovers an intricate

relationship between off-task thoughts and motor skill failure than previously recognized, emphasizing the importance of mental focus and preparation in golf performance.

Additionally, the findings of Timothy Fulton et al. [18] highlight the significant impact of visual distractions on golf putting performance and the protective role of a successful execution of Quiet Eye (QE) behaviors. The study revealed that longer QE periods were associated with more successful putting, indicating that anxiety can potentially undermine both QE and overall performance. However, the research showed that training in QE can act as a buffer against anxiety's negative effects on performance. Notably, the study also unveiled an additional advantage of effective QE behaviors – it mitigated the detrimental impact of camera flash distractions on putting performance. The elongation of the QE period during distracted conditions suggests that QE plays a pivotal role in the planning of motor actions, as supported by previous research. It is plausible that maintaining similar levels of putting performance in trials with and without distractions was due to the extended time provided to the brain for planning the putting action when distractions were present, underscoring the importance of cognitive focus in the face of visual interruptions during golf putting.

3.1.6 Multi-Modal Feedback Training

The project “Optimal Multi-Modal Sensory Feedback to Maximize Motor Learning Efficiency” led by Saba M. Hoesseini [19] integrates several forms of sensory input to analyze and provide feedback to a user and provides a collection of multi-modal feedback forms in order to study the effectiveness and response by a user. Intended for rowing sports applications, this system collects sensory data of user kinematics and speed of motion, as well as user force application on the machine during training. Following the processing of this data, the given metrics are used to analyze user performance and give multi-modal feedback of spatial, temporal, and force types.

This project serves as an example of sensor data collection for the provision of multi-mode feedback. As the project seeks to optimize motor learning efficiency during training, the outcomes and discoveries of this project can be applied to AutoCaddie. By incorporating relevant insight of the effects and means of multimodal feedback, whilst accounting for the optimal time for feedback of AutoCaddie users, more effective feedback and guidance can be designed for the users of AutoCaddie.

3.1.7 Putting It All Together

Overall, there are many existent technologies that give insight to some of the goals AutoCaddie aims to accomplish. Whether it be in terms of general coaching with AI assistance, custom-tailored golf feedback, or even optimizations via deep neural networks, there are many applicable examples. However, AutoCaddie will combine the best aspects of all of these areas in order to deliver the highest performance result.

Having the correct feedback given by an AI is necessary for the system to function properly. Creating the illusion that a system is personalized to the same level of feedback as a professional coach will help draw out the best results. A similar concept to this is the Turing Test [20] which is a physiological study proposed by Turing in 1950 in which a

machine passes if it can convince a person that it is not a program, but rather a real person. If AutoCaddie can establish accurate feedback on major components of the golf stroke, then the effectiveness of the product will rise.

This accuracy will be determinant on the effectiveness of the data analysis system. To boost results, AutoCaddie will implement a deep neural network that is trained on a collection of proper golf swing technique videos. By training a model on correct data, and developing consistent evaluation metrics, we can feed live data into the model and have it smartly calculate the given statistics and improvements.

As an additional means of feedback to supplement the feedback provided by the machine learning artificial intelligence model, IMU systems can be used to provide feedback regarding arm kinematics via quaternion data. Existing research and applications suggest that quaternion data from IMUs can be used to determine the effective kinematics and joint angles between limbs. These applications extend into fields such as rehabilitation and training examinations. As such, IMU quaternion data analysis can be used as a valid means of providing additional feedback to the users of AutoCaddie.

With respect to the implementation of the given feedback, the previous research in **Section 3.1.5** indicates that sustained cognitive focus is critical for performance, and that distractions can inhibit a golfer's ability during their swing preparation and swing action. As such, it can be inferred that forms of feedback, such as continuous stimulus to indicate correctible behavior during swing preparation may overall degrade the user's performance during training. Given this information, feedback should be reserved for intermediary stages between individual swings.

The strongest means of implementation can be via both hardware and software. Mainly, cameras can be used to capture action sequences of the user during a swing, in a similar fashion to existing phone coaching applications. However, having sensors also positioned on the user can help with synchronizing the data, as well as capture temporal data that may be less accurate taken from a 30-fps video stream. Therefore, AutoCaddie is targeted towards providing accurate data using the correct means of implementation.

3.2 Overall Structure and Relevant Technologies

3.2.1 System Design Overview for Technology Research

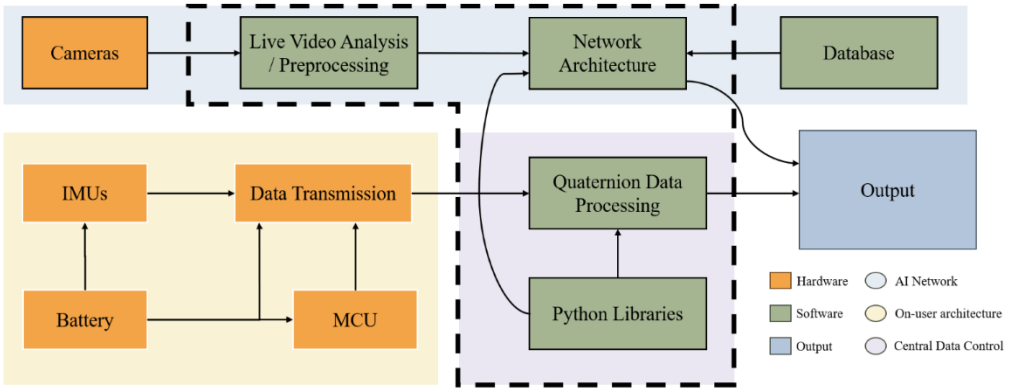


Figure 5: Diagram demonstrating the relationship between all researched components.

AutoCaddie comprises two main subsystems: the camera system and the IMU system. Each of these systems contains components of hardware and software and conjoin to provide the user with feedback pertaining to their golf swing.

The camera system captures live video data, which is then transmitted to a computer for further processing. The data undergoes frame extraction and preprocessing to prepare it for utilization within a neural network. This neural network is trained using a comprehensive database of proper golf technique swings, enabling it to analyze and evaluate the user's golf swing captured by the camera.

Simultaneously, the IMU system, which is affixed to the user, records spatial and rotation data in the form of quaternions. This system operates on battery power and transfers the collected data to a MCU. The MCU acts as an intermediary, forwarding the quaternion data to the computer with specific labeling. Within the computer, sophisticated quaternion data processing takes place, analyzing every timestamp to gain insights into the user's arm linearity during the swinging motion.

The integration of quaternion data processing, neural network operations, and frame preprocessing is facilitated through various Python libraries, providing a cohesive and efficient environment for computational tasks. These libraries enhance the connectivity of the different components within the system.

Ultimately, the results derived from each system are compiled and presented to the user through a friendly graphical user interface. This serves as a comprehensive feedback mechanism, which offers insights for the user's golf swing performance and provides valuable information for skill improvement.

The overall architecture of the AutoCaddie system can be tailored in various ways to accommodate different user feedback mechanisms. Since AutoCaddie is designed with a machine learning interface for user feedback, the architectural variations primarily

revolve around the system's observation of the user and the impact of the user's actions. The primary architectural modifications involve the inclusion of specific components, particularly video cameras and user guidance components. Based on these considerations, three potential architectures for the AutoCaddie system are as follows:

3.2.1.a Single-Camera Video Feed

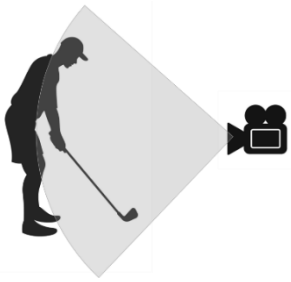


Figure 6: Graphical representation of single camera view target.

One of the most straightforward architectures for the AutoCaddie system involves utilizing a single camera input for capturing video footage of the user. This architecture, along with all subsequent architectures, will retain the IMU sensory system as is, employing wireless communication to interface with the artificial intelligence. The single-camera approach streamlines the process and reduces the volume of data to be processed, thereby enhancing processing speeds by reducing the volume of data that must be processed. However, the scope of data that can be analyzed by machine learning artificial intelligence is correspondingly reduced. In general, this architecture design prioritizes lower costs and optimal portability.

The prioritization of lower costs and optimal portability maximizes the potential scope of users that may seek to utilize AutoCaddie. By reducing costs, the financial barrier to entry is reduced, allowing more users to afford the system. Furthermore, the increase in portability reduces the necessary setup time for the system and allows the users to more easily take the system where they desire.

3.2.1.b Dual-Camera Video Feed

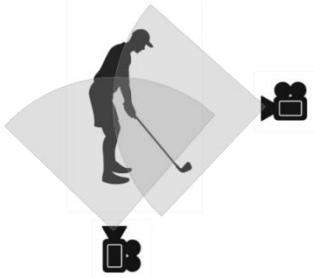


Figure 7: Graphical representation of single camera view target.

The second architecture of the AutoCaddie system introduces two cameras for capturing video footage of the user. This enhanced setup provides a more comprehensive perspective of the user's swing motion, enabling the artificial intelligence to analyze the swing with greater depth and accuracy. However, this doubling of data inevitably increases the computational demands on the system, potentially leading to slower

processing speeds. Despite this drawback, the two-camera architecture strikes a balance between data availability and portability, offering a cost-effective solution for those seeking a more detailed analysis of their swing mechanics.

To further explore the advantages of this architecture, it's important to recognize the enhanced data acquisition capabilities. With two camera inputs, the system can capture a wider range of motion at different angles, allowing for a more thorough examination of the user's swing technique. This comprehensive data set enables artificial intelligence to identify patterns of movement and areas of feedback relevant to each viewport of the user, which a single camera setup could not achieve. This deeper level of analysis can provide users with more specific and actionable feedback, ultimately improving their swing performance.

3.2.1.c Dual-Camera Video Feed with Golfer's Training Ring

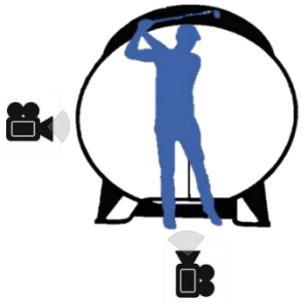


Figure 8: Graphical representation of a dual-camera setup with a training ring.

The third architecture of the AutoCaddie system builds upon the two-camera system, incorporating a training ring that serves both the user and the artificial intelligence. The user can utilize the training ring to ensure their swing pathing is correct and to develop proper muscle memory for swing path form. Simultaneously, artificial intelligence can analyze the user's path in relation to the ring and calculate variances to provide feedback. This architecture, while offering the most comprehensive user training, comes at the expense of increased cost and reduced overall portability.

Despite the advantages of a more robust training methodology using the training ring, this architecture does come with some drawbacks. The inclusion of a training ring increases the overall cost of the system, making it less accessible to some users. Additionally, the additional hardware component reduces the system's portability, making it less convenient for users who require a portable training solution.

3.2.1.d Architecture Selection

For the purposes of the AutoCaddie system design, the dual-camera video feed system will be selected. This system will provide the best balance of data quality to portability. The dual video feed system will provide the system will two perspectives of the user for data analysis, allowing for the system to provide analysis for multiple aspects of the user's performance. Regarding the lack of the implementation of the golfer's training ring, while the ring does assist the user in developing positive swinging habits, the ring only interacts

with the software as an additional mode of comparative analysis and does not produce any form of unique feedback. Furthermore, its inclusion would also increase costs, and would require the transportation of more materials. Regarding the inclusion of video cameras, the selection of video camera technology must be made in order to maximize the efficiency of the machine learning processing schema, as well as to best fit the video data to matched data.

3.3 Relevant Technologies: Computer Vision and Neural Networks

Video data streams play an important role as essential inputs for machine learning algorithms, particularly in applications involving real-time analysis of dynamic events. The establishment of a robust connection between frames extracted from live video data and frames sourced from a separate database enables the seamless integration of real-time information through an artificial intelligence system. In this context, cameras leverage the capability of comparing data keyframes extracted from an ongoing video data stream available in a training dataset. The feedback generated by artificial intelligence is a result of these intricate comparisons, facilitated by the pre-existing knowledge gained through prior training experiences. This process allows for the continuous and automated analysis of live events, showcasing the practical application of machine learning in extracting insights from video data.

3.3.1 Video Cameras

3.3.1.a Overview, Comparison, and Selection of Component Type

Video cameras have been chosen as the primary motion capture system for the AutoCaddie project's machine learning analysis. While lidar and ultrasonic sensor technologies are available and can be utilized for capturing user motion and posture at discrete moments, these technologies are not aligned with the overall requirements of AutoCaddie's design systems. Lidar systems rely on point-based 3D imaging, but the lidar scanning process is considerably slower when compared to video imaging, which does not meet the timeliness requirements of machine learning applications.

Ultrasonic sensors can be employed to determine the general movement and positioning of objects within a 3D space; however, the resolution of potential spatial imaging provided by ultrasonic sensors does not meet the precision demands for data analysis. Additionally, both lidar and ultrasonic sensor data will necessitate extra processing and produce data formats that are not supported by existing databases. Consequently, the preferred choice for data acquisition in the context of machine learning systems is video cameras that allow for generic video streaming, as they align more closely with the project's requirements for real-time, data capture and compatibility with existing databases, where keyframing must be used.

The most critical characteristic for the cameras to meet is live data streaming capabilities. The video data stream must be able to be streamed directly to the machine learning AI program for it to process the video stream data. For the video data streams to be effective, the video data streams should be at a minimum of 420-pixel (p) resolution at a 30 frames per second (fps) speed. The portability of the cameras must also be a feature, as the AutoCaddie system must be able to be set up at a region of the user's preference. Furthermore, the costs of the cameras must be minimized to reduce the market barrier costs for user access.

3.3.1.b HP 320 FHD

The HP 320 FHD digital webcam device with CMOS photosensor technology. With a 0.25in lens, the camera supports a 1080p resolution at a 30fps speed. Furthermore, the camera uses USB-A connectivity, so wired streaming is stable and limited power consumption is a non-issue. This camera is intended for webcam streaming purposes, so it is low-profile, and can be retrofitted for live streaming to an AI program. The total cost of this camera comes to $28.51.

3.3.1.c RunCam 2 FPV

The RunCam 2 FPV camera is a digital sports action camera. The camera uses CCD photosensor technology and uses a 1x optical zoom magnification. The camera supports a 1080p resolution at 60fps. As the camera is marketed for mobile robotics purposes, it is inherently portable. Further, the camera features Wi-Fi connectivity, allowing for a wireless video stream to a computer. The total cost of the camera comes to $99.99.

3.3.1.d WOLFANG GA100

The WOLFGANG GA100 is a digital sports mounting camera. The camera uses CMOS photosensor technology and uses a 1x optical zoom magnification with a 170-degree viewport. The camera supports a 1080p resolution at 60fps. As the camera is marketed for mobile dashcam and webcam purposes, the camera features Wi-Fi connectivity, allowing for a wireless video stream to a computer. The total cost of the camera comes to $49.99.

3.3.1.e Hardware Comparison Table

Factor	**HP 320 FHD**	**RunCam 2 FPV**	**WolfGang GA100**
Connectivity	Wired USB-A	Wi-Fi	Wi-Fi
Resolution	1080p	1080p	1080p
Speed	30fps	60fps	60fps
Portable	Yes	Yes	Yes
Cost	$28.51	$99.99	$49.99

Table 3: Hardware comparison table that compares video camera candidates.

3.3.1.f Conclusion

The selected video camera for the AutoCaddie system is the HP 320 FHD. This video camera was chosen due to its connectivity and cost characteristics of the device. The HP

320 FHD is roughly one-fourth the price of the RunCam 2 and is roughly one-half the price of the WolfGang GA100. This optimization of price reduces the total costs of the system, making it more available at market entry price for the user. Furthermore, regarding connectivity, a USB connection to a computer processing the video guarantees a more stable and faster data stream, as well as the fact that the camera does not need to rely on limited battery power. The expected video resolutions of each video camera are identical, and the limited 30fps video speed quality does not pose an issue for the AI processing algorithm, as it the machine learning based AI will be trained off of an existing database of videos of similar frame speeds. Should more keyframes be needed, frame interpolation algorithms can be implemented.

The video camera systems should both feed into the central computer where the primary data processing will occur. The computer system should be able to interface with both of the camera video feeds. These two video feeds must then be consolidated to a single processing schema of the machine learning algorithm, from which the video feed is analyzed with respect to an established analyzation process.

3.3.2 Live Video Analysis

To extract valuable insights from the video streams, real-time video analysis plays a crucial role in AutoCaddie. The system relies on capturing a continuous stream of live data covering a user's golf swing, which is then segmented into distinct actions. This segmentation is a fundamental step, as it allows for focused analysis of specific moments within the swing sequence.

Following the segmentation process, various preprocessing techniques are applied to the data. These techniques are essential for preparing it for transmission to a neural network, ensuring that the input data is in a suitable format for accurate analysis. The preprocessing steps may include tasks such as noise reduction, image enhancement, and normalization. By refining the data through these methods, the system can enhance the quality and reliability of the subsequent analysis.

While the intricate details of the neural network architecture will be discussed in **Section 3.3.3**, it is important to emphasize the methods used to ensure the accuracy of its calculations. This accuracy is pivotal in generating precise insights from the golf swing data. Notably, these efforts are essential to guarantee that the coaching and feedback provided by AutoCaddie are based on dependable analyses of the user's swing, contributing to an enhanced overall user experience.

3.3.2.a Frame Extraction

For AutoCaddie to achieve successful video analysis, it needs to be capable of frame extraction. In digital video processing, a video is a sequence of individual frames displayed in rapid succession, which creates the illusion of continuous motion. Each frame is an image that captures a specific instance of time. In the case of AutoCaddie’s live video feed, these frames capture images that represent the user across all instances of time during a golf swing.

The process of converting videos into frames involves breaking down the video file into individual images. Each frame represents a distinct snapshot of some action, enabling precise examination of the golfer's movements. These frames are then processed and analyzed using various techniques to extract information on swing trajectory, form, among other things. By dissecting the video stream into frames, AutoCaddie can precisely pinpoint the moments that matter, which helps for accurate assessment of the motion.

The process of capturing each frame separately from a video stream facilitates the application of preprocessing algorithms on visual data. Each frame within a video can be represented as a 2D matrix of pixels, with each pixel assigned a numerical value corresponding to its color intensity. This representation enables algorithms to work with visual data in a format conducive to manipulation.

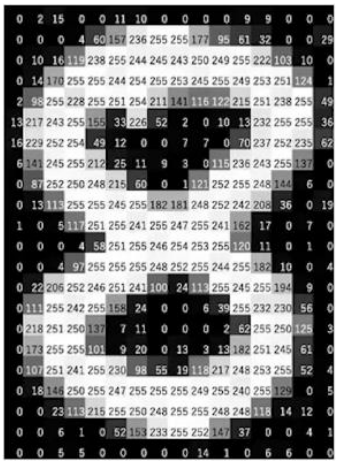


Figure 9: An image represented as a 2D array of numbers. The value in each matrix position represents the grayscale equivalent on a scale of 0 to 1. Referenced via [21] .

In this 2D matrix, the rows and columns correspond to the height and width of the frame respectively. Each element in the matrix represents the exact hexadecimal color equivalent of the corresponding pixel in the image. Hexadecimal is represented in a 16-bit format, where every group of 4 bits (or 1 byte) are equivalent to a specific color value. The first 3 bytes compose the levels of Red, Blue, and Green, where the last byte represents the transparency of the image.

By breaking down the visual information into these individual pixels and numerical values, algorithms can perform various operations on the data. In the context of AutoCaddie, these operations include object recognition, and feature extraction.

3.3.2.b Computer Vision

The term given to breaking down visual information from pixels within images in regard to pattern detection is computer vision. Computer vision is pivotal for the success of AutoCaddie, as it can drastically increase the efficiency of the software. At its core, it involves the extraction of meaningful information from frame data. Expanding, many different algorithms and techniques can be utilized to interpret entire video streams. In

this section, the fundamentals of computer vision will be elaborated upon, as well as its transformational potential.

Object detection is a primary research direction in the field of computer vision. Literally, object detection is the process of applying algorithms to an image to distinguish a particular object against its background. This process used to involve traditional detection algorithms, involving pre-processing, window sliding, feature extraction, selection, classification, and post-processing. However, it yielded high complexities and time investments to complete this process and produced results with no pertinence.

In 2012, Krizhevsjy [22] proposed an image classification model harnessing a convolutional neural network (CNN). This model, known as ImageNet, was subjected to rigorous evaluation in an image classification competition, where it demonstrated its superiority over traditional object classification methods by surpassing them by over 11% accuracy. This served as a catalyst for extensive research into deep CNNs for classification tasks.

Moving on, in recent years, the field of computer vision has shifted to this deep-learning approach. Three prominent categories of deep learning models have played large roles in reshaping this industry, namely CNNs, the “Boltzmann family” which includes both Deep Belief Networks (DBNs) and Deep Boltzmann Machines (DBMs), and Stacked Autoencoders (SdAs). Each category exhibits distinct characteristics, advantages, and limitations.

First, as referenced by A. Voulodimos et al., [23] CNN is a prominent topic in deep learning, especially for dealing with grid patterns in images. CNNs are designed to autonomously find spatial hierarchies of features, and further to distinguish patterns among them. The architecture of a CNN is constructed upon sophisticated mathematics, and features three fundamental building blocks: convolution, pooling, and fully connected layers.

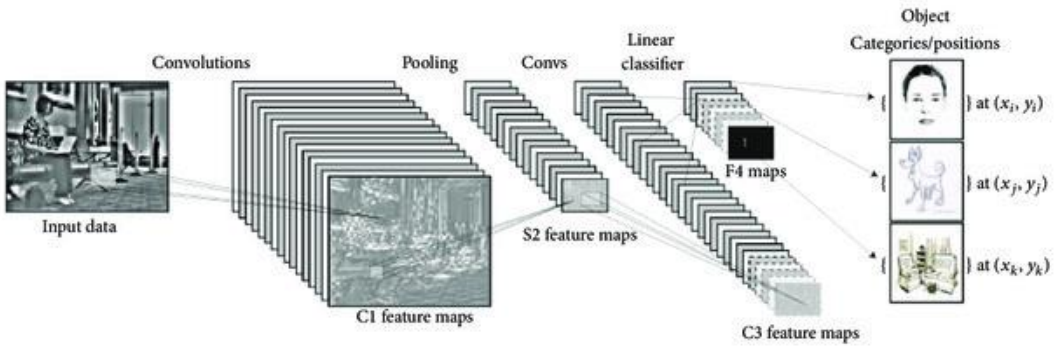


Figure 10: An example of a CNN used for object detection within an image. The image is split into different convolutions by extracting features. Then everything is pooled to refine the parameters. After a while, the features are classified. Referenced via [23] .

The convolution layer takes on the task of feature extraction. By representing an image as a 2D grid, an additional small grid of parameters, known as a kernel, is applied at every position within the image using matrix multiplication. This operation renders CNNs adept at image processing because features can manifest at any location within the image grid.

The pooling layer works synergistically with the convolution layer to refine and abstract these features. The pooling layer operates by down-sampling the spatial dimensions of the input data, reducing its resolution. This is a critical step for preserving essential information while progressively simplifying the operation.

The fully-connected layer is the culminating phase of the CNN architecture. It is responsible for mapping the features into a conclusive output, often in the form of classification. Through this layer, the CNN transforms its hierarchical understanding of spatial patterns into a final decision or classification.

A primary benefit of CNNs is the fact that they learn their features from the dataset provided, removing the need for manually crafted features. Their significance is showcased through object detection. However, a drawback of these networks is that they have a heavy reliance on labeled data for training, which introduces data preprocessing steps.

Second, the “Boltzmann” family of models presents a different approach to hierarchical representation learning. DBNs excel in unsupervised learning scenarios, obviating the need for labeled data during the initial training. However, their computational cost and limitation in handing two-dimensional structures in input images pose challenges.

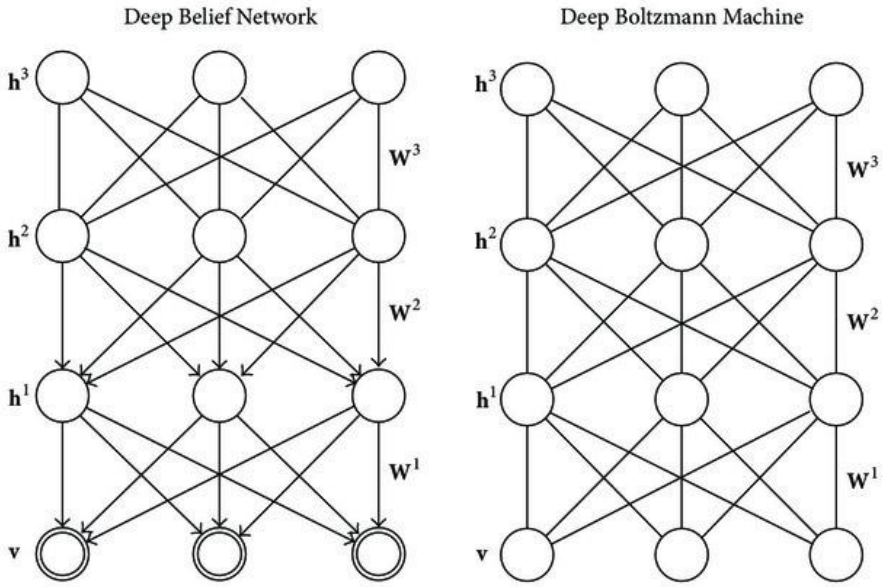


Figure 11: Deep Belief Network (DBN) and Deep Boltzmann Machine (DBM). In the DBN, the top two layers form an undirected graph. In a DBM, every connection is undirected. Referenced via [23] .

At the center of both DBNs and DBMs is the foundational Restricted Boltzmann Machine (RBM). RBMs are generative stochastic neural networks. They form bipartite graph, enabling more efficient training algorithms such as gradient descent. RBMs excel in extracting intricate hierarchical representations from data.

DBNs are probabilistic generative models that utilize RBMs as a layered structure. DBNs initialize their deep network efficiently by progressively refining hierarchical representations through stacking RBMs. This facilitates the extraction of complex features from the training data. Thus, this addresses the manual challenges of parameter selection, and eliminates the need for labeled data during the training process. However, DBNs encounter computational challenges and may overlook the two-dimensional structure of input images.

DBMs differentiate themselves by featuring undirected connections between all layers of the network. This is different from DBNs, where the top two layers form an undirected graph. The distinct advantage of DBMs lies in their ability to capture intricate representations of input data across multiple layers. Additionally, they are suitable for both unsupervised and supervised learning, making them flexible with diverse tasks. Notably, DBMs are set apart in the ability to handle uncertainty within inputs. However, similar to DBNs, a drawback of DBMs is their large computational cost.

Third, SdAs utilize autoencoders as their foundation. An autoencoder is trained to encode input data into a representation that facilitates accurate reconstruction. The training process minimizes reconstruction errors, ensuring that the output closely mirrors the input. The essence lies in learning features from the data, either by projecting inputs into principal components or, in the case of nonlinear hidden layers, capturing multimodal aspects of input distributions.

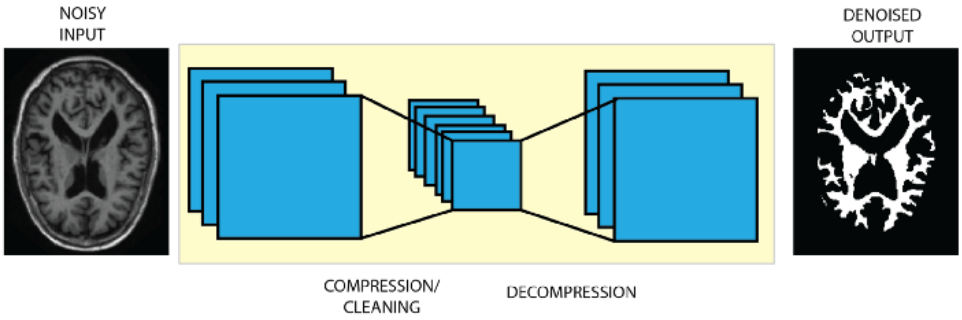


Figure 12: A diagram of denoising an image using a SdA. Referenced via [24] .

Denoising autoencoders introduce a corruption process to the input, challenging the model to encode the uncorrupted input while undoing the effects of the applied corruption. This stochastic approach involves predicting corrupted values from uncorrupted ones after the data has been applied with noisy transformations. Thus, this becomes a powerful tool for unsupervised pretraining of deep architectures.

SdAs create a deep network by feeding the latent representation of the layer below as input to the current layer. The unsupervised pretraining occurs layer by layer, with each

layer trained as a denoising autoencoder. After the process is completed, the network undergoes fine-tuning, which is often supervised by the developer. While DBNs often exhibit superior performance, comparative studies reveal instances where SdAs prove to be competitive. Plus, the adaptability of autoencoders in layer parametrization stands out compared to the other models.

To directly compare these three deep-learning approaches to applying computer vision for object detection, the chart below summarizes each model's advantages and disadvantages.

Model	**Advantages**	**Disadvantages**
CNN	• Feature Learning: CNNs excel at automatically learning hierarchical features from data, making them highly effective for image-related tasks. • Spatial Invariance: The convolutional and pooling layers provide spatial invariance, allowing CNNs to recognize patterns irrespective of their position on the input. • Pretrained Models: Pretrained CNN models on large datasets offer transfer learning advantages for specific tasks, requiring less training data.	• Computational Demands: Training CNNs can be computationally intensive, demanding substantial resources. • Interpretability: The internal representations learned by CNNs may lack interpretability, making it challenging to understand how and why certain features are detected.
DBN / DBM	• Unsupervised Learning: DBNs and DBMs can perform unsupervised learning, leveraging unlabeled data for feature extraction before fine-tuning for specific tasks. • Capturing Complex Representations: These models can capture multiple layers of complex representations, making them suitable for hierarchical feature learning.	• Computational Cost: Inference in DBNs and DBMs can be computationally expensive, especially in joint optimization for large datasets. • Limited Applicability in Computer Vision: DBNs may struggle with the two-dimensional structure of images, affecting their performance in computer vision tasks. • Challenges in Optimization: Optimizing DBNs involves challenges, such as potential poor local optima and difficulties in further optimizing the network based on maximum likelihood training approximation.
SdA	• Flexible Parametrization: Autoencoders allow almost any parametrization of layers, offering flexibility in architecture design. • Unsupervised Pretraining: SdAs can be pretrained in an	• Not a Generative Model: Unlike generative models like RBMs and DBNs, SdAs do not correspond to a generative model, limiting their ability to

	unsupervised manner, making them adept at learning hierarchical representations from unlabeled data. • Competitive Performance: Stacked Denoising Autoencoders can demonstrate competitive performance, particularly in comparison with Deep Belief Networks.	draw samples for checking learning outputs. • Reconstruction Error Limitation: The optimization process in SdAs focuses on minimizing reconstruction error, which may not guarantee successful compression for all inputs.

Table 4: A direct comparison between three separate deep-learning models applied towards object detection using computer vision.

Overall, CNNs demonstrate superior performance in meeting the specific requirements of the AutoCaddie project. Notably, CNNs excel in image processing tasks, precisely suited for the analysis of video frames to identify users and track their golf club swing sequences. Their robustness in handling spatial features removes the requirement for precise camera placement, so long as the user remains within the image dimensions.

In contrast, the limitations of DBNs, DBMs, and SdAs render them unsuitable for the project's objectives. Both DBNs and DBMs exhibit suboptimal performance when analyzing 2-dimensional image data, a critical requirement for precise image analysis. Additionally, the non-generative nature of the SdA approach renders it useless for predictive calculations essential in tasks such as object detection.

On a separate note, the adoption of CNNs creates the necessity to implement data preprocessing algorithms for image labeling and optimization. The following sections explore comprehensive research on the video preprocessing algorithms integrated into this system. Thorough investigation of existing technologies is imperative for this project's success, ensuring that the collected data can be analyzed with precision and performed quickly.

3.3.2.c Depth Tracking

Firstly, by pivoting two distinct cameras around the user during the swing sequence, we can gather data comprehensively. However, as the cameras were selected, additional research has been conducted on the importance of depth tracking within the video feed. Depth tracking refers to the process of capturing the three-dimensional positions of specific points within data or a given space. However, within the scope of the AutoCaddie project, where computer vision algorithms can detect a person and golf club, this technology is not necessary. However, it still provides useful investigation to understand the technology.

Soonchan Park et al. [25] performed a depth tracking technique that involves the implementation of depth tracking cameras at a hardware level to establish key points throughout the recorded swing sequence. At a high level, this method utilizes pose analysis, where the depth tracking cameras precisely track the movements and positions of various body parts during the sequence. This technique utilizes the Swing Analyzer (SWAN) system for pose analysis in golf. It uses a depth camera to estimate the 3D

positions of various joints during the swing, which contributes to a novel human pose estimation algorithm. This incorporates regression techniques to accurately localize 14 joints within the golfer's body. However, a concern presented by the study is that the depth tracking within the camera contributed to slower recording speeds, which did not coincide well with the fast swing of golfers.

Within the scope of the AutoCaddie project, comprehensive recording of the entire swing sequence is an established requirement. **Section 3.2.2** specifies that the video camera needs to possess the capability to maintain precise synchronization between the recording speed, measured in frames per second, of the live video feed and the selected training video database. This is necessary to ensure consistency and accuracy in the analysis of the captured swing sequences.

Additionally, it is important to recognize the existence of other technologies that render this research obsolete in this scope. Particularly, the advancements in action sequencing and computer vision, which will be elaborated on in consequent sections, provide more accurate results when analyzing the user data. Therefore, after careful consideration, it is not necessary to provide depth tracking within the video feed, as it is an extraneous mechanism that does not contribute extra information to the system.

3.3.2.d Edge Detection

Another popular research topic with neural networks is edge detection. Edge detection involves identifying and locating edges or boundaries in images. In the context of AutoCaddie, this is important in the context of preprocessing data frames in order to increase performance of the neural network. Being able to detect the outline of a person and separate them from an image background can help reduce the number of pixels being compared through the convolutional process. According to B. Tian and W. Wei, [26] there are various algorithms and techniques used for edge detection, ranging from classical methods to advanced deep learning approaches. The following paragraphs expand on some of these techniques, and weigh factors that attribute each method to this project.

First-order and second-order edge detection operators play a pivotal role in identifying small changes within an image. Some examples of this include between objects and backgrounds, separate regions of the same background, and primitive elements. These operators fall into two categories, first-order and second order. First-order operators focus on finding the derivative of the image's gray change, which makes them highly sensitive to drastic changes. An example of this is the Canny algorithm, which offers versatility by giving resilience against noise interferences and has the ability to identify genuine weak edges.

Traditional edge detection is a sub method of image segmentation. This topic can be split into several subjects. Firstly, edge detection involves extracting edge pixels, whereas edge enhancement focuses on intensifying the contrast between the edge and its background, enhancing the visibility of the edge. Additionally, edge tracing is a technique employed to collect edge pixels into a coherent list. The definition of an edge can vary based on specific contexts, with the ideal step edge being one of the most used

definitions. The process of edge detection hinges on identifying grayscale changes within an image, rooted in physical processes such as geometric disparities or optical phenomena. These complexities make subsequent data extraction challenging, especially when the image data is marred by noise. The extensive nature of numerical differentiation lengthens this process, where minor input signal changes lead to significant output signal differences. Balancing the elimination of noise and accurate edge location becomes a delicate and contradictory task in edge detection. Therefore, using these traditional edge detection methods can jeopardize the accuracy of the results.

Separately, in 2017, Wang et al. developed an advanced method for detecting cracks in images. They overcame the limitations of existing techniques by utilizing a combination of downsampling and normalized cuts at multiple scales. This method employed a specialized wavelet transform to efficiently extract edge features. By integrating the strength and location characteristics of different scales, they created similarity matrices. These matrices were processed, leading to down-sampled eigenvectors (in the context of this project, it is only worth noting that these vectors allow for complex data operations to be highly simplified due to matrix properties). These vectors were then refined and transformed into a final result. The approach significantly improved accuracy while reducing computation time, as demonstrated through experiments on various datasets.

In 2020, Wang et al. further enhanced their method by integrating a full convolutional neural network with structured forests. They designed multiple neural networks to capture intricate crack patterns and introduced a strategy based on multiscale structured forests to differentiate small cracks effectively. This combined approach demonstrated impressive results in accurately detecting cracks in complex backgrounds. Through existing libraries, which will be explored in **Section 3.2.11**, these algorithms can be implemented through minimal lines of codes.

3.3.2.e Bounding Boxes

Another technology that can be utilized for the same purpose as edge detection is the demarcation of boundary boxes. Ultimately, the goal of this technology is to separate the data AutoCaddie wants to observe from its background to improve processing speeds. A bounding box is a rectangular enclosure that surrounds an object or region of interest within an image. It is defined by its four corners, usually represented by exact pixel coordinates within the frame. Bounding boxes serve as a spatial reference for the location and existance of an object within an image.

One of the primary advantages of using bounding boxes is their simplicity and efficiency. Edge detection involves identifying abrupt changes in intensity between neighboring pixels in all directions. Bounding boxes are straightforward in the fact that that provide object localization. This simplicity makes them computationally efficient, and can perform quicker to match the theme of real-time processing as AutoCaddie demands.

In terms of research provided for bounding boxes, “Can we trust bounding box annotations for object detection” [27] explores different popular methods that are being utilized by developers in the modern day. Commonly, the Faster R-CNN (Region-based

Convolutional Neural Network) algorithm combines deep learning techniques with region proposal natworks to achieve high-performance object detection. In the context of AutoCaddie, Faster R-CNN demonstrates the effectiveness of bounding boxes by accurately localizing and classifying the golfer, as well as their club.

The architecture of Faster R-CNN involves a region proposal network (RPN) that generates candidate bounding boxes, followed by a Fast R-CNN detector that refines these proposals. This two-stage process allows for robust object localization while maintaining computational efficiency, making it suitable for real-time applications.

Another noteworthy example is the YOLO (You Only Look Once) algorithm, known for its real-time object detection capabilities. YOLO divides an image into a grid and assigns bounding boxes to each grid cell, predicting the class and confidence score for each bounding box. This approach is advantageous for AutoCaddie as it provides a holistic view of the environment, enabling efficient object detection in a single pass.

YOLO's ability to handle multiple object classes and its speed make it particularly relevant for AutoCaddie applications, where the algorithm must meet the requirement of identifying both the golfer as well as their club within a large number of frames.

For scenarios where computational resources are constrained, particularly within an embedded system, MobileNetV2 offers a compelling solution. MobileNetV2 is designed for efficiency without compromising performance, making it well-suited for real-time applications with limited hardware capabilities. By incorporating MobileNetV2 into object detection frameworks, bounding box algorithms can maintain accuracy while operating within the resource constraints of AutoCaddie. This showcases the adaptability of bounding box algorithms to diverse computational environments. However, in the context of AutoCaddie, since the data preprocessing will be completed within the main computing device (laptop), there is no strain on resources. The main selling factor with MobileNetV2 is the fact that it does not stress a computer's resource availability.

A direct comparison of each of these three algorithms is shown below.

Algorithm	**Advantages**	**Disadvantages**
Faster R-CNN	• Accurate Object Localization: Faster R-CNN is known for its precise object localization capabilities, making it suitable for applications where the exact location of objects is crucial. • Two-Stage Architecture: The two-stage architecture allows for robust region proposal generation and subsequent object detection, leading to high accuracy.	• Computational Complexity: Faster R-CNN tends to be computationally more demanding compared to other algorithms.
YOLO	• Real-Time Processing: YOLO's strength lies in its ability to provide real-time object detection.	• Potential Reduction in Localization Precision: While YOLO is efficient, its single-pass approach may lead to slightly lower precision in object

	• Single Pass Efficiency: YOLO processes the entire image in a single pass, making it computationally efficient and suitable for applications where low latency is a priority.	localization compared to other algorithms.
MobileNetV2	• Efficiency for Embedded Systems: MobileNetV2 is designed for efficiency, making it suitable for applications with computational constraints.	• Trade-off with Precision: While MobileNetV2 is efficient, it may sacrifice a bit of precision compared to deeper and more complex models.

Table 5: A direct comparison between three separate bounding box algorithms.

AutoCaddie must strike a balance between processing speed and precision. As a real-time golf swing coach assistant, its effectiveness is contingent on swift data analysis. Delays in data processing could diminish the program's utility compared to pure human communication. At the same time, maintaining data accuracy is imperative to meet customer expectations. Achieving an optimal balance between speed and precision is crucial, rendering Faster R-CNN unsuitable for this project.

In the context of accommodating diverse computing devices for consumer use, both YOLO and MobileNetV2 are fair choices. However, to enhance accessibility across as many computing devices as possible, MobileNetV2 is the superior choice for this project with bounding box annotation.

3.3.2.f Frame Standardization

On a separate note, for a CNN to maintain its effectiveness, the input data must be presented in identical format. CNNs' effectiveness is attributed to their ability to autonomously learn visual features without manual interventions. But, similar to an autonomous machine, it expects an input with specified dimensions in order to apply matrix multiplication and other algorithms to the data. Thus, the input data stream presented by the video cameras needs to be standardized.

It has already been researched that frames can automatically have bounding boxes applied over the golfer and club during the entire swing sequence. At this point, each of these images can be cropped to the bounding dimensions, which will be random by nature. Thus, to standardize the dimensions of each of these frames, images need to be enlarged. To address these filter border issues, padding techniques are employed. This section will compare the two most common methods: zero-padding vs. scaling with interpolation. [28]

Zero-padding involves enlarging smaller images to a fixed size by adding zero-value pixels around their borders. This approach offers two notable advantages. Firstly, it prevents the risk of deforming patterns in the image during the resizing process, ensuring that the original features remain intact. This is critical for image classification where maintaining the integrity of visual patterns is necessary for accurate results. Secondly, zero-padding is less computationally expensive than scaling with interpolation. Zero-padding simply inputs zeros along the image grid's border rather than perform neighboring calculations on every missing pixel.

Additionally, possible concerns about this method can be debunked. There is a common assumption that the CNN won't adequately learn features from the border areas due to the zeros inserted along the border of the image. This is incorrect because CNNs contain a weight-sharing property, where the convolutional layers employ synaptic weights across all of the matrix multiplication windows, ensuring equal feature extraction capabilities for both the central and border areas. Another worry about this method is that the zeros will produce adverse effects on weight optimization. This is also debunked through a long mathematical proof that highlights that zero-value pixels remain inactive during the propagation techniques. In other words, the zeros do not directly affect the features being extracted and remain inactive until they are filtered.

Scaling with interpolation is the conventional approach to resize smaller images. This method involves increasing the resolution of the image to match the desired fixed size. However, this process carries inherent challenges. First, scaling poses the risk of deforming features or patterns across the entire image, which would directly impact the accuracy of the remaining classification tasks. Interpolation attempts to fix this problem by smartly assigning pixel values in relation to nearby ones, but the inherent sloppiness of scaling remains a concern. Second, scaling is a more computationally expensive process than zero-padding, as it requires a small algorithm to determine what a predicted pixel value will be. Higher-resolution images occupy more memory space as well, which amplifies the complexity of the process.

Therefore, it is wise to select zero-padding as the proper frame standardization technique. This way, there are no present deformations within the input images as they are presented to the network, and the data is only consistent of the golfer and a club during the swing sequence. Using this method, the precision of the program can be maximized.

Figure 13: A small image being enlarged using two separate algorithms. (a) represents the original image. (b) represents the image resized using zero-padding. (c) represents the image resized using interpolation. Referenced via [29] .

3.3.2.g Action Detection

The last important detail of image preprocessing with AutoCaddie is action detection (also known as feature extraction). Being able to preprocess the data so that it is presentable to the network to be as accurate as possible is one thing. However, being able to provide specific insights about every section of the swing, rather than rate the overall score, is another. Action detection is the term given to computer vision algorithms that detect

specific motions, sequences, or patterns across a collection of frames that denote a specific action. In terms of the golf swing, this can be attributed to the address, backswing, impact, among others.

The research conducted by [30] delineates potential actions analyzable within a parent swing, categorizing the golf swing into eight distinct parameters:

1. Address: The frame before the initial movement begins.
2. Toe-up: The backswing stage where the golf club shaft is parallel to the ground plane.
3. Mid-backswing: The stage where the golfer's arm is parallel to the ground plane during the backswing.
4. Top: The stage when the golf club changes directions from the takeback to the downswing.
5. Mid-downswing: The stage when the golfer's arm is parallel to the ground during the downswing.
6. Impact: The stage when the golf club head hits the golf ball.
7. Mid-follow-through: The stage when the golf club shaft is parallel to the ground plane during the follow-through.
8. Finish: The frame before the golfer finishes their swing.

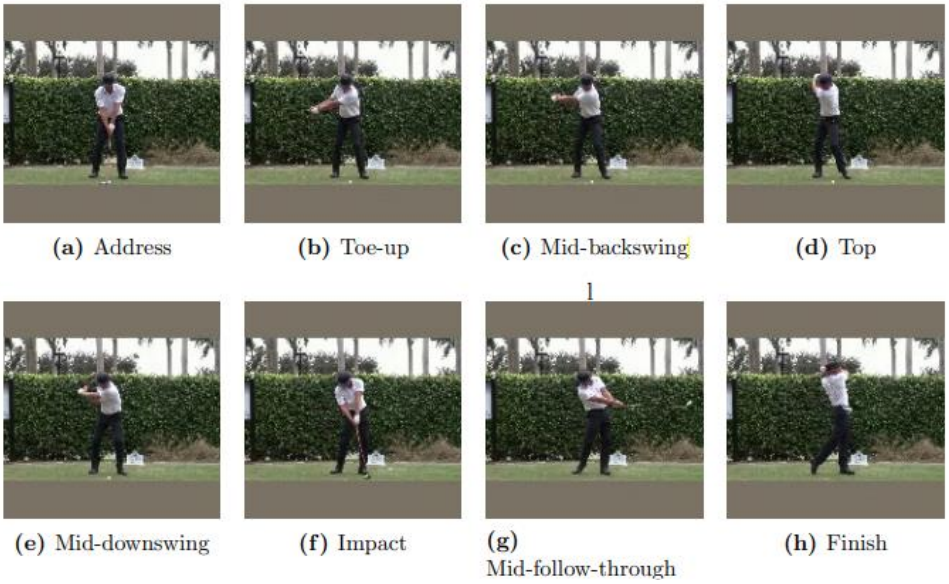


Figure 14: The eight actions within a complete golf swing. Referenced via [30] .

Classification in the golf swing context involves labeling specific instances of time corresponding to predefined events. Due to the fact that there are eight distinct events being labeled within this golf swing sequence, this problem is referred to as multi-class classification. CNNs, and deep learning neural networks in general, focus on accurately classifying input data to output features. AutoCaddie integrates this concept by offering coaching based on a user's swing, allowing for a more granular analysis of smaller, precise events. There are different classification models that can be utilized to approach the action detection problem, which are explained below.

LinearSVM is particularly well-suited for the One-vs-Rest multi-class classification problem – a strategy used to extend binary classifiers for applications with more than two classes. LinearSVM's preference in this context stems from its faster convergence compared to kernel-based support vector machines (SVMs). The choice of the optimal C parameter is crucial because it directly influences the cost of misclassifications.

CatBoost stands out as a scalable end-to-end ensemble Gradient Boosting Machine (GBM) designed for multi-class classification problems. However, default parameters may lead to overfitting, mitigated by a parameter called bagging temperature. Further, hyperparameter tuning becomes essential to fine-tune model fitting.

Decision Tree Classifiers demonstrate efficiency in multi-class classification scenarios. This classifier, characterized by its speed, outpaces other models within the proposed system. Effective hyperparameter tuning contributes to enhancing its performance. This model can be represented by a series of binary decisions, each representative of the existence of features within a data point.

Random Forests, a model leveraging multiple decision trees, is adept at handling large datasets. In contrast to the Decision Tree Classifier, Random Forests introduce randomness in feature selection, promoting generalization. Like the decision tree model, effective hyperparameter tuning is crucial for optimizing its performance.

K-Nearest Neighbors (KNN) is a simple distance-based algorithm that has proven to be successful in classifying problems characterized by irregular decision boundaries. An oversimplified explanation to this method is to predict a test data point by referencing the k nearest neighbors and making an informed decision. To avoid ties in a multi-class problem like the golf swing classification system, an odd number is chosen for k. KNN's effectiveness lies in its simplicity and ability to adapt to complex decision boundaries.

Moreover, each of these algorithms were brutally tested to compare the final accuracy when compared to existing training data. The table below summarizes the results, as well as the advantages and disadvantages of each method.

Algorithm	Performance	Advantages	Disadvantages
LinearSVM	• Particularly effective for multi-class one-vs-rest classification. • Achieved high accuracy across diverse experiments. • Outperformed other models in most cases.	• Highly accurate and efficient. • Well-suited for multi-class problems.	• Small amounts of misclassification are apparent. • Within this study, the largest number of misclassifications occurred between similar swing events.
CatBoost	• Achieved good results with optimal parameters. • Provided competitive performance in respect to the other algorithms. • Provided consistent results across diverse experiments.	• Handles categorical features well. • Robust to overfitting.	• Slightly lower accuracy compared to LinearSVM.
Decision Tree Classifier	• Achieved moderate results across diverse experiments. • Provided moderate accuracy when compared to the other algorithms.	• Simple and interpretable. • Less prone to overfitting.	• Lower accuracy when compared to more complex models.
Random Forests	• Slightly improved performance when compared to the Decision Tree Classifier. • Achieved moderate accuracy across diverse experiments.	• Improved robustness compared to a single decision tree. • Handles overfitting strongly.	• Moderate accuracy compared to more advanced models.
KNN	• Good performance when compared to Random Forests. • Achieved good accuracy across diverse experiments.	• Simple and easy to understand. • Effective for smaller datasets.	• Can be computationally expensive for large datasets. • Sensitive to outlier data or redundant features.

Table 6: Compares five separate classification algorithms for golf swing action detection.

As indicated by the table, the models consistently demonstrated moderate to satisfactory accuracy levels in the classification of golf swing events. Notably, LinearSVM and CatBoost emerged as the most robust candidates for integration into AutoCaddie. The Decision Tree Classifier exhibited comparatively lower classification accuracy than all other algorithms considered. While Random Forests exhibited a moderate improvement, its computational demands poses a challenge to maintaining quick preprocessing during

the live process. Although KNN displayed a marginally superior performance, its complexity escalates notably with larger datasets, which is critical considering the 30 fps video recording frequency. Nevertheless, when contextualizing the application within a golf swing scenario, LinearSVM and CatBoost emerged as the most viable choices.

In conclusion, the optimal algorithm for implementation in AutoCaddie is identified as LinearSVM. Across the algorithms considered, LinearSVM consistently outperformed others in diverse experiments, which is a useful characteristic given that the user is anticipated to be in various environmental conditions during the recording process. Notably, its effectiveness in scenarios involving the classification of multiple classes aligns harmoniously with the specific context of the problem at hand.

3.3.2.h Summary

There is much consideration towards properly analyzing live video data from camera input streams to a computer. Analyzing live video data in AutoCaddie involves parsing the video data into image frames, where each frame represents a 2-dimensional grid of pixels, suitable for computer vision techniques. CNNs were identified as the most effective approach for image analysis in this context.

To facilitate CNN processing, data preprocessing algorithms are employed to format input data efficiently. Labeling, particularly for identifying the user and their golf club in each image, is crucial. While edge detection proves inadequate for this project due to accuracy limitations, bounding box generation, specifically using MobileNetV2, emerges as the optimal model for accuracy and efficiency.

Standardizing input data is essential for error reduction. After marking a bounding box, images are cropped to match its dimensions and then expanded using the zero-padding algorithm to achieve a standardized dimension. This standardized format ensures that the CNN can accept images of proper dimensions, streamlining the process.

For precise coaching feedback, accurate action detection within a golf swing is vital. Identifying specific points representing the start of an event is crucial, and LinearSVM emerges as the most accurate algorithm for this purpose. With data preprocessed, it can then be utilized within the CNN.

Overall, being able to differentiate different segments of a golf swing into separate actions is critical for the functionality of this neural network within AutoCaddie. The purpose of this project is to provide a helpful insight to the user about their stroke, which can be brought down to analyzing each individual action composing the entire swing. If these algorithms can effectively standardize the data being presented, we can eliminate external errors being introduced into the system. From this point, this data can be presented to the network, which will perform comparisons of each feature to a version with proper technique and present similarity scores to be formatted for the user.

3.3.3 Network Architecture

The network architecture for the AutoCaddie project is a critical component designed to process and analyze golf swing footage effectively. Our chosen architecture leverages the strength of convolutional neural networks (CNNs), [31] which are particularly adept at handling image and video data. The following sections detail the rationale behind selecting CNNs, their relevance to golf swing analysis, and how they integrate with the other components of our project.

3.3.3.a Selection of a Neural Network Trained on GolfDB

The AutoCaddie system will employ a neural network architecture trained specifically on the GolfDB dataset to classify the actions observed in golf swing footage. This choice is made with the intention to detect and highlight various aspects of a golfer's swing, comparing it against a repository of professional swings to identify potential areas for improvement. The GolfDB dataset provides a rich source of labeled video footage, offering a diverse array of swings from different angles and under various conditions. This depth and variety enable the training of a robust model that can generalize well across different golfers and swing styles.

3.3.3.b Why CNNs Excel in Video and Image Recognition

CNNs have been established as the de facto standard in the field of image and video recognition due to their ability to autonomously learn spatial hierarchies of features from visual data. [32] Unlike other neural network architectures, CNNs are designed to map image characteristics directly to outputs, making them highly efficient for tasks such as image classification, object detection, and video analysis. The layers within a CNN—convolutional layers, pooling layers, and fully connected layers—work in concert to process pixel data and extract meaningful patterns.

In the context of golf swing analysis, CNNs can recognize and learn from the intricate features of a swing, such as the posture of a player at address, the angle of the club at the top of the backswing, and the position of the body at impact. For example, the 'top of the swing' event is a critical phase where the golfer's coordination, club position, and balance converge. CNNs can discern this event by learning the commonalities found in the GolfDB footage, despite variations in the golfer's appearance, background, or lighting conditions. By focusing on these learned features, the network can provide feedback on whether a user's swing deviates from the ideal models in the database and suggest specific areas for improvement.

3.3.3.c Integration of CNNs with AutoCaddie Project Topics

The application of CNNs within the AutoCaddie project is not limited to simple classification tasks. It extends to a comprehensive understanding of golf swing mechanics, where the network must recognize and evaluate complex sequences of movements. The architecture is designed to correlate specific swing phases with the associated biomechanical outcomes, such as ball trajectory and speed.

The network's capability to analyze video data frame-by-frame allows for an in-depth temporal analysis of the swing. It will enable the AutoCaddie system to observe the golfer's motion across the entire sequence of the swing, from the initial stance to the final follow-through. This sequential analysis is crucial for identifying timing issues, such as early or late impacts, which can significantly affect the swing's efficacy.

Furthermore, the adaptability of CNNs to different data inputs makes them suitable for implementation in a real-world environment where swings are recorded under varying conditions. By training the network with GolfDB's comprehensive dataset, which includes diverse environmental settings and camera angles, our system will be robust against overfitting to a specific setting or view type.

3.3.3.d Exemplification of CNNs in Golf Footage Analysis

The utility of CNNs in the AutoCaddie project is exemplified through the analysis of golf swings using GolfDB. The database labels eight key events within a swing, allowing the network to target these events for a focused assessment. For instance, when analyzing the 'impact' phase, the CNN can precisely detect the club's position relative to the ball at the moment of contact, a factor directly tied to the shot's quality. The multi-layered structure of a CNN can process the video data through successive filters, each designed to highlight different features such as edges which are fundamental in distinguishing between the nuanced positions of a golf swing.

3.3.3.e Balancing Precision with Performance in CNN Architecture

The architecture of the neural network for AutoCaddie is crafted to strike an essential balance between precision and performance speed. Precision is crucial in identifying the subtleties of a golfer's technique and providing accurate feedback. Our CNN architecture is designed to delve into the fine-grained details of each swing, capturing nuances that can influence the golfer's performance. However, the detailed analysis should not compromise the speed at which feedback is delivered. Golfers and instructors expect near-instantaneous responses from analytical tools to ensure they can quickly make adjustments and observe the outcomes of their efforts.

To achieve this, we have chosen a lightweight yet powerful version of the CNN, which maintains high accuracy without the computational lag often associated with deep, complex networks. Our architecture is optimized for the swift processing of video frames, enabling the analysis of golf swings in almost real-time. This optimization is particularly significant when considering the deployment of the AutoCaddie system on platforms. The decision to adopt a streamlined CNN model also stems from the need for operational efficiency, ensuring that our system can process data in reasonable time without a dip in performance. Thus, the chosen network architecture reflects a well-considered approach that addresses the project’s core demands for fast, accurate, and reliable golf swing analysis.

3.3.3.f Incorporating MobileNetV2 for Efficient Object Detection

For the AutoCaddie project, we chose the MobileNetV2 [33] architecture, renowned for its object detection capabilities with image preprocessing, as a pivotal element of our CNN. MobileNetV2, which can be imported through Keras, a part of TensorFlow, offers an effective balance between depth in layers and computational efficiency, a harmonious fit for real-time applications such as ours. This model is designed to operate with limited computational resources, which aligns with our deployment strategy.

MobileNetV2 employs depthwise separable convolutions which significantly reduce the number of parameters when compared to standard convolutions while maintaining a high level of accuracy. This characteristic makes it a suitable choice for the AutoCaddie system, where processing speed is as critical as precision. The lightweight nature of MobileNetV2 allows for quick processing of video frames, which means that swing analysis can be performed almost instantaneously.

The preprocessing of images is an important step in fine-tuning the input for optimal network performance. In GolfDB, video frames come from various lighting conditions and perspectives, which necessitates a robust preprocessing routine. Using Keras, we implement MobileNetV2's preprocessing layers to standardize input frames so that the network can generalize across swings captured in different environments. This step is crucial in preparing the data for feature extraction, ensuring that the model is not learning from noise and can focus on the critical elements of the golf swing.

Moreover, the use of MobileNetV2 supports the system's requirement for multi-angle analysis. Its proficiency in extracting features from diverse viewpoints ensures that the swing mechanics are captured comprehensively, regardless of the camera’s position. This flexibility is advantageous for AutoCaddie

3.3.3.g Incorporating Sex-specific Analysis in CNN Architecture

Recognizing the importance of sex-specific nuances in golf swing technique, our CNN architecture leverages the inherent categorizations present within GolfDB to tailor the analysis accordingly. The database's structure, which includes sex as a labeled variable, allows for a customized calibration process within the AutoCaddie system. By requesting the user's sex during the initial setup, our system can intelligently filter and reference only the relevant subset of GolfDB videos for comparison. This level of personalization ensures that the feedback provided is more accurate, as it considers physiological and biomechanical differences typically observed between male and female golfers. Such sex-specific analysis not only enriches the learning experience for the user but also aligns with contemporary coaching practices, which emphasize the value of customized training programs. Through this thoughtful integration, AutoCaddie will ensure that every user's experience is reflective of the diverse approaches in teaching and analyzing golf swings, thus enhancing the system's inclusivity and effectiveness.

3.3.3.h Conclusion

In sum, the network architecture of the AutoCaddie project is explicitly tailored to extract, analyze, and learn from the vast information presented in the GolfDB dataset. By utilizing CNNs, the project harnesses the power of deep learning to provide sophisticated, accurate, and practical swing analysis. The architecture not only meets the project's current analytical needs but is also scalable for future enhancements, such as integrating new data types or adapting to emerging analytical requirements in golf instruction.

3.3.4 Database Selection

3.3.4.a Rationale for GolfDB's Adoption

Upon defining the requirements for a swing analysis database within the AutoCaddie system, GolfDB was singled out as a prime candidate. A database, to be compatible with our system, needs to be comprehensive, specialized, and aligned with the project's high standards for accuracy and detail. GolfDB stands out in this regard, providing a dataset exclusively composed of professional golf swings, each methodically labeled across a spectrum of events essential for nuanced analysis. The database's structured approach to video labeling—encompassing the sequence of events from address to finish—ensures a level of detail that is unparalleled by other datasets. Furthermore, it includes vital metadata on the golfer, which are imperative for the system's multifaceted analysis algorithm. GolfDB's alignment with AutoCaddie's goals is thus made it a prime candidate for our data base for this project.

3.3.4.b Comparison with Other Data Sources

The extensive survey of potential databases underscored the challenges associated with unlabeled and non-specialized golf footage. Although alternative online sources sources for free golf images provide a wealth of visual content, the absence of golf-specific annotations renders the footage less actionable for targeted swing analysis. The process of converting this raw footage into a structured and analyzable form is fraught with difficulties that echo across data integrity, labeling accuracy, and resource allocation. In the case of services which provide these images, the diversity and scope of content were promising, but the lack of consistent swing phase labeling posed significant barriers to direct application in swing analysis. The use of GolfDB, pre-labeled with event frames and defined by clear classification criteria, eliminates these barriers, thereby facilitating immediate integration and use within our project.

3.3.4.c Limitations of Unlabeled Data and General Annotation Services

Unlabeled data presents a significant challenge, primarily due to the depth of knowledge required to accurately categorize golf swing mechanics. Generic annotation services, while potentially cost-effective, often fall short of capturing the specific biomechanical and technical nuances of golf swings. The risk of incorrect annotations is amplified when dealing with complex actions such as the golf swing, where the distinction between amateur and professional techniques can be subtle and highly technical. The precision

required to identify these subtleties is beyond the capabilities of nonspecialized services, which may not have the domain-specific training necessary for high-fidelity labeling. Consequently, the selection of GolfDB, which offers granularity and domain expertise in its annotations, was critical to avoid the pitfalls associated with generalized data services.

3.3.4.d Considerations Against Self-Recording of Swing Footage

In the development of AutoCaddie, we contemplated the feasibility of creating an independent database by recording and analyzing our own golf swings. This approach would have granted us complete control over the dataset, allowing for customization tailored to our system's specifications. However, this method was ultimately deemed unsuitable for several reasons. Primarily, none of our team members possess the level of expertise required to exemplify the 'perfect' golf swing, a benchmark necessary to establish a standard for comparison and improvement within the application. Moreover, the time required to learn, execute, record, and then analyze these swings to a competent standard was beyond our project's temporal scope. The undertaking of such a massive task would not only divert attention from the core objectives of system development and refinement but also risk introducing subjective bias and unverifiable accuracy in our analysis. Consequently, GolfDB’s expert-labeled dataset, which is both time-efficient and reliable, became the clear choice for integrating high-fidelity swing analysis into the AutoCaddie project.

3.3.4.e Compatibility of GolfDB with Convolutional Neural Networks

GolfDB presents itself as a well-suited repository for use with convolutional neural networks (CNNs), which are state-of-the-art in image and video recognition tasks. CNNs excel in identifying complex patterns in visual data and making sense of images and videos by learning hierarchies of features. Given that GolfDB comprises high-definition, annotated video data of golf swings, it fits seamlessly into the framework of CNN-based analysis. The database's structured format, with labeled events corresponding to different swing phases, provides a rich ground truth that aids in the efficient training of CNNs. This synergy is beneficial since CNNs require a substantial amount of pre-classified data to achieve significant accuracy. GolfDB's alignment with the requirements for CNN training ensures that AutoCaddie can capitalize on the power of deep learning for feature extraction and sequence prediction, leading to more accurate swing analysis. The high frame rate and quality of GolfDB videos also mean that the temporal resolution is sufficient for capturing the fast, nuanced movements of a golf swing, which are essential for producing a detailed and actionable swing analysis within AutoCaddie’s user interface.

3.3.4.f Advantages of Video-based Databases Over Sensor-based Systems

The use of video-based databases for swing analysis presents several advantages over sensor-based motion capture systems, particularly in terms of cost-effectiveness and non-invasiveness. While sensor suites provide detailed biomechanical data, they require the golfer to wear a cumbersome array of sensors, which can alter the natural flow of the swing. Moreover, the setup for such systems is time-consuming and financially

prohibitive, especially for a senior design project with limited resources. Cameras, on the other hand, offer a non-invasive and more practical method for capturing swings. They allow for the recording of a golfer's swing in a natural environment without the need for specialized equipment attached to the player's body.

Choosing a video-based approach aligns with the AutoCaddie project's objective to create a user-friendly and accessible tool for swing analysis. Using GolfDB, which is rich in video data, we can develop a system that provides accurate swing feedback by simply filming the golfer with standard cameras. This method significantly reduces the project's costs and eliminates the discomfort and behavioral alterations caused by wearing sensors. Thus, GolfDB not only provides a comprehensive and specialized dataset for CNN training but also promotes an unobtrusive and realistic golfing experience, enhancing the practicability and scalability of AutoCaddie.

3.3.4.g Consultations with Golf Experts

In the quest to build a system that stands up to professional scrutiny, we engaged with a PGA tour expert to understand the critical elements of a swing analysis tool. This expert, with years of experience in teaching and analyzing golf techniques, provided us with a checklist of essential swing mechanics and the corresponding visual indicators that should be captured for effective analysis. They emphasized the importance of precision in capturing the 'top of the swing' and 'impact moment,' which are crucial for determining the quality of a stroke. GolfDB's dataset reflects these expert inputs, offering meticulously labeled swings that cover all phases identified by the professionals. The contribution of this expert was not just in affirming the choice of GolfDB but also in reinforcing the necessity for an extensive, multi-dimensional swing analysis model, which is now a cornerstone of the AutoCaddie project.

3.3.4.h Incorporating Multi-Angle Video Analysis

The assessment of a golf swing from multiple angles offers a composite view that is vital for a comprehensive analysis. An accurate swing diagnosis cannot be confined to a single perspective, as it often fails to capture the dynamic interplay of movements involved in a golf stroke. Recognizing the importance of this multi-dimensional requirement, GolfDB's varied video angles are ideal for our purpose. The database includes both face-on and down-the-line videos, providing the foundational data necessary for evaluating swings in a manner that reveals the depth and intricacies of each shot. The ability to scrutinize a swing from various angles is crucial in developing a robust analytical framework for AutoCaddie, ensuring our analysis is as close to real-world conditions as possible.

3.3.4.i Technical Advantages for AutoCaddie's AI Model Training

The pre-labeled nature of GolfDB videos offers a unique advantage in training the AI model underlying the AutoCaddie system. By utilizing this dataset, we can bypass the initial hurdles of data preprocessing and directly engage in the more critical tasks of feature extraction and algorithm optimization. This direct path to model development not

only conserves resources but also enables a focus on enhancing the analytical capabilities of AutoCaddie. GolfDB's structured dataset provides a solid foundation for developing machine learning algorithms that can detect and analyze key swing events with high precision, thus streamlining the learning curve and enabling the delivery of a sophisticated, user-friendly analytical tool.

3.3.4.j Concluding on GolfDB's Selection

The strategic choice to integrate GolfDB into the AutoCaddie project is a reflection of our analytical and educational goals. By incorporating GolfDB, we leverage a dataset that was built with an understanding of the golf swing's complexity, as interpreted by experts. This decision aligns with our dedication to delivering an accurate and insightful analysis to golfers, enabling them to refine their swings effectively. GolfDB's use in the AutoCaddie project underscores our preference for a database that not only provides high-quality, detailed swing analysis but also enhances the learning experience for our target audience.

3.4 Relevant Technologies: Kinematic Data

Along with the primary source of feedback for the AutoCaddie system being the machine learning artificial intelligence, kinematic data of the user's swing action with their driving arm is also used as a supplementary source of data. This source of data is more direct and deterministic, as it uses set equations on collected data to determine the type of feedback given from the system. The kinematic data consists of quaternion vector data and acceleration data. This data is collected via the IMUs, packaged by the MCU, and is transmitted wirelessly to the central computer for processing by a wireless transceiver module.

3.4.1 Inertial Measurement Units

3.4.1.a Overview, Comparison, and Selection of Component Type

Inertial measurement units serve as the primary motion sensor of the AutoCaddie system. The IMU units will be used to track the motion of the user's arm and determine the user's arm linearity, where one factor of feedback will be provided. For these purposes, there are several characteristics that IMU candidates are considered by. These most important characteristics include cost, degrees of freedom (DoF), data output modes, data output types, data output speed, and size dimensions.

In the context of motion tracking and analysis of the user's swing motion, IMUs emerge as the favored technology. IMUs amalgamate the functionalities of gyroscopes, accelerometers, and magnetometers, providing comprehensive data on the user's swing dynamics. This integrated approach allows for a holistic understanding of the user's motion, offering data for the user's swing control and arm straightness. IMUs often come in two configurations, a 6 DoF configuration utilizing only a gyroscope and accelerometer, and a 9 DoF configuration utilizing both a gyroscope and accelerometer, along with a

magnetometer to stabilize and refine the data. As the 9 DoF is more accurate in circumstances void of magnetic interference sources, the 9 DoF configuration is preferable.

While Electromyography (EMG) devices can also be employed to measure muscle effort and strain during the swing action, determining the user's exertion level and the initiation of their swing, there are certain limitations to consider. EMGs often yield noisy data, potentially introducing inaccuracies in the analysis. Moreover, non-invasive EMG devices necessitate a significant amount of preparation before application on the user, which can be cumbersome and time-consuming. Given these considerations, the simplicity and ease of application of IMU devices make them the preferred choice for motion tracking and analysis, offering a robust and efficient solution for the AutoCaddie's needs of the user's arm kinematics.

3.4.1.b Adafruit BNO055/80 (Bosch)

The Adafruit BNO055 (extending to the 080 series) IMU is a 9 degree-of-freedom (DoF) unit that features the following output data: absolute orientation (Euler and quaternion), angular velocity, acceleration vector, magnetic field strength, linear acceleration vector, gravity vector, and temperature. The geospatial orientation vectors and orientations can be measured at 100Hz intervals. This system uses modified I2C communication standards as well as standard UART protocols. The overall dimensions of the BNO055 are 20mm x 27mm. To make the necessary linearity assessments, inverse kinematics calculations can be performed using the Euler and quaternion orientation vectors. The overall package cost totals $34.95.

3.4.1.c InvenSense MPU-9255

The InvenSense MPU-9255 is a 9 DoF multi-chip module IMU, which combines two die modules to form a singular system. The MPU-9255 combines a 3-axis gyroscope, 3-axis accelerometer, and a 3-axis magnetometer. The device features support for an "Automatic Activity Recognition" library, allowing for activity-induced measurements by the wearer from a low-power state without direct mode manipulation. This device supports both SPI and I2C communication standards. At normal low-power applications, the data output can output data at 500Hz. The overall dimensions of the MPU-9255 are 31.11mm x 16.84mm. Similar to the BNO055, inverse kinematics calculations can be performed using the Euler and quaternion orientation vectors to make the necessary linearity assessments. The overall price of the IMU package is $39.99.

3.4.1.d InvenSense MPU-6050

The DFRobot MPU6050 is a 6 DoF IMU device that combines a 3-axis gyroscope and 3-axis accelerometer onboard a digital motion processor. Along with the gyroscopic and accelerometer data, the unit provides a digital motion processor, which offloads some of the data processing workload of the central modules. This unit specializes in low-power, low-cost applications. Due to the reduced data vectors and processing offloading, the IMU unit can produce output at frequencies up to 1kHz. This IMU unit uses I2C communication standards. The overall dimensions of this unit are 21mm x 14mm. The overall price of the IMU unit is $9.90.

3.4.1.e Hardware Comparison Table

Factor	BNO055/80	MPU-9255	MPU-6050
Unit cost	$34.95	$39.99	$9.90
DoF	9	9	6
Output modes	I2C, UART	I2C, SPI	I2C, SPI
Output types	Absolute orientation (Euler and quaternion), acceleration vectors, gravity vectors, magnetic field vectors, and temperature.	Quaternion, Gyroscopic angular rotation vectors, and acceleration vectors	Gyroscopic angular rotation vectors, acceleration vectors, magnetic field vectors, and temperature.
Output Speed	100Hz	500Hz	1000Hz
Dimensions	20mm x 27mm	31mm x 17mm	21mm x 14mm

Table 7: Hardware comparison table that compares the IMU candidates.

3.4.1.f Conclusion

Based on the above research, the chosen IMU unit will be the BNO055 unit. Regarding its output mode and data types, UART is a standard communication method, which is readily available in compact libraries. Additionally, I2C communication is an efficient form of communication as it is both scalable and stable in implementation, which can be used as another applicable form of communication should its implementation be required. Furthermore, the unit provides a quaternion absolute orientation vector data type, which allows for cross-quaternion calculations for limb linearity. The MPU6050 does not provide for this data type, so it is less preferable than the BMO055. Regarding the BMO055's output speed, it is inferior to that of the other modules, however, it is still fast enough for any latent differences to be negligible to the user's perception and changes in arm kinematics. Regarding the dimensions of the IMU, any size close to each of the candidates' dimensions is acceptable. Regarding the costs, the BNO055 is better than that of the MPU-9255 by $5. This betterment of price allows for the final product to be more affordable for the end user and allows for more cost-effective development. As such, considering all the appropriate factors, the BMO055/80 IMU series is the chosen IMU for the AutoCaddie project.

As the IMU data is collected during the swing action period, the data must be formatted into a package that can be wirelessly transmitted to the central computer for further processing. This wireless transmission must be done as to reduce the presence of wires that extend off the user which may burden the user or may be caught on the user and cause inconveniences or damage.

3.4.2 Wireless Data Transmission Components

3.4.2.a Overview, Comparison, and Selection of Component Type

The wireless transceiver is the component responsible for tying together hardware and software; regardless of the variant chosen, the transceiver will communicate between the microcontroller and the target device, delivering the data gathered from the Inertial Measurement Units (IMUs) to the device performing analysis on the video feed (likely a laptop or desktop computer). For the purposes of this project, some important factors to

consider are connectivity options, power consumption, output power, data rate, and maximum transmission distance.

In the selection of a wireless transceiver, many options exist which could effectively perform the tasks required by AutoCaddie. The options researched are Wi-Fi, Radio (RF), and Bluetooth.

Radio transceivers are a considerable option for the AutoCaddie project. However, when compared to Bluetooth and Wi-Fi transceivers, they present drawbacks which must be examined prior to selection. RF transceivers generally transmit over great distances, with high-power transmitters being capable of traversing hundreds of miles. The AutoCaddie project is unlikely to exceed 100 meters (about 328.08 ft) of range; therefore, this extreme range could present unnecessary power consumption and complexity. Bluetooth Low Energy, for instance, is designed to perform over ranges between 10 and 100 meters, which is exactly applicable for this project. RF transceivers generally offer low data rates, with the AM and FM encoding processes consuming time and power far exceeding those of Bluetooth and Wi-Fi. In projects where the data to be transmitted could be measured in bits, this is acceptable; however, AutoCaddie will be transmitting in the range of 13.6 KB, significantly larger than the data rate of RF transceivers could transmit in a reasonable time. Moreover, RF transceivers are often complex to configure and use for those who are unfamiliar with their applications. Therefore, in a project oriented towards accessibility and ease of use, Bluetooth and Wi-Fi are better options. RF transceivers operate in the unlicensed 2.4 GHz ISM band, which is often crowded by other wireless devices. Without a frequency hopping feature, this can result in signal interference by other RF devices. RF transceivers do not have similar levels of universal compatibility like Wi-Fi and Bluetooth, and therefore is generally challenging to access for the common consumer.

Wi-Fi transceivers are a significant improvement over RF devices. However, in comparison to Bluetooth, there are still inferiorities to consider. Like RF transceivers,Wi-Fii transceivers offer significantly higher ranges of communication than Bluetooth. However, as has already been explored, the purposes of AutoCaddie do not require ranges exceeding 100 meters (about 328.08 ft) for reasonable applications, therefore Wi-Fi is a less than energy-efficient choice for a battery-operated project. Wi-Fi connections, while less complex than RF connections, are more challenging to configure than Bluetooth pairing. Many devices require complex network connections and configurations, reducing the accessibility of the project. Wi-Fi also operates in the 2.4 or 5GHz bands, which are shared by many other wireless devices. This opens the project to the possibility of external interference without the introduction of a frequency hopping feature (like that boasted by Bluetooth). WiFi offers data ranges which range to the extreme, which can be excellent for high-definition video streaming or the transmission of large files. However, with an average file size of 13.6 KB, this extreme data rate is not required and can result in unnecessary power consumption. Furthermore, Wi-Fi is less universally compatible than Bluetooth, especially when using legacy devices. Ensuring Wi-Fi compatibility across different platforms can be more challenging than an industry standard such as Bluetooth pairing.

Bluetooth offers excellent power efficiency, with numerous devices using Bluetooth Low Energy (BLE) which is optimized for low-power consumption. For a battery-operated project such as AutoCaddie, this is an extremely attractive feature. Additionally, Bluetooth utilizes output powers which are suitable for short-range connectivity, which is the most likely application of AutoCaddie. Bluetooth offers data rates which are more than adequate for the purpose of transmitting IMU data; the collection rate of data from the IMUs is approximately 100Hz, and with a general data rate of 9600 bps (configurable to higher or lower as needed), this transmission option is capable of exceeding a reasonable data rate for, for instance, a UART output which could range upwards of 13.6 KB. Moreover, Bluetooth boasts a maximum transmission distance of approximately 100 meters (about 328.08 ft), which is significantly more than would be required for a reasonable application of AutoCaddie, which is intended to be short ranged.

Bluetooth is also very accessible, with the majority of modern devices available in the market containing Bluetooth Serial chips, therefore communicating to a user's device is as simple as turning it on and selecting it from a pairing list. Bluetooth uses adaptive frequency hopping to mitigate signal interference, which, since it uses the 2.4 GHz ISM band, is useful in maintaining a stable connection in an environment crowded with other wireless devices. Bluetooth is well-established, with a wide range of chips, development tools, and resources available to facilitate development and ease of use.

With these factors researched, the most applicable options in the Bluetooth range of devices will be considered. Bluetooth boasts low power consumption, adequate range, excellent configurability, universally accepted connectivity options, and non-excessive data rates, as well as security features such as adaptive frequency hopping.

3.4.2.b HC-05

The HC-05 is a very popular wireless transceiver, most often used in Arduino-integrated projects (ATMEGA328P MCU) as a Bluetooth communication device. The use of Bluetooth serial as a communication mode is extremely applicable in this case, as, depending on the transmission distance of the transceiver, it can be used for virtually all modern devices, especially laptops. The device requires UART to properly receive data for transmission, something which the vast majority of MCU chips boast, and virtually all computers use. The transceiver consumes 30 mA of power while actively transmitting at a default data rate of 38400 bps (Baud), though this rate can be adjusted manually to match the default 9600 Baud rate of most computers. The output power is +4dBm. The transmission distance is at a maximum of 10 meters (about 10 adult steps).

3.4.2.c HC-06

The HC-06 transceiver is the sister device to the HC-05, boasting a greater output power of +6dBm at a default data rate of 9600 bpm (Baud), with a significantly greater maximum transmission distance of 100 meters (about the length of a football field). The device requires UART to receive data with a supporting option of USB connectivity, communicating across Bluetooth Serial. The HC-06 operates at 40mA while transmitting.

3.4.2.d nRF24L01+

The nRF24L01+ wireless transceiver is a very popular radio transceiver. It operates at 2.4 GHz ISM with an operating power consumption of 26 µA. It boasts an output power of 11.3mA @ 0dBm, with a data rate (reception) of 13.5mA @ 2Mbps. The transmission distance for this device, as it operates via radio, will be significantly greater than the purposes of this project require, and thus has not been included in this section.

3.4.2.e Hardware Comparison Table

Factor	**HC-05**	**HC-06**	**nRF24L01+**
Connectivity	UART, Bluetooth Serial	UART, Bluetooth Serial, USB	RF (2.4 GHz ISM)
Power Consumption	~30mA Operating	40mA Operating	26 µA
Output Power	+4dBm	+6dBm	11.3mA @ 0 dBm
Data Rate	Default 38400 bps (Baud Rate)	Default 9600 bps (Baud Rate)	13.5mA @ 2Mbps
Tx Distance	~10m	~100m	Irrelevant (RF)

Table 8: Hardware comparison table that compares wireless transceiver module candidates.

3.4.2.f Conclusion

Based on the above research, the transceivers to be employed on the AutoCaddie architecture will be the HC-06 wireless transceivers. These devices boast an excellent transmission range, nearing 100 meters (about 328.08 ft) which will allow for an excellent level of flexibility. The HC-06 device utilizes Bluetooth Serial communication, something which is generally supported natively in the vast majority of modern devices, particularly laptops, which will be the primary target for data reception. The transceiver requires UART to be used to send the data to be transmitted via Bluetooth, which is supported by the MSP430FR6989IPZ, and is very easily configured on laptops and the MCU chip selected. The default data rate is 9600 bps, which will ensure that the feedback timing requirements are met and exceeded, allowing the user to view their individualized feedback without data bottlenecking significantly in the hardware. This component, however, like most data transmission modules, draws much more power as compared to other standard components of a PCB. As such, a battery power source must be selected to properly account for the use case of the transceiver's power draw.

3.4.3 Battery Power Source

3.4.3.a Overview, Comparison, and Selection of Component Type

Batteries are a critical part of the sensor system architecture that is worn by the user. Without the batteries, the IMU and the wireless data transmission systems cannot be powered and will not be functional, thus disabling a core part of the AutoCaddie system. The batteries implemented in the wireless data transmission PCB must provide enough charge to power the user-mounted system for at least 2 hours. Furthermore, the battery weight must be minimized so as to reduce the overall weight of the system mounted on the user. Additionally, rechargeable batteries are preferred to reduce battery waste from the system.

There are several available battery types suitable for use in AutoCaddie hardware

systems, with alkaline, lithium-ion, and lithium-polymer batteries being commonly employed in PCB powering applications. Lithium-ion batteries are rechargeable, relying on lithium ions stored within a liquid electrolyte, offering relatively high energy densities and a long-term lifespan when used correctly. On the other hand, lithium-polymer batteries are similar to lithium-ion batteries but store ions within a polymer material, resulting in a slightly higher energy density while being less resilient to damage compared to their lithium-ion counterparts.

Alkaline batteries represent another battery type suitable for powering the hardware system. Alkaline batteries are disposable and generally more robust than other types, but they can pose risks if damaged and are not rechargeable due to their disposable nature. For the AutoCaddie project, lithium-ion batteries were chosen as the preferred battery type because they are rechargeable and generally more durable, a crucial consideration given that the battery will be integrated into a wearable circuit system subject to inertial impacts and movements that may cause wear.

3.4.3.b Tenergy 7.4v 2.2Ah Li-ion 18650

The Tenergy 7.4V lithium-ion battery pack is a rechargeable, high-capacity battery. With an energy capacity of 2200mAh and a continuous discharge capacity of 2.2A, this battery can provide multiple hours of charge should charge consumption be optimized. Since this battery pack consists of two standard 18650 2.2Ah batteries, the approximate weight of the system comes to 100g. The price of this battery pack totals $16.99.

3.4.3.c Adafruit 3.7V 2.2Ah Lith-ion 18650 (PKCELL)

The Adafruit 3.7V lithium-ion single-cell battery pack is a rechargeable, lightweight battery cell. With an energy capacity of 2200mAh and a continuous discharge capacity of 1A, this battery can provide about two hours of charge even at continuous standard draw. As a single 18650 size battery cell, the weight of this product is 46g. The price of this battery pack totals $9.95

3.4.3.d Adafruit 3.7V 4.4Ah Lith-ion 18650 (PKCELL)

The Adafruit 3.7V lithium-ion dual-cell battery pack is a rechargeable, high-capacity battery pack. With an energy capacity of 4400mAh and a continuous discharge capacity of 1A, this battery pack can provide several hours of charge with charge consumption optimization. As this battery pack contains two 18650 battery cells, the weight of this product comes to 95g. The price of this battery pack totals $19.95.

3.4.3.e Hardware Comparison Table

Factor	**Tenergy 7.4v 2.2Ah Li-ion 1865**	**Adafruit 3.7V 2.2Ah Lith-ion 18650 (PKCELL)**	**Adafruit 3.7V 4.4Ah Lith-ion 18650 (PKCELL)**
Energy Capacity	2.2Ah	2.2Ah	4.4Ah
Discharge Capacity	2.2A	1A	1A
Weight	~100g	46g	95g
Rechargeable	Yes	Yes	Yes
Cost	$16.99	$9.95	$19.95

Table 9: Hardware comparison table that compares battery candidates.

3.4.3.f Conclusion

Comparing the battery pack candidates, the Adafruit 3.7V 4.4Ah Lithium-ion battery was chosen as the best candidate. This rechargeable battery pack provides the most charge capacity of the other candidates. Furthermore, this battery pack is comparable in weight to the Tenergy battery pack, which has only half the charge capacity. The high capacity of the battery pack was the most influential factor in the selection of this component, as it guarantees the sensor and wireless data transmission systems will be able to be powered for a sufficient amount of time. The 1A discharge capacity is an acceptable amperage, as the system should not exceed this amperage as a requirement. Should more amperage be required, current regulators can be implemented. Regarding the price of the battery, though it is the most costly selection, it remains within a similar price index to the other selections (maximum $25.00 price range), and thus should not pose a large impact to the total costs of the AutoCaddie system.

Along with the data transmission systems, which are the primary power draw of the hardware system, the batteries must also supply power to the IMUs and the Microcontroller unit. The MCU can also control the general power draw of the external components, such as the wireless transmission unit. By idling the given components, their overall power draw can be reduced.

3.4.4 Microcontroller Unit Selection

3.4.4.a Overview, Comparison, and Selection of Component Type

The MCU (Microcontroller Unit) chip will be the lynchpin of the entire project's sensory systems. This processor will collect data from the sensors (IMUs) attached to the user, perform arithmetic upon the data, and finally send the packeted data to a wireless transceiver unit. Integrated onto the PCB, without the MCU chip, nothing is collected or sent, therefore selecting the proper device is paramount to the success of the project. The most important factors considered when evaluating MCU chips are cost, power consumption, processor frequency, number of GPIO pins (analog and digital), connectivity options (UART, I2C, SPI, Phillips I2C), memory (type and size), low-power modes, and wireless transmission options.

Before concluding with the use of a microcontroller, other options such as FPGAs may be considered. An FPGA (Field-Programmable Gate Array) is an extremely versatile and configurable device, excelling at highly specialized tasks requiring high speed, parallel processing, and custom digital logic design. However, the AutoCaddie hardware will very simply receive data from the IMU (Inertial Measurement Units) components, format them to an easily processed file, and output the formatted data to a wireless transceiver. The versatility and configurability of an FPGA is not an applicable advantage in this context. Furthermore, FPGAs are typically significantly more expensive than microcontrollers, therefore projects that do not require their particular upsides incur unnecessary costs via their use. While FPGAs excel at highly specialized tasks, they are less suited for general-purpose processing, such as formatting I/O data and outputting it. FPGAs are generally fixed in terms of their hardware configuration; projects which implement them typically

limit their scalability to the limited reach of their FPGA, while a microcontroller has the capability to receive data from I/O devices added to the project later. Microcontrollers, such as the MSP430, generally have intrinsic hardware support for common communication interfaces such as UART and I2C, making them more applicable for interfacing with simple I/O devices such as IMUs. Finally, FPGAs typically consume greater power than microcontrollers, enabling their advantages but in the context of a simple I/O data transmission, results in extraneous and unnecessary power consumption.

3.4.4.b MSP430FR6989IPZ

The MSP430FR6989IPZ is an extremely versatile MCU (Microcontroller Unit) chip which easily satisfies the computation and transmission requirements of this project. The chip is compatible with all input and output connectivity requirements demanded by the I/O devices included in the PCB, those being UART and I2C, with an added peripheral option of SPI. As was specified in the PCB requirements, this chip has no native wireless transmission capacities, requiring external transceivers to be employed. There are 16 analog inputs and 83 digital GPIO pins. The power consumption in Standby mode is 100 µA/MHz, which is sufficiently low as to avoid unnecessary draw on the battery. The MSP430FR6989IPZ also boasts 3 low-power modes, each reducing the power consumption by a factor of 100 A when certain components are not required. The cost is a conservative $10.21 per unit.

3.4.4.c ATMEGA328P

The ATMEGA328P chip is used most frequently in Arduino development boards, making it easily one of the most popular and documented MCU chips on the market. It boasts a processor frequency of 20 MHz and achieves 20 MIPS, 32KB of flash memory, USART, SPI, I2C connectivity, and more. As was delineated in the PCB requirements, this chip has no innate wireless transmission capabilities, requiring the use of external transceivers. The chip boasts 32x8 GPIO registers with an active power usage of 200 µA/MHz. Also extremely important, the chip has 2 low-power modes which allow the user to conserve energy when certain features are not required.

3.4.4.d ESP32-C3

The ESP32-C3 chip is extremely unique among MCU chips. Advertising an extremely fast processor with a frequency of 160 MHz, 384KB ROM and 400 KB SRAM, in terms of performance (excluding power) it vastly outperforms its counterparts. It boasts UART, SPI, I2C, I2S, USB/JTAG connectivity, making it the most versatile in terms of connectivity among those evaluated for the purposes of this project. In terms of wireless communication, it is capable innately of Wi-Fi, Bluetooth, and radio (RF) communication, making it capable naturally of what this project requires. It boasts 22 GPIO pins with a power consumption of 335 mA, significantly higher than the other chips on this list. However, it compensates for this with 4 low-power modes.

3.4.4.e Hardware Comparison Table

Factor	MSP430FR6989IPZ	ATMEGA328P	ESP32-C3
Processor Frequency	16 MHz	20 MHz (20 MIPS)	160 MHz
Memory	128KB FRAM	32KB Flash, 1KB EEPROM, 2KB SRAM	384KB ROM, 400 KB SRAM
Connectivity	UART, SPI, I2C	USART, SPI, I2C (Phillips compatible)	UART, SPI, I2C, I2S, USB/JTAG
Wireless Transmission	None (PCB Req)	None (PCB Req)	Wi-Fi, Bluetooth, RF
GPIO	16 Analog In, 83 D I/O	32x8 GP Registers	22 GPIO
Power Consumption	Active 100 µA/MHz	(@1MHz) Active 200 µA	Active 335 mA
LPM	Standby (0.4 µA), Real-Time Clock (0.35 µA), Shutdown (0.02 µA)	Power-Down (0.1 µA) Power-Save (0.75 µA)	Modern-Sleep (28 mA) Light-Sleep (130 µA) Deep-Sleep (5 µA) Power Off (1 µA)

Table 10: Hardware comparison table that compares MCU candidates.

3.4.4.f Conclusion

Based on the above research, the MCU chip to be integrated into the PCB will be the MSP430FR6989IPZ. This chip has 128KB FRAM, which is nonvolatile memory and is useful in all applications. The use of this chip has been the subject of prior study, and therefore is familiar to all members of the AutoCaddie team. The chip has more than sufficient analog and digital I/O pins, as well as multiple clocks which can be used for synchronicity of input/output devices. The chip does not have native wireless transceiver capabilities, which is exactly in line with the PCB requirements outlined, those being that external transceivers must be utilized to accomplish any goal necessitating wireless communication. The low-power modes available will ensure that no unnecessary power is utilized, which will allow the device to maximize battery life and leverage the greatest usability of the AutoCaddie architecture.

The wireless transceivers to be used on the PCB will require UART serial communication, which is natively supported by the MSP430FR6989IPZ, and is easily configured on the chip. The availability of other serial communication modes, namely I2C and SPI allow for a level of flexibility in hardware selection, should a situation arise which requires a change in devices. While not a general concern in MCU chips, as they are generally very small, the MSP430FR6989IPZ chip is very small, which will allow for the PCB to maintain a nonintrusive, ergonomic form that does not interfere with the user's improving swing. Due to the memory limitations and time constraints of the data transmission protocol with regards to the demands of the AutoCaddie system, much of the data processing will occur on the central computer, in order to save computation and memory resources on the microprocessor aboard the PCB. Namely, preprocessing the quaternion data aboard the PCB will utilize large computational resources due to the level of computation required, thus such processing is reserved for the main computer.

3.4.5 Quaternion Data Processing

Within AutoCaddie's demand for linear data processing, quaternion data plays a crucial role in capturing and interpreting the spatial and rotational dynamics in a golfer's swing. This section explores quaternion data, in terms of what separates it from Euler data, and

the methods that can be used for real-time calculations. These insights contribute to the fundamental understanding of the procedures undermining AutoCaddie's ability to analyze the arm linearity during a golfer's swing.

Euler angles represent a set of three angles used to describe the orientation of an object in a three-dimensional space. These angles represent rotations about the axes of a fixed coordinate system and are commonly used in various fields, such as robotics and aerospace engineering.

Specifically, according to J. Diebel, [34] we can define these angles as a rotation sequence, which is defined as a sequence of three rotations around different axes. The order of these rotations is important and can be represented by three integers: (i, j, k).

These angles are represented as a three-dimensional vector denoted by $u \coloneqq [\phi, \theta, \psi]^T$ .Here, ϕ, θ, and ψ are the angles of rotation about the specified axes. The Euler angles are used to compute a rotation matrix $R(\phi, \theta, \psi)$, which represents the orientation of an object after the specified rotations.

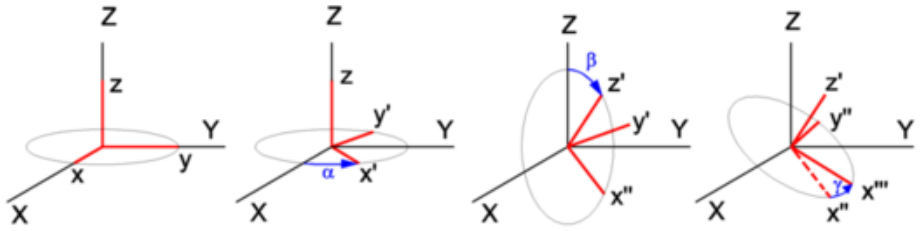


Figure 15: Euler angles. The far-left plot represents the original (x,y,z) axis. The second-leftmost plot represents applying angle ϕ across the z-axis. The second-rightmost plot represents applying angle θ across the y-axis. The far-right plot represents applying the angle ψ across the x-axis, completing the Euler angle. Referenced via [35] .

The time-derivative of the Euler angle vector gives the vector of Euler angle rates, representing how fast each angle is changing with time. Angular velocity, which describes how fast an object is rotating, is related to the Euler angle rates through specified matrices. In the context of AutoCaddie, this is important in determining the rate of change of the bend of the user's least dominant arm during the swing motion.

Specifically, the following process explains how to calculate the straightness between two points over time using Euler angles. First, each Euler angle can be converted into a 3x3 rotation matrix. The conversion process is highly dependent on the order of rotations. Next, interpolation can be utilized to obtain a series of intermediate rotation matrices that represent the rotation over time. A common methodology for this process is linear interpolation (LERP), with matrix operations shown below.

$$\begin{bmatrix} 1 & x_0 & y_0 & z_0 & x_0y_0 & x_0z_0 & y_0z_0 & x_0y_0z_0 \\ 1 & x_1 & y_0 & z_0 & x_1y_0 & x_1z_0 & y_0z_0 & x_1y_0z_0 \\ 1 & x_0 & y_1 & z_0 & x_0y_1 & x_0z_0 & y_1z_0 & x_0y_1z_0 \\ 1 & x_1 & y_1 & z_0 & x_1y_1 & x_1z_0 & y_1z_0 & x_1y_1z_0 \\ 1 & x_0 & y_0 & z_1 & x_0y_0 & x_0z_1 & y_0z_1 & x_0y_0z_1 \\ 1 & x_1 & y_0 & z_1 & x_1y_0 & x_1z_1 & y_0z_1 & x_1y_0z_1 \\ 1 & x_0 & y_1 & z_1 & x_0y_1 & x_0z_1 & y_1z_1 & x_0y_1z_1 \\ 1 & x_1 & y_1 & z_1 & x_1y_1 & x_1z_1 & y_1z_1 & x_1y_1z_1 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \\ a_6 \\ a_7 \end{bmatrix} = \begin{bmatrix} c_{000} \\ c_{100} \\ c_{010} \\ c_{110} \\ c_{001} \\ c_{101} \\ c_{011} \\ c_{111} \end{bmatrix},$$

Figure 16: A matrix multiplication method to solve linear interpolation. $(x_0, y_0, z_0), (x_1, y_1, z_1)$ *are defined, and vector c is defined as function values. Referenced via [36] .*

From this point, once a series of rotation matrices are calculated to represent the orientation over time, calculations can be made to find the straightness between two subsequent points using the Euclidian distance formula.

However, a large weakness of Euler angles is the presence of singularities. Singularities refer to specific angle configurations where the representation becomes problematic. This can lead to problems such as gimbal lock. Gimbal lock occurs when two of the three rotational axes become parallel, resulting in a loss of one degree of freedom. This makes it challenging to uniquely represent orientations near the singularity, leading to ambiguity in interpreting the rotations.

Depending on the sequence of rotations, singularities may occur, making certain orientations difficult to represent accurately. These singularities can result in discontinuities, making it challenging to interpolate smoothly during the calculation process. Since AutoCaddie requires accurate calculations, jeopardizing data during the swinging process is unacceptable. That is why, to mitigate these issues, alternative representations of rotational data are often used, primarily quaternions.

Quaternions represent a numerical way to represent complex numbers in three dimensions. As provided by J. H. Challis, [37] the complex number form of a quaternion is shown below (also known as Hamilton's quaternion formulation).

$$q = q_0 + q_1 i + q_2 j + q_2 k$$

Equation 1: The complex number form of a quaternion data point.

In this equation, q_0, q_1, q_2, and q_3 represent real numbers, and i, j, and k are imaginary components. Separately, we can say that the four-tuple form of a quaternion is shown as the equation below.

$$q = (q_0, q_1, q_2, q_3)$$

Equation 2: The four-tuple form of a quaternion.

Separately, the scalar and vector form of a quaternion is shown in the equation below.

$$q = q_0 + v,\ v = (q_1, q_2, q_3)$$

Equation 3: The scalar and vector form of a quaternion.

On a separate note, Hamilton's quaternion formulation allows direct visualization as a rotation about an axis, avoiding the ambiguity of Euler angles. The change in orientation can be visualized from its quaternion. Specifically, given a single quaternion, the rotation angle can be extracted from the equation below.

$$(a,b,c) = \left(\frac{q_1}{\sin\left(\frac{\theta}{2}\right)}, \frac{q_2}{\sin\left(\frac{\theta}{2}\right)}, \frac{q_3}{\sin\left(\frac{\theta}{2}\right)}\right),\ \theta = 2\cos^{-1}(q_0)$$

Equation 4: The rotation angle θ, and the axis of rotation (a,b,c).

Backtracking, the presence of singularities within Euler angles leads to ambiguities. The gimbal lock problem arises when certain orientations lead to a loss of one degree of freedom, which is the result of the event when two of the three rotational axes become aligned. However, quaternions represent rotations in a different way that avoids this issue.

By considering the set of all possible 3D rotations, this set forms a mathematical structure known as the rotation group (SO(3)). The unit quaternion space, when used to represent 3D rotations, acts as a double cover of the rotation group SO(3). In other words, the rotation space of unit quaternions forms a hypersphere in a four-dimensional space. For every point on this hypersphere, there are two antipodal points that represent the same rotation in the SO(3) space. Knowing this, when interpolation is introduced to find rotational data in this quaternion space, if there is a gimbal lock present, an equal rotation point will be available. Therefore, there will always exist smooth interpolation path, and singularity is entirely avoided using quaternion data.

By analyzing this information, it is safe to conclude that quaternions are a superior choice for rotational data recording in the context of AutoCaddie. By utilizing quaternions, there will not be a case where data is invalidated by discontinuities.

Additionally, there is a straightforward equation that can be used to find the angle between two quaternion points. It can be derived as follows.

Given two unit quaternions (the magnitude of a unit quaternion is equal to 1), $q_1 = (w_1, x_1, y_1, z_1)$ and $q_2 = (w_2, x_2, y_2, z_2)$, the dot product between them and the cosine of the half angle between them can be defined by the following equations.

$$q_1 \cdot q_2 = w_1 w_2 + x_1 x_2 + y_1 y_2 + z_1 z_2$$

Equation 5: The dot product between two quaternions.

$$\cos\left(\frac{\theta}{2}\right) = \frac{q1 \cdot q2}{||q_1||\,||q_2||} = q1 \cdot q2$$

Equation 6: The cosine half angle between two unit quaternions.

Therefore, by solving for the angle θ, the equation for the angle between two unit quaternions is shown below.

$$\theta = \cos^{-1}(2 < q1, q2 > \ -1)$$

Equation 7: The angle between two quaternions.

Furthermore, by utilizing this equation, AutoCaddie's non-dominant arm linearity calculation can be computed efficiently. Like the frame extraction discussed earlier, the MCU will transmit a packet of quaternion data to the computing device, representative of the spatial and rotational data during every instance of time measured from the beginning to the end of the swing. Primarily observed between specific events of the golf swing, the non-dominant arm of the user is required to be hyperextended to align with proper technique. By performing this angular calculation between subsequent points throughout the dataset, it is simple to identify any significant arm straightness deviations during the swing process.

This will be implemented via the software system of AutoCaddie. Since the process can be simplified to a simple equation, it becomes also possible to simplify the required code to a simple function. In the next section, the programming language used for this calculation will be discussed as well as useful libraries that will facilitate the implementation of other subsystems, specifically the other data preprocessing techniques, the neural network, and the software design.

3.5 Relevant Technologies: Software Integration

3.5.1 Overview and Language Selection

Within AutoCaddie's domain, the choice of programming language plays one of the most pivotal roles in shaping the product's functionality, efficiency, and overall effectiveness. The focus of this section is the rationale behind the selection of Python as the dominant programming language, and the specific libraries that can be imported to improve many features of this project. First, by examining programming languages and analyzing benefits and drawbacks, the most informed decision can be made.

In the context of this project, optimal developmental efficiency is anticipated through the alignment of the selected programming language with the developers' existing familiarity. Additionally, through an exhaustive examination of popular languages supporting the creation of CNNs, four programming languages have been selected as candidates. These languages are Python, Java, C++, and JavaScript.

First, Python [38] is a dynamic and versatile programming language. It stands out for its unique characteristics that distinguish it from traditional languages. It embraces flexibility and clear coding design to enhance readability. It also benefits from its widespread usage, as it is known for its extensive library collections.

There are many advantages to Python. Its simple syntax makes it one of the most readable languages, especially in comparison to the other languages listed prior. It is also versatile, as it accommodates both procedural and object-oriented programming. It is efficient for rapid development, which is useful in the AutoCaddie project for the developmental procedure. Also, it showcases true portability by being able to run on any

system that supports it. Additionally, it automatically performs memory allocations and garbage collection, which eliminates memory-related issues. Most importantly, it contains an extensive collection of built-in libraries, third party libraries, and open-source libraries that contain mostly every algorithm and optimization currently researched. A strong example of this is for developing CNNs, where multiple libraries currently offer support for development.

However, Python also presents disadvantages. It is not a very fast language due to the nature of it being dynamically typed. This also makes it memory intensive, which makes it difficult to use for memory-constrained environments. Additionally, it is not very popular for desktop or mobile applications, as other languages are stronger for this problem. It is also not optimized for custom database access, and it does not have multithreading support, which poses potential concern for neural network development.

Second, Java [39] stands as a versatile, high-level programming language celebrated for its robustness, security, and object-oriented nature. Notable, its syntax, designed for readability, resembles the English language, contributing to its accessibility. It is also platform-independent, which can allow for seamless execution across separate platforms.

Java contains many benefits. Its straightforward syntax and automated memory management simplify the learning curve for this language. It also utilizes object-oriented programming by containing classes, inheritance, encapsulation, polymorphism, and abstraction. Also, it excels in security with the absence of explicit pointers, execution within virtual machines, and dynamic class loading. Plus, it has strong memory management, exception handling, and type checking. Lastly, it has support for multi-threading, which allows for tasks to be parallelly executed. This is an important concept for training certain neural networks, particularly random forests, where unrelated processes can be completed in parallel to achieve more results at the same time.

However, it also contains drawbacks. Java interpreted runtime may lead to slower performance when compared to other languages such as C++. It also relies on the Java virtual machine, which results in higher memory consumption. Also, due to the lack of the ability to explicitly declare pointers, Java has minimal machine interaction, which disables certain computational benefits. Lastly, there is no direct method for manual memory release, which may increase memory demands over time.

Third, C++ [40] is a programming language that is known as an extension of the basic C language. It stands out for being versatile and powerful while also containing object-oriented programming methods. It is portable and allows for low-level maneuverability. Overall, C++ has become essential in diverse applications over the years, including compilers and operating systems.

There are many advantages to C++. First, it facilitates efficient problem solving through object-oriented principles such as classes, data abstraction, etc. Next, it is highly portable, which can allow for seamless integration of code throughout multiple systems. It is recognized for low-level maneuverability, which allows for device-specific optimizations.

Lastly, it has comprehensive memory management, multi-paradigm flexibility, and scalability.

However, there are many drawbacks to C++. First, the language's complexity poses a barrier to entry. Notably, C++ lacks support for certain modern programming concepts such as functional programming and automatic memory management. Also, the absence of built-in garbage collection, security vulnerabilities due to direct memory manipulation, and array limitations underscore this language's usability in the scope of this project.

Fourth, JavaScript [41] a lightweight and object-oriented scripting language, plays a large role in crafting dynamic HTML pages with interactive effects on the web. Primarily used for enhancing user interfaces and adding dynamic functionalities to websites, JavaScript's versatility extends to game development and mobile app creation. Its syntax is heavily influenced by C, and it allows for web tools to be integrated seamlessly into projects.

JavaScript has many advantages. First, it supports interfaces, modules, and classes, which covers a large range of programming objectives. It can operate in a relationship of both the client-side and server-side. Also, it empowers developers to create responsive interfaces, reacts to user interactions, and can run on any browser. It also facilitates the development of large-scale applications.

However, JavaScript presents crucial drawbacks in the scope of this project. AutoCaddie is a program that will be downloaded locally, so immediately the usage of JavaScript to make a local program is outweighed by the other three listed languages. Additionally, it lacks support for networking applications, which limits its utility in that domain. Further, JavaScript supports only single inheritance, but not multiple level inheritance like other object-oriented languages provide. For these reasons, without much comparison, JavaScript will not be the selected language for this project.

Putting everything together, Python, Java, and C++ all provide object-oriented programming that can run programs efficiently. C++ presents the largest learning curve, but in terms of practicality, that is not a limiting factor for development for this project. The primary selection criteria to be considered is the available tools provided for each language for developing the neural network, as well as tools that can automate data preprocessing. As the neural network is the driving force behind AutoCaddie, ensuring that the CNN is constructed optimally is the main concern. Therefore, due to the overwhelming community support for neural network libraries being developed in Python (elaborated upon in **Section 3.5.6**), as well as the provided libraries for matrix operations to improve processing speeds (elaborated upon in **Section 3.5.7**), Python is the best choice for the programming language for AutoCaddie.

3.5.2 Introduction to Data Preprocessing Libraries

As covered earlier, there are extensive data preprocessing techniques that need to be incorporated into AutoCaddie to allow for the smooth flow of live data analysis. There are five separate data manipulation algorithms that need to be addresses: frame extraction, bounding box labeling, frame standardization, action detection, and quaternion data

calculations. First, when the video stream is fed into the code, there needs to be logic for parsing it into a list of frames representative of every time stamp throughout the swinging process. Second, for every frame in the list, a bounding box around the golfer and club needs to be automatically drawn using an object detection system.

As previously researched, it was determined that MobileNetV2 is the strongest model for this purpose. Third, once the images have been reduced to the bounding boxes, they need to be resized to match a standardized format, which can be completed using zero-padding. Fourth, by utilizing LinearSVM, it is possible to perform action detection for a series of subevents within the parent golf swing action. Fifth, by performing basic arithmetic, it is possible to compute quaternion data calculations for rotational shifts over time. Each of these topics will be explored in the subsequent sections, with research towards potential Python libraries to be utilized by AutoCaddie.

3.5.3 Matrix Operations and Zero-Padding

One of the primary selections for AutoCaddie involves the handling of matrix operations. Optimal data management is critical for AutoCaddie's performance, so having access to tools to combine similar data operations into single variables such as matrices can reduce the time to complete complex computations. Not to mention, each frame from the video data can be represented as a 2D grid of pixels, which stresses the importance of having access to matrix operations within the code. The three most popular Python libraries for this task are NumPy, SciPy, and pandas.

NumPy [42] short for numerical Python, constitutes a powerful library encompassing multidimensional array operations. Numpy's utility extends to operations related to Fourier transforms, shape manipulation, and comprehensive support for linear algebra functions, along with random number generation capabilities. Thus, it significantly enhances computational efficiency when dealing with arrays and matrices.

NumPy offers an array of advantages. First, NumPy arrays are designed to be up to 50 times faster than traditional Python lists, ensuring efficiency in mathematical operations. The array object comes equipped with numerous supporting functions, simplifying operations on ndarray. Additionally, NumPy's compatibility with Python and straightforward installation further enhance its appeal.

However, there is also an array of disadvantages present with NumPy. First, NumPy has separate support for "not a number" values, which makes it difficult for the user to compare values in cross-platform settings. Additionally, it requires a contiguous allocation of memory.

SciPy [43] is an extension of the NumPy library. SciPy stands out as a comprehensive collection of mathematical algorithms and utility functions. It provides high-level commands and classes for efficient data manipulation and visualization. Overall, it can transform a Python session into a robust data-processing session rivaling MATLAB.

SciPy's integration with Python creates versatile equation creation using a readable design. The library's expansive collection of additional modules, contributed by developers globally, covers diverse areas of programming from parallel programming to web interaction. The high-level commands and classes in SciPy simplify complex mathematical operations in the same regard that NumPy does. However, SciPy has more flexibility than NumPy in that it has no constraints of homogeneity.

However, it does bring limitations. The primary difference of SciPy versus NumPy is the processing speed. SciPy was developed in Python while NumPy was developed in C, so inherently NumPy completes operations quicker. Not to mention, SciPy is a larger library, which presents more dependencies and lookups that may slow down specific functions. Also, SciPy's official documentation is still a work in progress, so there exists the possibilities of errors or incomplete information while referencing functions.

Pandas [44] is another highly popular Python software library that specializes in data manipulation and analytics. Pandas offers extended data structures for holding diverse types of labeled and relational data. It facilitates a range of operations, including merging, joining, reshaping, and concatenating data. It is also built off the foundation of NumPy, requiring its usage for optimal functionality.

Pandas also presents many benefits. Its ability to reshape and pivot datasets, along with merging and joining operations, makes it a powerful tool for handling complex data structures. The DataFrame object in Pandas adds another layer of functionality, enabling data manipulation and indexing. Other noteworthy features include robust support for data alignment, integrated handling of missing data, and extensive tools for reading and writing data in different file formats.

However, Pandas also presents certain drawbacks. Its memory consumption is relatively high compared to NumPy, making it less efficient for handling large datasets. The indexing of Pandas is slower than NumPy arrays, and the library may not be as performant as NumPy for datasets exceeding 500,000 rows. Additionally, pandas does not allow easy appending of data entries as quickly as regular Python.

The table below summarizes the advantages and disadvantages of each of these libraries. This way, each can be directly compared, and a result can be determined.

Library	Advantages	Disadvantages
NumPy	Efficient handling of numerical data. • Fast execution of operations on arrays. • Supports matrix multiplication and linear algebra. • Supports object-oriented approach using ndarray. • Efficient handling of arrays, matrices, and large datasets. • Broadcasting functions for uneven array shapes. • Consumes less memory compared to Pandas and SciPy. • Easy appending of data entries.	• Primarily designed for numerical data. • SciPy and pandas extend NumPy's features. • No complex data structures. • Limited statistical functions. • Memory overhead for large arrays.
SciPy	• Efficient handling of numerical data. • Optimized numerical operations and algorithms. • Extensive linear algebra routines and solvers. • Object-oriented design with high-level commands. • Additional modules for various specific data domains. • Broadcasting functions for arrays.	• Primarily designed for numerical data. • Memory consumption is higher than NumPy, and is dependent on operation and size. • Indexing may be slower for certain operations. • Appending data operations are slow.
Pandas	• Supports numeric, alphabetic, and heterogeneous data. • Efficient for data manipulation. • Object-oriented with DataFrame and Series. • Extensive tools for data manipulation and analysis.	• Limited linear algebra support compared to NumPy and SciPy. • Does not support broadcasting. • Higher memory consumption compared to Numpy. • Indexing is slow for Series. • Limited support for appending data quickly.

Table 11: Comparison between three popular Python libraries with matrix operation utilities.

For the purpose of AutoCaddie, the selected library needs to balance processing speed with resource consumption. In terms of operations, it is important to maintain a list of frames, crop an array to the confines of a bounding box, and apply zero-padding to match predefined dimensions. Overall, NumPy stands out as the ideal choice for this project for several reasons. When considering processing speed and resource consumption, NumPy is the strongest in both subjects. Of the three libraries, NumPy excels the most with large datasets due to its nature of being programmed in C. It can also easily maintain a list of frames using its array object, ndarray, which is optimized for performance over convenience, which does not pose a threat to the developers. This also makes operations involving quick and parallel computations efficient, specifically in regard to the quaternion data calculations.

The quaternion data calculation can be summarized into a single equation. However, by conjoining all adjacent data points into vectors, which we can represent by the matrix below, this equation can be simplified to a single call. Then, iteratively, the resultant matrix

can be analyzed for large shifts in rotational movement, which satisfies the linearity objective in AutoCaddie.

$$\Theta = cos^{-1}(2 \cdot < Q1, Q2 > - 1_{m-1}),$$

$$\Theta = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \dots \\ \theta_{m-1} \end{bmatrix}, Q_1 = \begin{bmatrix} q_1 \\ q_2 \\ \dots \\ q_{m-1} \end{bmatrix}, Q2 = \begin{bmatrix} q_2 \\ q_3 \\ \dots \\ q_m \end{bmatrix}, 1_{m-1} = \begin{bmatrix} 1 \\ 1 \\ \dots \\ 1 \end{bmatrix},$$

$$\Theta, Q_1, Q_2, 1_{m-1} \in R^{m-1}$$

Equation 8: Using a 2D matrix of quaternion data points to determine a vector of linearity data.

Moreover, NumPy's array manipulation capabilities, including cropping arrays to bounding boxes and applying zero-padding, are implemented with high performance in mind. Specifically, using array slicing, portions of images containing the contents within a bounding box can be easily separated from the rest of the array. Also, NumPy provides numpy.pad, which allows for array to be padded with zeros efficiently. This function is flexible and can be applied dynamically to different image input dimensions.

It may be the case that SciPy and Pandas have similar methods for this logic, but it is also the case that both libraries contain extra resources which are not necessary for the scope of AutoCaddie. Combine this fact with their extra memory management due to the large number of resources, and overall, both libraries negatively impact the storage requirements of AutoCaddie. Therefore, due to its high performance and smaller package size, NumPy is the correct library to utilize.

3.5.4 Frame Extraction

Moreover, to correctly apply these matrix operations, the system needs image data. As the video cameras record the user completing a golf swing, the live broadcast is sent to the system, and stored as video data. From there, AutoCaddie must rely on another Python library to extract frames from these videos for the calculations. There are three packages that are considered for this project. Specifically, they are OpenCV, FFmpeg, and video2images. Each of these libraries aim to accomplish the same task, but provide subtle differences in their implementations.

OpenCV [45] or Open-Source Computer Vision Library, stands as a versatile and powerful tool for video editing, image processing, and computer vision tasks. Its capabilities extend to techniques such as image scanning and face recognition, making it a crucial component in various applications. With OpenCV, users can perform a multitude of operations on videos, including frame extraction and cropping.

Since OpenCV is the most popular computer vision library, it is available with many benefits. Firstly, it has extensive functionality, offering a wide array of functions for image and video processing. In the context of AutoCaddie, it has methods built-in for frame extraction and cropping, which is important for the data preprocessing. Additionally, OpenCV benefits from a large community of developers, ensuring regular updates, but fixes, and improvements. Lastly, it is cross-platform supported, making it available for use with Windows, Linux, and macOS.

However, several drawbacks of OpenCV are as follows. It has a steep learning curve due to its extensive feature set, which might prolong the development process of this project. Additionally, some advanced functionalities have complex implementations, leading to challenges in understanding and properly utilizing them.

FFmpeg-python [46] is a versatile tool for video processing. While numerous Python FFmpeg wrappers exist, what sets ffmpeg-python apart is its exceptional support for complex filter graphs, making it suitable for both simple and intricate signal graphs. This library simplifies video manipulation by offering operations like flipping, trimming, overlaying, and more.

The advantages of FFmpeg are as follows. It excels with supporting complex filter graphs, enabling users to create intricate video processing pipelines effortlessly. It also utilizes a Pythonic interface, which makes video editing more readable and accessible. Lastly, it has a flexible installation process, which allows users to choose platform-dependent methods.

However, there are several major flaws with FFmpeg in the context of this project. Similar to OpenCV, there is a large learning curve with this library. It utilizes command-line interfacing, which poses a challenge for developers. Also, users need to ensure proper installation by configuring the $PATH environment variable, which can conflict with an existing environment variable. Lastly, FFmpeg is targeted towards complex video editing, which differs from the goal of AutoCaddie to analyze a short video of a golf swing. This library solves a problem entirely different than what is being sought after by this project, which makes OpenCV a stronger choice. Therefore, FFmpeg will not be used by AutoCaddie.

Videos2images [47] is another Python library designed to simplify the process of converting volumetric video data into image frames. The library addresses the need for customizable frame capturing rates during video annotation tasks, allowing users to extract frames from a video or a specific video segment efficiently. Videos2images proves to be beneficial in scenarios where specific frames are required for video annotation, and the flexibility it provides in terms of output format and output directory makes it a strong tool for video processing tasks.

There are several benefits for videos2images. Firstly, it aims to simplify the video-to-image frame conversion process, providing a user-friendly interface for efficient extraction. Next, it allows for users to define custom frame capture rates, enabling precise

control of the number of frames extracted per second. Also, it allows users to specify the output format and directory, offering flexibility in organizing and saving the extracted frames. Lastly, it also supports command-line usage.

However, there are also several drawbacks for videos2images. First, this library depends on external Python libraries such as tqdm, imageio-ffmpeg, and moviepy, which may introduce unnecessary dependency issues within AutoCaddie. Next, it has limited video format support by only covering .mp4, .avi, and .mkv. Lastly, the command-line interfacing can prove to be confusing, creating another learning curve necessary for the developers to overcome.

Between OpenCV and videos2images, OpenCV is the superior choice for AutoCaddie for a multitude of reasons. Firstly, OpenCV contains a more extensive documentation repository, which allows for the learning curve of the library to be quicker to overcome for the developers. Similarly, OpenCV has robust community support, which helps ensure that this library will have minimal errors during deployment. Secondly, OpenCV's code implementations are more straightforward in this context, which enhances the readability of AutoCaddie's codebase. Specifically, the code implementation of frame extraction of a video is shown below.

```
import cv2

def video_to_frame_list(video_path):
    vid_capture = cv2.VideoCapture(video_path)
    frames = []
    while True:
        success, frame = vid_capture.read()
        if not success:
            break
        frames.append(frame)
    vid_capture.release()
    return frames
```

Moreover, the code implementation for cropping a frame to specified dimensions in the context of a bounding box is shown below.

```
import cv2

def crop_frames(frames, x, y, width, height):
    cropped_frames = []
    for frame in frames:
        cropped_frame = frame[y:y+height, x:x+width]
        cropped_frames.append(cropped_frame)
    return cropped_frames
```

Furthermore, when comparing the two libraries, OpenCV stands out as a self-contained library, whereas videos2images introduces external dependencies. This distinction ensures that AutoCaddie remains more self-sufficient and less prone to dependency

errors. Putting all of this together, OpenCV will be utilized within the AutoCaddie project.

3.5.5 Required Libraries for MobileNetV2 and LinearSVM

As researched earlier, MobileNetV2 is a powerfool tool for object detection tasks, specifically in the context of annotating bounding boxes. It is designed as a pretrained network that can be implemented into Python projects to smartly approach the object detection problem. Upon importing, developers can create an instance of the model, and set the “weights” parameter to “imagenet” to download pretrained weights and save time and computational resources – a primary concern when utilizing a network such as this, especially in sequence with the primary AutoCaddie CNN. However, MobileNetV2 is available through the Keras Python library.

Keras [48] is a deep learning API written in Python. It stands out as a critical component of tne TensorFlow machine learning platform (TensorFlow will be explained further in Section 3.2.11.f). Keras prioritizes facilitating rapid experimentation, emphasizing the importance of transitioning from ideas to results swiftly to enhance the research process. As fine-tuning the object detection model becomes a concern during AutoCaddie prototyping, it is beneficial to have quickly-adaptable model programming, which is what Keras provides. Keras has demonstrated industry-strength performance and scalability, with prominent users such as NASA, YouTube, and Waymo.

In the context of image classification, Keras introduces developers to fundamental data structures: layers and models. The Sequential model, a linear stack of layers, serves as a simple starting point, while the Keras functional API enables the construction of complex layer graphs. Keras facilitates model configuration through compilation, where learning processes are specified with loss functions, optimizers, and metrics. The library supports an iterative training process an evaluation on test data, making it accessible for users at various skill levels. It is worth mentioning that, at a high level, the iterative training process occurs before deployment on AutoCaddie, so users will not have to worry about object detection taking extensive time periods to compute. Rather, this is a concern the developers need to factor into.

On a separate note, LinearSVM stands out as a particularly effective solution for the multi-class classification challenge encounted in golf swing action detection. This algorithm proves well-suited for delineating distinct golf swing events, such as the address, backswing, and others. LinearSVM’s preference in this context arises due to its consistently high accuracy across diverse experiments, proving its robustness.

Scikit-learn (sklearn) [49] is a machine learning library in Python that provides a range of tools for working with various machine learning tasks. In the context of SVMs, sklearn offers a comprehensive implementation, including support for classification, regression, and outlier detection. LinearSVC is a class within sklearn with the objective of a faster implementation of Support Vector Classification for cases where a linear kernel is applicable, such as golf swing event spotting. LinearSVC is an approach to implementing the LinearSVM model with increased overall speed.

For classification tasks, LinearSVC is fully capable of approaching multi-class scenarios. LinearSVC employs the squared_hinge loss and is efficient with linear kernels. It follows the “one-vs-the-rest" strategy, which is identical to the LinearSVM model. Conversely, OneClassSVM is sklearn’s direct SVM implementation with included tools for density estimation, but it does not perform as efficiently as the LinearSVC model.

Also, sklearn emphasizes the optimization of parameters during model training. Careful selection of parameters is important but can also be determined via brute force methods during development such as GridSearchCV, which is an algorithm that tests every possible combination of parameters and navigates to the best performing combination. Sklearn's LinearSVC implementation is backed by well-established mathematical formulations, which ensures its accuracy.

In short, Keras is a deep learning API that supports many deep learning operations, notably MobileNetV2’s model integration. Also, sklearn is another machine learning library that defines a large range of tools for working with machine learning tasks, such as establishing a LinearSVM model using the LinearSVC class. Overall, Keras and sklearn provide the necessary tools needed to implement these topics into AutoCaddie.

3.5.6 Network Libraries: TensorFlow vs. PyTorch

For the AutoCaddie project, TensorFlow [50] is an apt choice, especially with the use of MobileNetV2 for object detection tasks. MobileNetV2 [33] is a lightweight deep neural network architecture designed for mobile and edge devices but also suitable for our laptop-based application due to its efficiency and speed. TensorFlow's integration with Keras simplifies the import and utilization of MobileNetV2, making it conducive for the image preprocessing required in our project.

The advantages of Using TensorFlow with MobileNetV2 for AutoCaddie are many fold. MobileNetV2 is designed to be efficient and performant which is paramount for processing video data without the extensive computational resources of a desktop system. The ease of Integration with Keras as a part of TensorFlow, offers a high-level API that makes it straightforward to deploy MobileNetV2 with minimal code, enhancing developer productivity. It does this by preprocessing and augmenting the data.

TensorFlow provides extensive support for image preprocessing and augmentation, which can be beneficial for preparing golf swing data for object detection and subsequent analysis. Transfer learning is very useful because it leverages pre-trained weights of MobileNetV2 via Keras allowing for utilizing transfer learning to reduce training time and improve model robustness by learning from a wide array of image data.

While the project has settled on using TensorFlow and Keras for importing MobileNetV2, PyTorch also offers equivalent functionalities that could have been considered. The Torchvision [51] module provides access to pre-trained models, including those optimized for mobile devices, with easy-to-use interfaces for computer vision tasks. PyTorch's dynamic computation graph could allow for more customized adaptations of MobileNetV2 if necessary, which may be advantageous for specific golf swing detection requirements.

TensorFlow's comprehensive toolset which includes the TensorFlow Object Detection API and TensorFlow's data API can be directly applied to the AutoCaddie project. These tools streamline the model development pipeline, from data loading and preprocessing to model training and evaluation. The use of MobileNetV2 through Keras in TensorFlow offers the following specific advantages for AutoCaddie's development. Rapid Development, this is due to the ease of using Keras with TensorFlow. This accelerates the development of object detection models and enables rapid iteration. Performance Tuning, With TensorFlow's profiling and optimization tools this will be invaluable for tuning MobileNetV2's performance on the AutoCaddie laptop setup. And Deployment Readiness, This is because TensorFlow's model serialization and deserialization functionalities facilitate the saving and loading of models, making the transition from development to deployment seamless.

By choosing TensorFlow with MobileNetV2 integrated via Keras, the AutoCaddie project benefits from a streamlined, efficient workflow that is both powerful and flexible enough to meet the demands of golf swing analysis on a laptop-based platform. This setup ensures that the project can maintain high performance without the need for extensive computational resources.

3.5.7 Graphical User Interface Libraries

Up to this point, all of AutoCaddie's internal processing has been defined through code. Python is the overbearing language of this project and wraps all the components into a centralized style for accessibility and compatibility purposes. In terms of simplifying complex mathematical operations, matrix calculations and image padding can be completed using NumPy. For extracting frame data from the live video feed, OpenCV provides the most overwhelmingly supported solution which will integrate high accuracy into this process. Also, Keras, sklearn, and Tensorflow are additional libraries that facilitate the usage of deep neural networks, whether it be smart preprocessing algorithms or the development of an internal CNN. However, the remaining piece of the puzzle to complete AutoCaddie's software implementation is to present the output to the user in a well-formatted method. That is where the importance of using a GUI is apparent.

In the realm of Python GUI development, various different frameworks offer distinct features and benefits. Each framework caters to a specific preference and requirement, making it essential to explore and compare strengths and weaknesses. For the purpose of AutoCaddie, five prominent Python GUI frameworks will be analyzed: PyQt5, Tkinter, wxPython, Kivy, and PySimpleGUI.

PyQt5 [52] is a powerful and versatile GUI framework, offering extensive capabilities for developers. Its integration with the Qt framework, active community support, and comprehensive documentation make it a compelling choice for building cross-platform desktop applications. However, developers need to remain aware of licensing considerations and be prepared for a large learning curve.

The strengths of PyQt5 are as follows. Firstly, it is powerful in the fact that it allows developers to develop visually appealing, as well as functional, applications. Also, it has

cross-platform compatibility, making it able to be developed and deployed across various operating systems. Next, its Qt integration allows developers to leverage the speed of C++ while working with Python, which is a solution to the major drawback of the Python language. Additionally, PyGt5 benefits from a largely active community, ensuring continuous improvements and support. This feeds into a comprehensive documentation, making it easier for developers to utilize all of its features. However, PyQt5 shoulders certain weaknesses. Mainly, PyQt5 is licensed under the GPL license. Developers must be mindful of licensing considerations, especially in commercial projects. Also, creating standalone executables may be challenging, and the resulting files may be larger compared to other frameworks. This can impact the distributability of AutoCaddie on deployment.

Tkinter [53] is an open source Python GUI library which is renowned for its simplicity and user-friendly features. Tkinter comes pre-installed with Python, eliminating the need for additional installations and forwarding its accessibility. Tkinter's advantages lie in its ease and speed of implementation, flexibility, stability, and the absence of the need for external downloads.

Some advantages of Tkinter are as follows. Firstly, Tkinter is one of the quickest GUI toolkits to implement compared to other popular choices. Also, it is flexible and stable. Next, it is largely accessible, as it is included in the installation of Python. Overall, it is referred to as the "beginner friendly" framework because, along with all of the accessibility and simple to implement code, it is very simple to understand, eliminating the large learning curve for developers.

However, Tkinter does have drawbacks. First, it does not include advanced widgets. To have access to advanced features and tools, external downloads are necessary, which defeats a large aspect of the accessibility of this framework. Additionally, it does not have a similar tool like the Qt Designer within PyQt5. Also, based on community feedback, sometimes Tkinter makes debugging difficult, and it does not fully have a reliable UI.

wxPython [54] stands as a cross-platform GUI toolkit for Python. It serves as an interface to the wxWidgets library, a popular cross-platform library written in C++. Notably, wxPython is open-source, aligning with Python free usage philosophy. Additionally, wxPython Phoenix is a project aimed at enhancing the speed while eliminating complexities of the original wxPython. Both versions of this GUI framework are available with stable cores.

The advantages of wxPython are as follows. Significantly, wxPython has a native look and feel across platforms, which allows for the GUI elements to integrate seamlessly across separate operating systems. This is attributed to its wrapping of native wxWidgets components. Additionally, wxPython offers flexibility in coding, allowing for specific adjustments to accommodate platform differences.

However, wxPython presents other weaknesses. Since this framework advertises heavily on cross-platform compatibility, the fact that its installation on macOS is difficult

undermines its very principles. Additionally, despite it providing many features, it lacks the same level of flexibility as PyQt5, especially with customization options. Not to mention, the nuances with cross-platform development adds complexity that developers may stray away from.

Kivy [55] is a roust and open-source Python library that is also designed for building cross-platform applications. This library enables the creation of mobile applications using Python, emphasizing user-friendly and interactive UIs. Kivy's framework supports the development of applications with distinct looks and feels across different platforms.

The strengths of Kivy are as follows. Kivy excels in cross-platform development, allowing developers to create applications that can run in various environments. It also provides built-in support for multi-touch interactions, making it well suited for mobile development. Kivy also introduces the Kv language, which facilitates the creation of customized widgets. This intermediate language streamlines the process of defining classes and widgets, making it easier to configure and tailor applications. Lastly, Kivy holds the ability to have developers write code once and reuse it across different platforms, eliminating platform-specific implementations.

However, Kivy presents many weaknesses as well. Kivy's user interface is non-native, which poses challenges for users unfamiliar with the platform. Additionally, the package size of the Kivy framework is large in comparison to the other libraries, which is because of the inclusion of the Python interpreter within the Kivy package. Also, Kivy suffers from small community size, resulting in limited support for developers. Support requests may take longer to be addressed, and less overall debugging has been completed on the framework, suggesting a higher probability of roadblocks for development. Lastly, the documentation for Kivy is deemed improper and incomplete, which makes utilizing the entire framework difficult.

PySimpleGUI [56] is a Python package designed to simplify GUI development by transforming frameworks like Tkinter, Qt, and wxPython into more straightforward interface. It streamlines window definition using Python core data types such as lists and dictionaries. Also, it changes event handling from a callback-based model to a message passing one, allowing for a more intuitive approach. The package doesn't mandate an object-oriented structure, and its simplicity doesn't limit its usability to only basic problems.

Therefore, PySimpleGUI presents the following strengths. Primarily, it provides an extremely easy-to-learn interface compared to the other GUI frameworks, requiring less code for the same functionality. Also, it can be implemented using either pip install or the downloading of a single source code file. Similar to many other frameworks, it supports cross-platform compatability, and allows the developers to run the same GUI by changing just one line of code. It also have extensive documentation, tutorial, example code, and videos, and can be integrated with various popular packages, notable OpenCV which is being utilized for bounding box annotation within AutoCaddie's live video feed. Some

more features are as follows: it is is highly customizable, open source, backwards compatible with support for both Python 2.7 and Python 3, and receives frequent updates.

However, PySimpleGUI also presents various weaknesses. Traditionally, PySimpleGUI deviates from the normal Pythonic approach, which can be tricky for veteran developers who are used to creating GUI applications prior to AutoCaddie's development. Additionally, the documentation, despite being extensive, lacks structure and adopts a case-by-case approach rather than a comprehensive walkthrough. PySimpleGUI also lacks specific tools that other frameworks possess, such as a forms designer. Lastly, this framework is considered best only for simple GUI development, and might not be suitable for complex commercial projects such as AutoCaddie.

In short, each of these five frameworks presents many strengths and weaknesses. To gain a better understanding of the big picture, each of the frameworks are presented in the table below.

Feature	**PyQt5**	**Tkinter**	**wxPython**	**Kivy**	**PySimpleGUI**
Open Source	Requires a commercial license.	Yes	Yes	Yes	Yes
Cross Platform	Windows, Mac, Android, Raspberry Pi.	Windows, Mac, Linux.	Windows, Mac, Linux.	Windows, Mac, Linux, Android, iOS, Raspberry Pi.	Windows, Mac, Linux, Raspberry Pi.
Python Version	Python 3 only.	Python 2 and 3.	Python 2.7 and 3.	Python 2 and 3.	Python 2.7 and 3.
Installation	Requires separate installation (not pre-installed).	Usually comes bundled with Python.	Can be installed using pip.	Requires installation, not pre-installed.	Can be installed via pip or single source file.
Ease of Learning	Moderate, QtGUI and QtDesigner modules assist.	Beginner-friendly, simple layouts and widgets.	Simple to use with good documentation.	Moderate, Kv design language, good community support.	Extremely easy, especially for beginners.
Widget Collection	Extensive set of modern and customizable widgets.	Vast collection, including standard and Ttk widgets.	Native look with standard widgets.	Customizable look with built-in widgets.	Provides a variety of widgets, may lack some features.
Form Designer	QtDesigner module provides a visual interface.	No built-in form designer.	No built-in form designer.	No built-in form designer.	No built-in form designer.
Commercial Use	Requires a commercial license.	Free to use.	Free to use.	Free to use.	Free to use.
Community Support	Strong community support and resources.	Well-established, abundant resources.	Active community.	Growing community, online resources available.	Active community, official Cookbook

					and Udemy course.
GUI Design Focus	Well-suited for both small- and large-scale applications.	Suitable for desktop apps, less focus on multimedia.	Suited for simple portable desktop applications.	Primarily designed for touchscreen-oriented interfaces.	Simplified GUI development, focus on simplicity.

Table 12: Comparison between five popular Python GUI frameworks.

By analyzing the table above, the following conclusions can be drawn. PySimpleGUI is suitable for beginners due to its simplicity and extensive documentation. WxPython is the strongest choice for simple portable desktop applications as it provides native widgets and ease of use. For powerful desktop applications, PyQt5 is recommended due to its comprehensive support and modern interfaces, but developers need to recognize the licensing. For mobile application development, Kivy is recommended as it is designed for mobile support and touchscreen integration. Tkinter is another valid desktop application framework, and provides benefits over PyQt5 in being open source, easier to understand, and more accessible. However, Tkinter does not have all of the available tools that PyQt5 provides, so for production it is less recommended.

In the context of AutoCaddie, a complex GUI design is necessary. The system needs to be able to interact with the user, provide calibration steps, format and present readable output, and showcase accessibility at a high enough level to maintain interest with the user. Therefore, PySimpleGUI is not suited for this application, as it does not possess enough features to justify its selection. Similarly, due to the nature of AutoCaddie's software deployment being a desktop application, Kivy is rendered unusable.

Overall, wxPython is the best selection for AutoCaddie. It offers portability between different computing devices, provides widgets and tools that are comprehensive enough to support AutoCaddie's requests, and gives developers a non-stressful learning curve in comparison to Tkinter. The primary justification for selection of wxPython of Tkinter is the ease of access for the developers to ensure quick development of the software. Additionally, PyQt5 is not selected due to the licensing restraints, where the budget of this project outweighs the framework's benefits. Therefore, wxPython is the framework that will be utilized for creating an intuitive and accessible GUI for communication with the user.

Chapter 4: Related Standards and Realistic Design Constraints

4.1 Standards

In this section, we delve into the usage of standards for maintaining consistency, safety, and compatibility throughout the AutoCaddie project.

The American National Standards Institute (ANSI), [57] functioning as a non-profit entity, orchestrates the intricate world of standards and conformity assessment. Its mission revolves around fostering global competitiveness and enhancing the quality of life in the U.S. It acts as a conduit for different stakeholders, including standards developers, government bodies, manufacturing entities, and various associations. Overall, ANSI ensures the integrity of standards development by accrediting procedures of over 240 organizations. The American National Standards (ANS) process mirrors this precision, involving consensus, public scrutiny, and a meticulous appeals system. ANSI's vigilant oversight ensures the entire standards framework operates seamlessly, akin to the careful observation of IMU data's linearity in a swing, delivering reliable user feedback.

Throughout this chapter, standards and constraints relevant to this project will be researched within ANSI and ANSI-accredited standards. From there, each topic will be explained in terms of significance and overall contribution.

4.1.1 Hardware Standards

Regarding the implementation of hardware, the sensor data collection and data transmission must adhere to various standards. Most particularly, data communication standards and circuit design standards must be accounted for. For circuit design standards, standards relevant to the designing of a PCB device must be accounted for. These standards may also relate to standards for data communication, which includes standards on communication means incorporated within the AutoCaddie project.

4.1.1.a IPC-2221

IPC-2221 is a widely recognized industry standard document that provides guidelines and requirements for the design of PCBs. Developed by the Institute for Interconnecting and Packaging Electronic Circuits (IPC), the standards document addresses a range of topics with auxiliary documents and standards categories. These topics of standards include board layout, conductor sizing, thermal management, and electrical characteristics. Overall, the IPC-2221 standards ensure that designed PCBs are developed with reliability and manufacturability in mind. Some relevant discussions of standards and guidelines relevant to the PCB design for the AutoCaddie system are as follows:

Signal Integrity: This section discusses the importance of maintaining signal integrity in high-speed digital and analog circuits. It covers topics such as controlled impedance, trace length matching, and signal routing techniques, which are crucial for reliable data transmission. Most importantly, this section outlines the placement of parts with respect to cycle frequencies and power sources, with lower-frequency parts being separated from

the power source and higher-frequency parts. This considered placement of elements maintains signal integrity between active elements and reduces chances of crosstalk. This section also discusses board spacing width with respect to applied voltage. For example, voltage levels from 0 to 15 require a minimum spacing of 0.05 to 0.1mm.

Power Distribution: Proper power distribution is essential for stable and noise-free operation, which is critical when dealing with data collection and transmission. This section provides guidelines for designing power planes, decoupling capacitors, and managing power delivery networks. A primary consideration that is encouraged by the document is to use decoupling with respect to power and ground traces.

Grounding: Proper grounding is crucial for reducing noise and maintaining signal integrity. The IPC-2221 document discusses grounding techniques and considerations that are relevant to data transmission circuits. As an extension of the guidelines for power distribution, the document outlines that if different grounds are used, particularly those for different measurement references, the grounds should be kept as separate as possible.

Thermal Management: In some cases, data collection and transmission circuits can generate heat, which can affect performance and reliability. This section addresses thermal management techniques, including heatsinking and proper component placement. Considerations of heat transfer are emphasized, including those of the mechanics of heat conduction and convection.

Environmental Considerations: Data collection and transmission devices may be deployed in various environments. The IPC-2221 document provides guidelines for selecting materials and design practices that can enhance the PCB's reliability under different environmental conditions. Considerations of environmental conditions should account for the application of the PCB and its potential environments, such as impact and environmental electromagnetic noise.

4.1.1.b I2C Standards

Standards for I2C Communication are written by NXT Semiconductor, originally Philips Semiconductor.

1. I2C Communication traditionally contains 2 bus lines: a unidirectional serial data line (SDA) and bidirectional serial clock line (SCL).
2. I2C boasts collision detection and arbitration to prevent data corruption if two or more controllers simultaneously initiate data transfer, making it a true multi-controller bus.
3. Serial, 8-bit oriented, bidirectional data transfers can be made at up to 100kb/s in the Standard mode, up to 400kb/s in the Fast-mode, up to 1 Mb/s in the Fast-mode Plus, or up to 3.4 Mb/s in the High-speed mode.
4. Serial, 8-bit oriented unidirectional data transfers up to 5 Mb/s in the Ultra-fast mode.
5. On-Chip filtering rejects spikes (outliers) on the bus data line to preserve data integrity.

6. The number of ICs that can be connected to the same bus is limited only by a maximum bus capacitance. More capacitance can be allowed under the following conditions: lowered operating frequency, using devices with higher drive current (Fast-Mode Plus), bus buffers (divide the bus into segments so that each segment has a capacitance below the allowable limit), switched pull-up circuit (alternately accelerate rising edges by switching a low value pull-up in and out when needed).

I2C will be the communication mode which collects data from the IMUs and transmits it via soldered wires (2 communication lines per device) to the PCB. The speed capabilities of I2C ensure that it will not be the limiting factor in terms of latency, and the built-in anti-corruption features ensure that data is significantly less likely to be damaged through the delivery process.

4.1.1.c Bluetooth Communication Standards

The HC-06 Wireless Transceiver to be implemented on the PCB is characterized as Bluetooth Class 2, and thus the characteristics of Bluetooth Class 2 will be summarized below.

1. Bluetooth power class 2 generally has a safe operating range of approximately 30 meters but can range higher depending on the specific device.
2. Bluetooth operates between 2400 – 2480 MHz, 2.5 GHz, and 3.5 GHz, but generally at 2.4 GHz in a globally available ISM band.
3. Bluetooth power class 2 has a maximum output power between 0 and +4 dBm.

Bluetooth is intended to be the exclusive wireless communication mode employed on the AutoCaddie project. Its projected use is to transmit a standard packet of data, approximately 13.68 kB in size, from the PCB directly to an external transceiver in a laptop or similar device. With a range of approximately 30 meters, a safe distance from the golf swing can be achieved, ensuring that no peripheral devices are damaged through the data collection process. The +4dBm output power makes the possibility of losing data due to signal weakness very unlikely, especially if the distance standard is adhered to.

4.1.1.d UART Communication Standards

UART will be the communication mode which transmits data from the MCU to the wireless transceiver module (HC-06). UART is a very widely used serial communication option, one of the staples of peripheral communication in computing.

1. The transmission process consists of 1 START bit, data bits (5, 6, 7, 8), 1 PARITY bit (optional), and 1 STOP bit. The following is a visual representation of this arrangement:

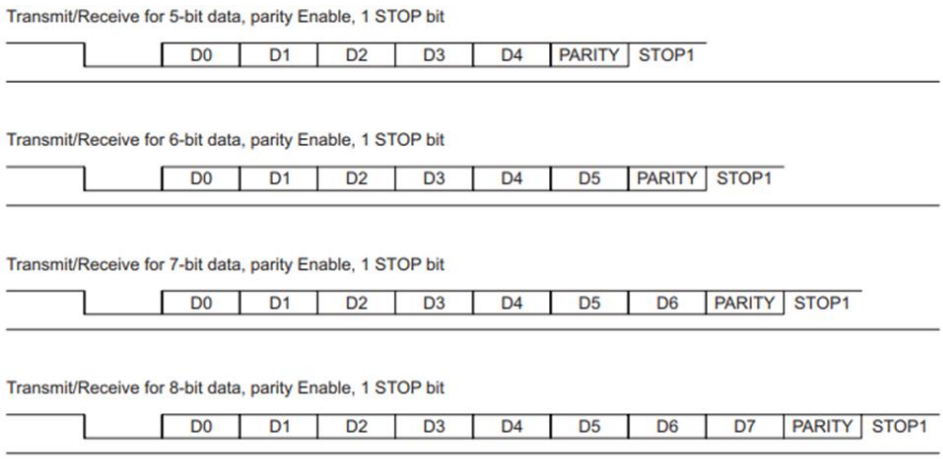


Figure 17: UART Protocol Formats.

2. UART peripherals adhere to a data rate referred to as “Baud Rate,” in b/s. Most devices operate in a rate range of 2400 b/s to 30000000 b/s. The default reception rate is 9600 b/s.
3. UART adheres to a hardware implemented queue called FIFO (First In First Out) that forces data to be processed in order of reception.
4. UART can operate synchronously or asynchronously. Asynchronous communication transmits data without a shared clock signal, while synchronous communication uses a clock signal to ensure precise timing. The asynchronous case is most common for general-purpose data transfer, including the AutoCaddie project.

4.1.2 Software Standards

In terms of the software implementation, there are many aspects of the project to account for. Regarding device communication, there are necessary standards for data validation and device benchmarks. For utilizing Python, standard syntax is necessary. Regarding the machine learning model, there are training standards, data processing methods, and validation tests to reference. Lastly, for the user experience, there are guidelines for the design, accessibility, and interactivity of the feedback.

4.1.2.a Device Performance Benchmarking

In terms of measuring the complexity of the model, this will need to be addressed during implementation. However, PyTorch is implemented with a benchmark module [58] to measure and compare code performance.

The benchmark module is used to validate that code meets performance expectations by providing proper insights about storage, memory allocation, optimizations, among other relevant details for a solution. They often utilize call graph analyses to delve deep into the internal workings. Currently, benchmarking can be applied to evaluate a multitude of performance concerns. During testing, it can be used to measure execution time and suggest possible optimizations. It can also help de-noise the data in case potential bad readings skew the input stream.

4.1.2.b Syntax Standards

For readability purposes, it is important to maintain a standard syntax style. Therefore, by referencing official Python documentation, we are recommended to use PEP 8, [59] or Python Enhancement Proposal 8.

PEP 8 serves as the official style guide for writing clean, readable, and consistent Python code. It encapsulates the Python community's best practices for code formatting, ensuring that Python codebases are maintainable and comprehensible. PEP 8 advocates for a uniform coding style, with recommendations covering aspects such as indentation, variable naming, whitespace usage, and commenting.

In PEP 8, code should be indented with four spaces per level, ensuring consistency in code structure. Variable and function names should follow a “lowercase_with_underscores” naming convention, and classes should use CamelCase. Whitespace should be used judiciously, with particular attention to maintaining consistent spacing around operators and after colons. Comments should be clear and concise, providing helpful explanations where necessary. Adhering to PEP 8 not only enhances the readability of Python code but also promotes collaborative development, making it easier for developers to work on projects collectively.

4.1.2.c Model Training Standards

Google, a leader in technology, has taken up the mantle of defining common model training standards for developers. In a comprehensive document, [60] Google outlines essential rules and insights gathered from extensive research discussions. These rules serve as beacons, illuminating the often-intricate path of machine learning model training.

The research paper distills Google's extensive experience into a set of fundamental principles for model training. In the following paragraphs, a list of rules will be given – with proper explanations and justifications of importance.

Rule #1 emphasizes the significance of understanding the problem at hand deeply. It stresses the importance of clarifying objectives, a foundational step often overlooked. Rule #2 echoes this sentiment, underlining the need for precise definitions of success, ensuring that everyone involved shares a common understanding of what constitutes a successful outcome.

Rule #3 introduces the concept of the "no free lunch theorem," emphasizing that there's no universally superior algorithm. Instead, the choice of algorithm should be tailored to the specific task and dataset. Rule #4 emphasizes the iterative nature of model development. It stresses the importance of prototyping and continuous refinement, highlighting that the first iteration is seldom the final solution.

Rule #5 sheds light on the critical role of human evaluation. Despite the rise of advanced algorithms, human judgment remains indispensable. Rule #6 champions the value of a strong feedback loop, ensuring that models continuously adapt to changing real-world scenarios.

Rules #7 and #8 underscore the significance of data quality. Garbage in, garbage out, as the saying goes – emphasizing the need for clean, reliable data to train effective models. Rule #9 delves into the crucial aspect of feature engineering, emphasizing the art of transforming raw data into meaningful inputs for machine learning algorithms.

Rules #10 and #11 emphasize the importance of regularizing models, preventing overfitting, and ensuring their generalizability. Rule #12 touches upon the vital concept of ensemble models, where combining predictions from multiple models often outperforms individual ones.

The paper introduces Rules #13 to #17, highlighting the challenges associated with online learning and emphasizing the need for robust, scalable systems that can handle vast amounts of data in real time. Rule #18 introduces the essential notion of fairness and bias, emphasizing the ethical responsibility associated with machine learning models. Rules #19 to #28 cover an array of topics, including feature selection, regularization, and the intricate balance between complexity and simplicity.

Rules #29 to #37 delve into the nuanced aspects of training-serving skew, importance weighting, and the challenges posed by changing data. Rules #38 to #42 explore the complexities that arise in later stages of model development, emphasizing the need to align objectives, simplify ensembles, and seek qualitatively new sources of information.

In essence, this research paper provides a comprehensive guide, distilling Google's wealth of experience into a set of actionable rules that illuminate the often-intricate path of machine learning model training. By emphasizing the importance of clear objectives, continuous iteration, human evaluation, and adaptability, Google's standards provide invaluable insights, shaping the future landscape of machine learning.

However, it is also important to note that, although there are important rules to follow, many of the rules provide ambiguity, which allows for creative freedom upon implementing a neural network.

4.1.2.d Data Processing Standards

A good benchmark to measure the network complexity of AutoCaddie is to observe SwingNet, [61] which is a network architecture deployed to analyze the golf swing using GolfDB.

The data processing standards for the SwingNet neural network architecture involve various hyperparameters that are essential to its effective training and deployment. These standards are crucial for determining the computational resources required for this task and optimizing performance.

One critical aspect of these data processing standards is the choice of hyperparameters. In this regard, an extensive ablation study was conducted to identify suitable configurations. The hyperparameters explored include the input size (d), sequence length

(T), batch size, number of LSTM layers (N), and the number of hidden units in each LSTM layer (H). The study also investigated the impact of initializing the network with pretrained ImageNet weights and the use of bidirectional LSTM layers. The goal was to identify a configuration that maximizes performance while considering limited computer resources.

Interestingly, the study found that the use of pretrained ImageNet weights was essential for the model's training success, suggesting that initializing with pre-trained weights is critical for domain-specific tasks where appearance variation is minimal. The sequence length (T) had a significant impact on performance, emphasizing the importance of temporal context in golf-swing sequencing. Moreover, increasing the batch size was shown to dramatically improve performance, although it may impact convergence speed. Bidirectionality in LSTM layers led to a 12.1-point improvement in performance. These findings provide valuable insights into the hyperparameters crucial for SwingNet.

The study also revealed that the correlation between input size and performance did not follow the expected pattern, as input sizes of 160 and 128 outperformed the input size of 192. This suggests that choosing an input size of 160 is more cost-effective. These insights help establish a solid foundation for defining data processing standards that balance computational efficiency and performance in SwingNet.

It's worth noting that the model's reliance on pre-trained ImageNet weights led to the exploration of freezing some of the ImageNet weights without significant performance loss, allowing for larger sequence lengths and batch sizes. This finding contributed to the development of a baseline SwingNet configuration with an input size of 160, a sequence length of 64, and a single-layer bidirectional LSTM with 256 hidden units. This configuration, combined with pre-trained weights and freezing some layers, facilitated training on a single GPU with 12GB of memory and faster convergence.

Therefore, it can be noted that a model for AutoCaddie can be trained sufficiently with 12GB of memory. However, it is possible to utilize smaller sequence lengths for testing to reduce the memory requirements of the network. But, since 12GB memory is such a low requirement, it is not necessary to do so.

4.1.2.e Validation Standards

In short, the purpose of validation data in a neural network is to test that it has learned how to analyze input rather than simply memorize it. An analogy for the validation process is passing test cases on a programming assignment. The validation process ensures that a coding solution is robust enough to solve any input case, rather than having hard-coded solutions for specific input cases. By completing validation on the neural network training, we can ensure that the model has been trained appropriately.

This is implemented by segmenting the database used to train a model into separate groups: training, validation, and testing. The training data is iterated over initially, which creates a matrix of features that are analyzed by the system. Then the validation data is presented to ensure that the network learned the hyperparameters rather than memorized them. This set is the one that is used repeatedly to ensure the given model is the best fit

and allows for tweaking of the hyperparameters to find the lowest error. Once that is found, the test dataset is used to provide a final unbiased evaluation of the system. Therefore, there are presented questions of what makes a strong validation set, and what the signifying factors are that a model is well fit.

To gain a proper understanding of these standards, we can reference the following IEEE/EIA Standard developed under the considerations of ANSI:

- 12207.0 - Standard for Information technology – Software Life Cycle Processes (March 1998). [62]

Additionally, we can reference “Verification and Validation of Neural Networks: A Sampling of Research in Progress” [63] to understand how the validation standards directly apply to neural networks.

The validation plan encompasses any items subject to validation. As referenced prior, the pre-trained neural network (PTNN) is the item subject to validation, and the performance needs to be measured to ensure it falls within an acceptable range. This can be observed through a simulated testing process.

The testing process involves several advanced techniques. These techniques include unit testing, incorporating both requirements-driven (black box) and design-driven (white box) approaches. Requirements-driven testing focuses on aspects like computational correctness, boundary conditions, stress scenarios, error handling, and recovery. Design-driven testing delves into internal logic paths, examining various elements such as interfaces, critical code elements, and system response. Additional tests involve frequency response, phase and gain margins, failure modes and effects testing, sensitivity analysis, timing tests, system resource evaluation, and adaptation time assessment. These thorough testing methods ensure the accuracy, stability, and reliability of neural networks in diverse scenarios.

4.1.2.f Data Receiving Standards

As defined by the Software Life Cycle Process Standard (March 1998), the data acquisition process needs to be outlined by the acquirer. In terms of a software standpoint, the system needs to be fully capable of acquiring data and utilizing it properly. It can be summarized into a 5-step process:

1) Initiation
2) Request-for-Proposal preparation
3) Contract preparation and update
4) Supplier monitoring
5) Acceptance and completion

As outlined by the hardware, we are utilizing Bluetooth Class 2 with UART communication to transmit data from the PCB to the computer. The data recording process is monitored via time steps, so after a short duration, the computer will begin receiving data, and the PCB will send packets over wireless transmission.

It is also important to mention that there is no direct request for proposals, as the systems work independently to conserve power. The frame recording system begins by observing live-action sequencing using CV algorithms, and the IMU recording begins via a predefined timer. Once the CV algorithm initializes the action sequence, the computer begins acquiring video data, and at the end of the sequence, becomes available to receive data.

4.1.2.g User Experience Standards

As outlined by “User Experience Design (UX) Standards and Guidelines” by Arizona State University, [64] there are many design standards and guidelines that contribute to a strong user experience. These can focus on design, accessibility, usability, navigation, information architecture, content, and search engine optimization. Accessibility is a large topic and will be covered in a separate standard. To ensure consistency and a positive user experience, the Unity Design System, launched in August 2020, serves as a foundational framework across all asu.edu pages and subdomains.

The Unity Design System encompasses various components such as global headers, primary navigation, content blocks, form fields, and page templates, including those for degrees, events, news, and directories. The system is continuously evolving based on community feedback and contributions, emphasizing a collaborative and adaptive approach. To facilitate adoption, the system provides resources like the Arizona State University UI kit, Adobe XD templates, and guidelines for design elements like color palette, typography, spacing, icons, and focus states. Additionally, the website encourages community engagement through platforms like the Unity Design System Slack channel, inviting users to propose new components and provide valuable input, ensuring the ongoing refinement and effectiveness of the UX standards.

The Unity Design System provides documentation for each of these aspects. When designing the software application for AutoCaddie, it will be important to reference this documentation. Some examples include color palette, typography, spacing, navigation, and content.

4.1.2.h Accessibility Standards

There are essential guidelines and tools for ensuring the accessibility of websites and digital tools, in adherence to the Revised 508 Standards and the W3C Web Content Accessibility Guidelines (WCAG) 2.0 Level AA. [65] Web designers, developers, and content managers are pivotal in this process, focusing on areas like design, navigation, and usability.

Additionally, the Interagency Trusted Tester Program promotes a unified testing approach to reduce redundancy and save resources across federal agencies. The program employs ANDI (Accessible Name & Description Inspector) [66] and Color Contrast Analyzer (CCA) [67] to assess accessibility. ANDI, developed by the Social Security Administration, is a bookmarklet tool used for testing websites and web-based

applications. CCA, created by the Paciello Group, assesses color contrast when it cannot be programmatically identified by ANDI.

Elaborating on CCA's color contrast analysis, the Web Content Accessibility Guidelines (WCAG) provide accessibility standards and benchmarks. These guidelines specify contrast ratios, which are crucial for readability. For WCAG 2.0 Level AA, the contrast ratio for normal text should be at least 4.5:1, ensuring clear visibility. Larger text, vital for those with visual impairments, should have a ratio of 3:1. In the updated versions, WCAG 2.1 and 2.2 Level AA, a contrast ratio of 3:1 is required for graphics and user interface components, enhancing accessibility for various elements. For the highest standard, WCAG Level AAA, normal text requires a contrast ratio of 7:1, ensuring maximum clarity, while large text should have a ratio of 4.5:1.

Moreover, Universal Design [68] is a standard in which products are designed for usability with all people. This extends to those with disabilities. By adopting universal design principles, information throughout the software becomes more available to the consumer. The principles are outlined as follows.

Equitable Use ensures designs are marketable to diverse abilities, promoting equal access and appeal. *Flexibility in Use* accommodates various preferences and methods, ensuring ease of use regardless of individual differences. *Simple and Intuitive Use* focuses on clarity, consistency, and effective feedback for users of diverse backgrounds and literacy levels. *Perceptible Information* emphasizes communication effectiveness, using multiple modes and maximizing contrast. *Tolerance for Error* minimizes hazards and errors through careful design and feedback mechanisms. *Low Physical Effort* prioritizes user comfort, employing reasonable forces and reducing repetitive actions. *Size and Space for Approach and Use* ensures elements are reachable, graspable, and usable for individuals of all body sizes and abilities, fostering universal accessibility.

These principles collectively promote inclusivity and usability, fostering environments that cater to everyone's needs. By incorporating them into AutoCaddie, the user will be able to utilize the resources more comfortably.

4.1.3 Design Impact of Relevant Standards

In the realm of product design, adhering to the provided standards holds large significance. The standards serve as guidance for the pathway of design to be established. For AutoCaddie, maintaining all of the relevant hardware and software standards will shape the product into one that is safe, efficient, and accessible.

In terms of following the specified hardware standards and specifications, the design of the hardware systems of AutoCaddie should especially account for standards that are directly related to the application and purpose of each respective part.

Regarding PCB design, since multiple instances of data are active in transit during sensory data collection and transmission, part and trace placement should account for noise and potential cross-talk, so signal isolation and integrity should be a foremost

consideration. Additionally, the PCB should be robust enough to withstand environmental forces such as impacts and temperature shifts.

Additionally, considerations of communication standards should be attended to. With regards to the requirements of the autocaddie systems, standard common implementations and specifications of communication methodologies will be selected that meet the specific needs of the application of the transmitted data. For example, a sufficient speed standard will be selected for the UART communication via Bluetooth that is fast enough to transmit all necessary data in the shortest period of time possible.

In terms of adhering to the software standards, AutoCaddie will implement these topics through its digital system. These ideas apply everywhere within the deployed neural network, processing, and the output application.

Firstly, it is important to measure computational efficiency throughout the application creation process. AutoCaddie will utilize PyTorch, which includes large amount of training calls and data management. By embedding benchmarks into the code, we can quantifiably measure the efficiency of the system.

Furthermore, this can expand to device validation standards. By benchmarking the performance of the system, we can analyze the effectiveness of a current training model during the validation process. If the model is not deemed to be effective, we can tune the hyperparameters and retest until a satisfactory performance measurement is reached. Utilizing benchmarking with the validation standards can ensure that the neural network system designed is optimal in performance.

On a similar note, to increase the efficiency of production, PEP8 will be referenced for a common Python coding style. That way, as trouble arises during development, the code will be more accessible to the developers, and debugging will simplify.

While incorporating PyTorch, proper model standards will be adhered to. By referencing a similar architecture to SwingNet, we can embed PyTorch into the system while designing an optimal analysis program.

For the device output to be used, the computing device just needs to contain 12GB of memory. This will be essential in standardizing the benchmarks, and for observing the performance of the completed system.

Separately, making sure that the system is designed properly will maintain data receiving standards. The camera and PCB data transmission will be sent separately, so there needs to be accountability with the design. The computer will use CV algorithms to define action sequencing on live video feed, which will define a final action and terminate the frame input stream. From there, it will be open for receiving packet data from the PCB, which will be initiated via a separate time step counter. Once the timer finishes, the data will be transmitted to the computer, where it will begin its analysis.

In terms of software design, there are many accessibility and user experience standards to adhere to. The list of features has been defined previously, so making sure that each of these points is accounted for will make the final design more transparent to the user. Using the recommended testing programs such as ANDI and CCS will ensure that the result is comfortable for the user, which will improve the experience.

4.2 Realistic Design Considerations and Constraints

4.2.1 Economics and Time

4.1.2.a Economics:

Initial Budgetary Constraints: With an estimated budget of under $450, AutoCaddie's development process must carefully allocate resources to ensure that each component and stage of development remains within the budget. Overstepping this budget could hinder the project's completion or compromise its quality.

Component Selection: The choice of the Adafruit 3.7V 4.4Ah Lithium-ion battery, while being the most effective in terms of performance, is also the most expensive battery option at $19.95. It is essential to balance the need for optimal components against the overall budget, ensuring that the quality of other components isn't compromised due to overspending on any particular item.

Unexpected Costs: There may be unforeseen expenses in the development phase, such as software licensing, additional components, or replacement of any malfunctioning parts. An emergency fund, or at least some flexibility within the budget, is advisable to cater to such eventualities.

4.1.2.b Time:

Battery Life: The chosen battery, the Adafruit 3.7V 4.4Ah Lithium-ion, provides several hours of charge, ensuring that the AutoCaddie system remains operational for the duration of a standard golf training session. However, optimizing the system to maximize battery life and ensure efficient energy usage is vital. Any reduction in battery life could lead to incomplete sessions and impact the system's utility.

Testing and Debugging: While building AutoCaddie, there will likely be a need for multiple testing and debugging sessions, especially given the complexity of integrating hardware components with the machine learning algorithm. Allocating sufficient time for these processes is essential to ensure a fully functional and reliable product upon completion.

Finalization: As this is a senior design project, it's crucial to allocate time towards the end of the project timeline for comprehensive review, documentation, and any final modifications. This ensures that the project is not only complete but meets the set standards and objectives.

Dependency Management: Some tasks will be dependent on the completion of others. For instance, the hardware cannot be fully tested without the completion of certain software modules. Managing these dependencies efficiently and ensuring that no task becomes a bottleneck is critical to maintaining the project timeline.

In conclusion, while the AutoCaddie project might not face traditional market-driven economic and time constraints, the need for meticulous planning, budget adherence, and strict time management is paramount to its successful and timely completion.

4.2.2 Environmental and Political

AutoCaddie is an unobtrusive, safe, environmentally friendly, and politically noninteractive platform which seeks to improve the golfing abilities of all users. Therefore, the following constraints are minor and can be considered beyond the project's main concern.

4.2.2.a Environmental Concerns:

AutoCaddie employs a Lithium-Ion battery of small size and yield. Lithium Ion is generally sourced from mines which utilize large, energy inefficient mechanisms of extraction. However, due to the minute quantity of this metal interacting with the project, the environmental impact of the Lithium-Ion battery will be negligible even on a large scale.

AutoCaddie will be accessible via readily available electronics such as laptops and desktop computers, and thus the user interaction component of the project will cause no further environmental impact than the production of these devices has already caused. The hardware components utilized on the PCB attached to the user consist of easily sourced and acquired metals with little environmental footprint such as copper, aluminum, iron, and gold. These metals are all present in exceedingly small quantities, and due to their chemically inert nature pose no environmental hazards, even upon malfunction.

4.2.2.b Political Impact:

AutoCaddie is a platform directed towards the improvement of athletic ability in golf, and therefore has no political affiliation, interaction, or direction whatsoever. However, golf as a sport could cause political concerns when viewed through a social lens; golf is colloquially perceived as a sport directed towards wealth: to play, one must purchase golf balls, drivers, and clubs, as well as pay to use fields which can range to be unattainably expensive for many. AutoCaddie will be accessible to all but has the potential to be sequestered naturally to those who can financially justify playing golf. The components present in AutoCaddie are not costly, and therefore the training platform will be affordable and accessible to the majority of golf players interested in real-time, accurate feedback on their swings. AutoCaddie will not contribute to the financial barrier-to-entry present in the sport of golf. Moreover, as AutoCaddie has little environmental interaction and potential for harm, there will be no cause for political activity surrounding the project.

4.2.3 Health and Safety

4.2.3.a Electrical Safety Constraints:

The implementation of AutoCaddie introduces health and safety concerns, primarily revolving around electrical hazards. A significant aspect to address involves the careful routing of power wires within the athletic sleeve worn by the user. If any of these wires were to be exposed, there exists a potential danger. However, it is noteworthy that the system operates on low voltage, thereby minimizing the associated risks. The intentional design of the sleeve to function with low power plays a pivotal role in ensuring overall user safety. This design choice not only reduces the likelihood of electrical accidents but also establishes the product as inherently safe for skin contact.

4.2.3.b Environmental Safety Constraints:

To enhance the longevity of the device and prevent unintended circuit shorting, it is imperative to shield the system from excessive water exposure. Environmental constraints dictate that the system should not be used in heavy rain, as moisture infiltration can compromise its functionality. Furthermore, considerations must be made regarding user-generated sweat, a common occurrence during physical activities. While human sweat is unlikely to disrupt the system significantly, the presence of live wires within a protective sheath further safeguards against potential issues, ensuring the device remains operational even in sweaty conditions.

4.2.3.c Physical Safety Constraints:

Incorporating AutoCaddie into athletic activities necessitates careful physical preparation. While the athletic sleeve helps alleviate arm soreness during golf motions, users may still experience stress in other body parts such as shoulders, back, elbows, or legs. Proper stretching routines play a vital role in mitigating these challenges. It is essential for the AutoCaddie team to provide users with comprehensive knowledge on appropriate stretching exercises to perform before engaging in the activity. Additionally, guidelines addressing how to manage sore muscles are indispensable. Taking responsibility for users' physical well-being, the AutoCaddie team should offer expert recommendations, enhancing the overall user experience and ensuring safety during golfing activities.

4.2.4 Ethical and Social

With regards to ethics within societal context, the primary concern that is raised by the development of the AutoCaddie project is the fact that it may be used to completely phase out and replace human professional trainers. In a vacuum, the AutoCaddie system is intended to provide a mode of feedback for those who either do not have the resources or ability to otherwise receive feedback while they train. However, as the AutoCaddie system may become available to all Golfers intending to train their swings, some may seek to use the AutoCaddie to replace professional trainers.

Though this risk does exist to some degree, it should be emphasized that the AutoCaddie system should be used as a supplement to traditional training methods if they are available, rather than a complete replacement. Without the presence of a professional AutoCaddie serves as a mode of adaptive feedback as an objective observer of a user’s

feedback, allowing the user to understand some avenues of improvement that should be pursued. With the presence of a trainer, the AutoCaddie system becomes a supplement that can serve as a reinforcement or addition to provide guidance and can exist to process real-time data and data analysis. As the current technology of the AutoCaddie stands, it cannot serve as a complete replacement of the ability of professional trainers, as they can more readily provide exact tailored feedback without needing to be exposed to a precise database like the AutoCaddie does. Should this concern of human replacement still exist, however, the scope of the AutoCaddie system can remain limited to not overstep into the overall coverage of a professional trainer.

4.2.5 Manufacturability and Sustainability

The manufacturability constraints of the AutoCaddie system primarily revolve around the selection of the components and parts. To maintain availability and due to limitations to costs, the design of the system should prioritize cost-efficiency and availability by selecting market-available parts, such as in-market IMUs and video cameras. This reduces the need for proprietary parts, which can require higher short-term manufacturing costs and manufacturing resources. The PCB, which is one custom-designed part, will be outsourced to a single manufacturer, centralizes and compartmentalizes external manufacturing costs. Other custom parts, such as PCB housings and mounts, can be created and fitted in-house, thus reducing manufacturing and resource costs.

Sustainability is another consideration in the design of the AutoCaddie project. With the present design of the project, there is no actively disposable part of the system that is repeatedly spent and replaced. As such material waste as a result of the use of AutoCaddie is not a primary concern. However, as with all physical systems, degradation and wear does pose an issue. As such, parts selection and design must account for longevity and robustness. With these design facets in mind, Part wear and breakage will be reduced, improving sustainability as well as reducing waste and long-term costs.

Chapter 5: Comparison of ChatGPT with other Similar Platforms

5.1 ChatGPT

In the process of designing a research paper, ChatGPT, [69] developed by OpenAI, stands out as a cutting-edge conversational AI model. Its capabilities have significantly influenced various domains, including academic research and project development. In the context of AutoCaddie, ChatGPT can be an invaluable resource, offering many different features that can streamline the reading and writing process.

One feature ChatGPT offers is creativity. During the report creating process, it can be difficult to brainstorm fully coherent thoughts and ideas and immediately transcribe them into work. ChatGPT can foster creativity by generating diverse ideas and suggesting other approaches to problems present with the project. Unlike traditional research tools, it doesn't just provide information; it engages in dynamic conversations, stimulating creative thinking and offering unique perspectives.

Due to the large quantity of open-source data that ChatGPT is trained from, it serves as a vast repository of knowledge – enhancing research capabilities. Its extensive database provides access to information before January 2022, which, outside of neural networks, covers every topic from within the AutoCaddie project. Furthermore, it can expand on information rather than simply provide it, which creates a more personalized method of understanding new material.

ChatGPT is also efficient at creating drafts and providing revisions. The model's ability to generate coherent paragraphs has alleviated the burden of repetitive tasks, which allows the report process to be focused on the core content. Moreover, ChatGPT's grammar and style suggestions have enhanced the overall readability and professionalism of the document.

The language model and capabilities of ChatGPT can also be compared to other platforms. Traditional search engines include vast amounts of information updated with present events, as well as other documents and pieces of work that can be accessed by special instruction (not open source). ChatGPT, however, goes beyond delivering static content such as a search engine would; it engages users with dynamic conversation and adapts responses based on context. This interactive nature fosters a deeper understanding of topics and facilitates collaborative exploration, setting it apart from traditional search engines.

Moreover, ChatGPT is not confined to rigid templates or structures as conventional writing tools are. It adapts to specific needs, generating content tailored to a request. Additionally, it can understand complex queries and provide nuanced responses, which yields more power than that of standard writing tools. ChatGPT serves as an intelligent writing

assistant that can offer suggestions and insights that enhance the quality and depth of this paper.

On a separate note, its generative style is unique. Below is a block quote excerpt from ChatGPT that shows the transformative impact it has in elevating the quality of this report:

> In the process of developing our Senior Design paper, ChatGPT proved instrumental in generating insightful content and refining our ideas (OpenAI, 2023). Its interactive nature, expansive knowledge base, and efficient drafting capabilities streamlined our research and writing processes, elevating the overall quality of our project documentation. [69]

5.2 Similar Platforms

ChatGPT is a staple for generative AI available to the public. Since its takeoff, there has been a surge in users seeking AI solutions. Primarily, ChatGPT has gained widespread popularity. However, it is not the sole contender for AI solutions; several alternatives offer similar or even superior services.

HIX.AI [70] offers a comprehensive AI experience, combining accessibility with a diverse set of functionalities. Its chatbot, HIX Chat, covers a large database of topics while also demonstrating remarkable adaptability by processing uploaded PDF documents and summarizing complex web content. The integration of HIX.AI with a Chrome extension further streamlines tasks, automating processes like drafting and revising text in Google Docs. This seamless integration makes HIX.AI a versatile tool for various professional and personal applications.

Chatsonic [71] stands out for its powerful AI capabilities. Using Google Knowledge, a graphical information base, it provides factual responses and offers a range of tones to suit different conversational contexts. This versatility makes it an asset for businesses and individuals seeking context-specific interactions. Microsoft Bing, [72] powered by GPT-4, adopts a multifaceted approach, generating responses in different styles. Its integration of AI into online searches makes it a valuable resource for users seeking accurate and comprehensive information. Despite its slightly slower response times, its commitment to precision and creativity positions it as a contender in the realm of AI platforms.

YouChat [73] introduces multimodal functionality, allowing information exchange in forms including and outside of text. This approach enables YouChat to process textual, app, and link input and output, enhancing its overall adaptability. Claude, [74] available as both a chat and an API, demonstrates efficiency in looking up information and providing creative responses.

Google Bard, [75] although experimental, benefits from the technological prowess of Google. It showcases exceptional processing speed but holds challenges such as plagiarism and lack of resource citations. Auto-GPT, [76] requiring some coding knowledge, offers semi-autonomous functionality, allowing users to set goals and let the

chatbot handle subsequent prompts and responses. Finally, Copy.ai [77] specializes in article summarization and content creation, providing a customizable platform for users seeking specific writing tones and organizational features.

5.3 Platform Comparisons

5.3.1 HIX.AI

HIX.AI embodies a robust platform that offers numerous advantages to AutoCaddie. Its notable AI capabilities, encompassing a comprehensive suite of diverse AI solutions catering to various areas such as article generation, advertising, social media, and text rewriting and formatting, render it versatile and functional across a wide range of tasks. Additionally, its free tier provides access to many advanced features.

The following excerpt is taken directly from HIX.AI, which condenses the contents from G. Oppy and D. Dowe. [20]

> The summary discusses various aspects and objections to Turing's claim that machines can possess intelligence. It addresses the slow progress in creating machines that can pass the Imitation Game and the criticism of the test for only recognizing intelligence in conversation-sustaining machines. The author also explores objections to Turing's claim, including theological concerns and fears about the consequences of thinking machines. The text mentions Lady Lovelace's objection to machines originating anything and the Lucas-Penrose constraint. The author concludes that further exploration is needed to determine the validity of these objections. Additionally, the summary touches on different arguments regarding machine capabilities, consciousness, and the behavior and decision-making differences between humans and machines. Lastly, it discusses the standing and interpretation of the Turing Test and its role in determining intelligence. [70]

Being able to summarize links by providing nothing but a URL saves critical while conducting research relevant to the project. Rather than spending hours browsing multiple research articles on the same topic, HIX.AI can save time by providing comprehensive analyses on each article, helping the selection process narrow down the options.

Nonetheless, HIX.AI does have certain drawbacks. The integration with Google Chrome, one of its main selling points, is irrelevant to this particular project. Moreover, while some features are freely accessible, others require a subscription, making it not entirely free software. A primary example is GPT-4: its usage is locked unless the full tier is purchased. Furthermore, it occasionally produces generic responses, a contrast to the creative content generated by ChatGPT in response to input queries. At this point the main research of the project has been conducted, so having access to a breakdown of article information is relevant only for development purposes.

5.3.2 Chatsonic

Chatsonic is a powerful AI tool with a wide range of capabilities. Its integration with Google Knowledge enhances accuracy through cross-referencing information, ensuring reliable responses. The ability to mimic different tones enhances its adaptability, improving creativity in language usage throughout a report. In the realm of content revision, where attention to nuance is crucial, Chatsonic stands out by empowering users to experiment with word choices, effectively refining paragraphs.

However, the features of Chatsonic are unlocked through a subscription-based model. In contrast to HIX.AI, which offers certain advanced features for free, Chatsonic relies heavily on subscriptions, which can pose financial challenges, particularly for projects with limited budgets like AutoCaddie. This makes it a difficult choice to select for usage when HIX.AI provides the same features for free, and ChatGPT provides more robust conversational output.

5.3.3 Microsoft Bing

Microsoft Bing helps enhance its search engine capabilities by utilizing seamless integration of AI within its core functionality. In response to its user activity, the platform is constantly evolving, providing additional information alongside search results. Additionally, it can generate three different styles of responses: Creative, Precision, and Balanced, which can help narrow searches based on user preferences.

However, despite these advancements, Microsoft Bing has its limitations. One drawback is the speed of generating responses, which may be slower compared to traditional browsing methods. Users experience delays in receiving generated responses, whereas a direct search on traditional engines may provide faster results. In the context of AutoCaddie, having the report process streamlined does coincide with efficiency, and other platforms can provide more efficiency in extracting information than Microsoft Bing. Specifically, HIX.AI can browse through websites faster, and ChatGPT can help foster ideas directly.

5.3.4 YouChat

YouChat’s point of interest is its multimodal input/output generation. The capability of interpreting textual, app, and link data for free gives it a competitive edge against ChatGPT.

For example, YouChat summarized the article by G. Oppy and D. Dowe, which is the same example referenced prior by HIX.AI. The results are shown below:

> The article titled "The Turing Test" explores the concept and implications of the Turing Test, a thought experiment proposed by Alan Turing in 1950. The test aims to determine whether a machine can exhibit intelligent behavior indistinguishable from that of a human. It discusses the role of natural language processing, machine learning, and the limitations of the test. The article also examines the ethical considerations and potential impact of creating machines that can pass the Turing Test. Overall, it

provides a comprehensive exploration of the Turing Test and its significance in the field of artificial intelligence. [73]

As a comparison to HIX.AI, it can provide an equally thorough summary. Despite being comparable in analytical ability to HIX.AI, it does not possess as many features that can improve developmental efficiency.

Although it excels in managing diverse data formats, its application integration is somewhat restricted. Users might encounter difficulties with seamless integration of specific applications, which can adversely affect their overall experience. Moreover, despite its impressive multimodal capabilities, YouChat lacks the ability to generate AI images. In the case of projects like AutoCaddie that heavily rely on visual data, the absence of this feature could impede the planning and creation of diagrams.

5.3.5 Claude

Claude promises a state-of-the-art AI model that provides users with accurate responses. It offers users meticulous and dependable responses, which can meet the demands of data analysis projects such as AutoCaddie. Moreover, it is accessible via API, which allows developers to integrate its capabilities into many different applications directly.

However, Claude's brilliance is partly overshadowed by its limitations. While a free plan is available, the functionality within this tier is restricted and often falls short in delivering significant results. This limitation raises concerns regarding the feasibility of relying solely on the free version of this platform for extensive data analysis requirements. Additionally, Claude's functionality deviates from the interactive and user-friendly conversational style of ChatGPT. Its unique approach may present challenges, particularly when revising existing work. The distinctiveness of Claude's style necessitates a learning curve that could potentially affect user experience and slow down efficiency.

Furthermore, although the API functionality shows promise, it doesnot align perfectly with the specific requirements of AutoCaddie. The GUI primarily focuses on displaying similarity and angular calculations rather than generating text, which makes the API integration pointless in this context.

5.3.6 Google Bard

Google Bard contains the backing of the tech giant Google, providing access to large amounts of resources and expertise, similar to ChatGPT. Additionally, it excels with fast speeds for output generation, even for complex input queries. This yields a competitive edge to ChatGPT, as overall efficiency may improve.

However, Google Bard's is currently in an experimental phase, which brings notice of inconsistent output generation, which ultimately raises concerns about data reliability. In AutoCaddie, where accuracy and consistency are critical, relying on an experimental tool with unpredictable outcomes may jeopardize the integrity of the analysis.

Additionally, Google Bard's inability to provide resources or verifiable data sources for its responses raises questions about the authenticity of the generated information. Without traceable origins, the data becomes less credible, limiting its usability in research-intensive projects.

5.3.7 Auto-GPT

Auto-GPT serves as a ChatGPT alternative implemented via a Python interface. This gives freedom to developers who can incorporate this platform directly into their projects. Moreover, Auto-GPT is semi-autonomous, or it allows the user to provide goals and follow-up information as well as incorporate chatbot functionality. Alongside that, it uses GPT-4 without the need of a purchased tier.

Conversely, the platform being implemented via Python is also a drawback. It poses a necessary learning curve, which negatively impacts efficiency for streamlined development. Additionally, it does not integrate well with AutoCaddie, as only the software design section of the project is dependent on Python, and the final product will not require any chatbot functionality.

5.3.8 Copy.ai

Copy.ai is different from its competitors in that is not directly a fully-capable chatbot. Conversely, it is powerful with regards to condensing text when provided a website URL. It performs rapid article summarization, as well as advanced writing tools for revising existing paragraphs.

As an example, Copy.ai's summary when given the article by G. Oppy and D. Dowe, which was also analyzed by HIX.AI, is shown below:

> The article discusses the concept and history of the Turing test, a proposal made by Alan Turing in 1950 to assess the question of whether machines can think. The article covers various aspects of Turing's proposal, including his description of the "Imitation Game," which involves a person, machine, and interrogator trying to identify which is the person and which is the machine. The article also explores the conceptual and empirical questions raised by Turing's predictions and the current state of research into artificial intelligence. Finally, the article briefly discusses the Chinese Room argument and the question of whether the Turing test is an appropriate goal for researching artificial intelligence. [77]

Seemingly, this summary coincides with the format of HIX.AI. On a negative note, Copy.ai provides fewer generative AI features overall. Thus, HIX.AI can complete the same generative AI tasks as Copy.ai with more overall results, which makes selecting this platform difficult.

Moreover, it requires a paid plan to access the writing tools. As free alternatives exist, there is no necessity to purchase a tier of a platform that has the same features as its rivals. It does not compete in total functionality with ChatGPT's conversational AI.

5.4 Platform Selection

For AutoCaddie's development process, ChatGPT emerges as the strongest choice. It highlights a blend of strong qualities but excels with interactivity with the user. In the context of this project, where accuracy, creativity, and user engagement are necessary, ChatGPT is the strongest choice.

In the realm of accurate data comprehension, ChatGPT's prowess is unmatched. Its ability to decipher intricate queries is a skill that many of these platforms hold, but being able to support the output with examples and references is crucial for data validity.

Creativity is another domain where ChatGPT is powerful. As mentioned previously, ChatGPT has the power to generate beyond standard responses and provide narratives and explanations. This can help expand the project developers' perspective on relevant problems within this project.

There are other powerful platforms. HIX.AI stands out as one of the most powerful online tools against ChatGPT, yet suffers from its own limitations. For one, having the requirement of purchasing tiers, along with usage credits, limits its availability. Many of the other models fall to this dilemma, including YouChat, Chatsonic, Claude, and Copy.ai. Not to mention, HIX.AI does not foster the same creativity as ChatGPT as it is not as generative with its standard output.

Overall, ChatGPT is the most effective choice as an AI platform to streamline the process of documenting AutoCaddie.

Chapter 6: Project Hardware and MCU Design Details

6.1 PCB Subsystem Overview

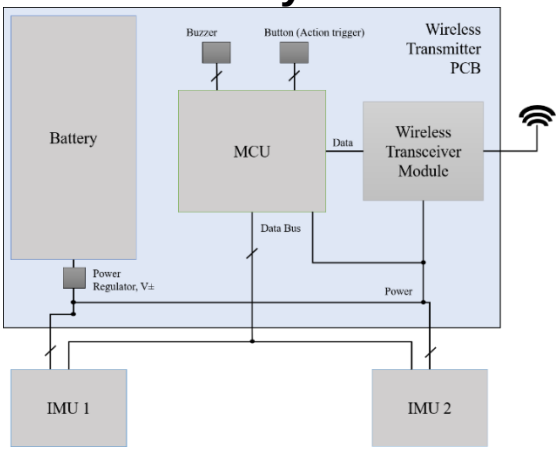


Figure 18: Block diagram showcasing the physical implementation of the wireless transmission subsystem.

The above diagram outlines the overview of the wireless transmission and IMU circuit. The data that is collected and is to be transmitted to the central computer system originates from the IMU devices. The IMUs collect absolute orientation quaternion vectors and acceleration vectors from kinematics of the user's driving arm. This data is collected by a microcontroller unit (MCU), which then packages the data and passes the data packet onto a wireless transceiver module. Finally, the data packet is transmitted to the central computer from the wireless transceiver module. A connected battery powers all components of the system, including the IMUs, a button that serves as an action trigger for the MCU to begin collecting IMU data for a period of time, and a buzzer module that notifies the user of action sequences.

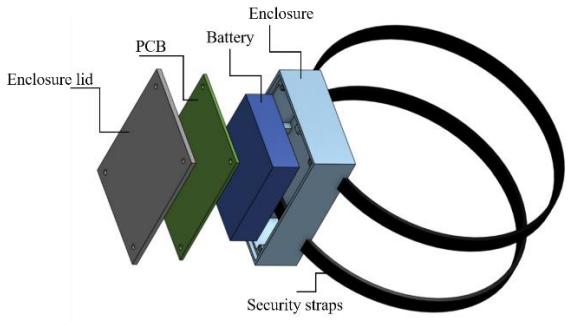


Figure 19: Explosion diagram of PCB and battery within enclosure, including security straps.

As shown in the above explosion diagram, the PCB and battery will be enclosed within a containing box. This box will ensure that the PCB is nonmobile with respect to the user. The using secure straps, the enclosure box can be mounted to the user's body. The battery is placed to the bottom of the enclosure box, such that it is placed closed to the user. This will minimize the moment of inertia for the weight of the enclosure should

it shift when placed on the user. The enclosure box will be placed on the user's waist as to avoid getting in the way of the user's swing.

6.2 PCB Design

The PCB to be used on the AutoCaddie project is an entirely original design incorporating multiple hardware components, including a microcontroller, linear voltage regulator, wireless transceiver, and Molex connectors for further hardware connections.

6.2.1 PCB Schematic

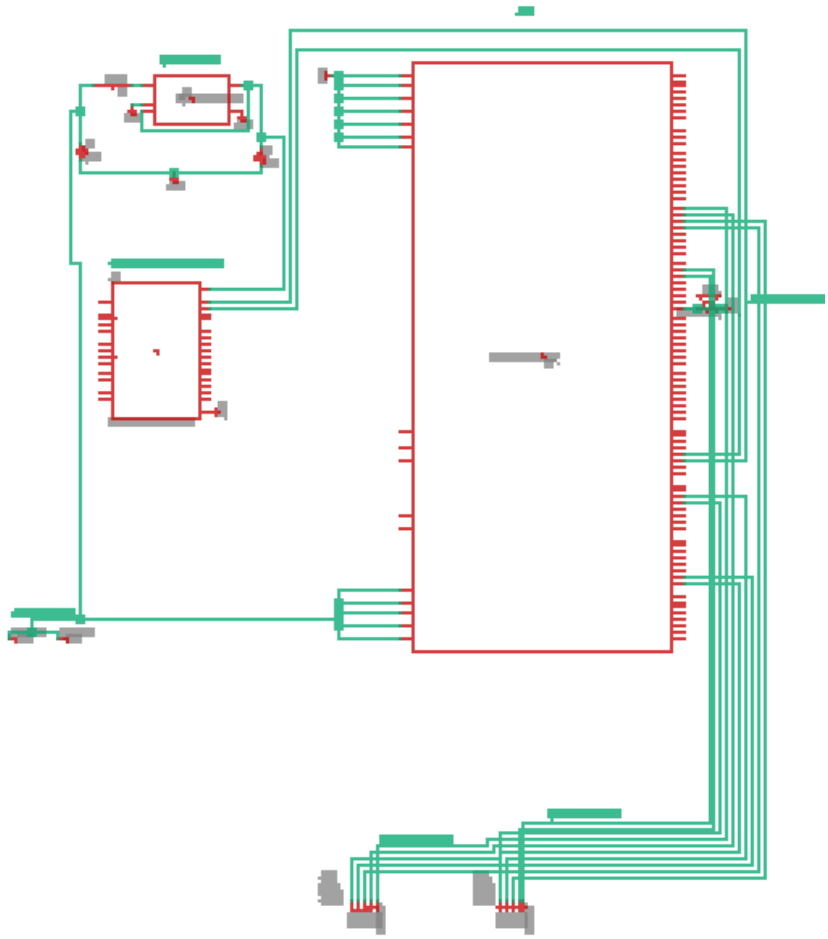


Figure 20: PCB Schematic Diagram

This PCB was designed using Autodesk Eagle. It consists of 2 inductors, a linear voltage regulator, 2 capacitors as a 3.6V to 5V voltage convertor, a Molex connector for a 3.6V battery connection, 2 Molex connectors for 2 BNO080 Inertial Measurement Units, an SMT-0540-S-R Buzzer Speaker, and an HC-06 Bluetooth Wireless Transceiver. The schematic is HIGHLY subject to change as the project progresses, as per the advice of Dr. Arthur Weeks and Dr. Zakhia Abichar.

6.2.2 PCB Board Layout

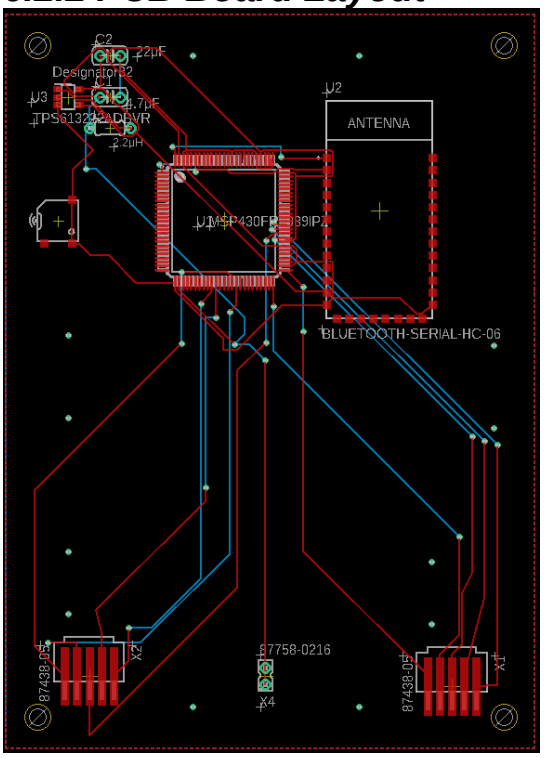


Figure 21: PCB Board Layout

The above figure was created using Autodesk Eagle's board generator. All traces were laid using Eagle's autoroute feature, manually tweaked afterwards to ensure that no wires overlap. The board is 64.968mm (about 2.56 in) wide and 90.368mm (about 3.56 in) tall. It consists of 160 pads, 39 vias, 4 holes, and 2 copper layers. This is highly subject to change in the future.

The connectors are laid such that they all lay on the same side of the board, ensuring that all wires enter in the same direction. This aims to reduce the intrusion of the board on the player, as if the Molex connectors all faced different directions the wires would inevitably occupy much more space. The RLC components are placed close together and distant from the wireless transceiver to minimize interference with the output signal from the PCB. The wireless transceiver is placed as close as possible to the MCU to minimize trace length between the two and, by extension, reduce the possibility of interference from external sources.

The PCB was designed following the guidelines set forth in Dr. Samuel Richie's EEL3926L (Junior Design) course and is being edited following the recommendations of Dr. Arthur Weeks.

6.2.3 Voltage Converter

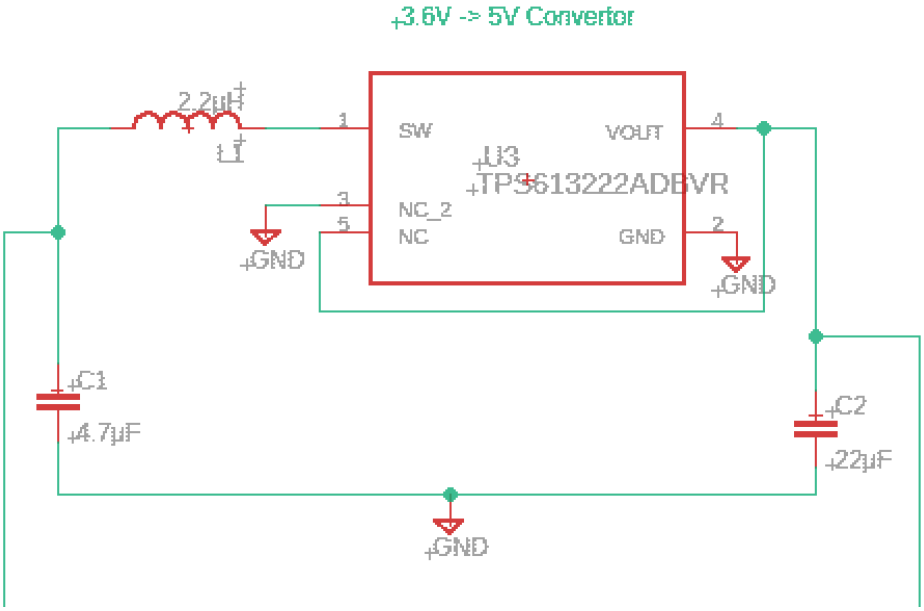


Figure 22: Circuit schematic section of the voltage regulator/voltage converter.

The purpose of the voltage converter is to receive a 3.6V input and convert it to 5V out. This is done such that the HC-06 wireless transceiver receives a 5V input, dictated as adequate in the HC-06 datasheet:

2	Vcc	+5V Positive supply needs to be given to this pin for powering the module

Figure 23: Section of HC-06 datasheet dictating voltage supply requirements.

The voltage convertor was designed using the Texas Instruments WEBENCH Circuit Designer, [78] which allows users to dictate input and output voltages, automatically selecting a linear voltage regulator and component values to maximize efficiency with the dictated input/output requirements.

The voltage convertor consists of the TP3613222ADBVR Linear Voltage Regulator, 2 capacitors (22 µF and 4.7 µF), 1 inductor (2.2 µH), and 3 grounded traces.

6.2.4 HC-06 Wireless Transceiver

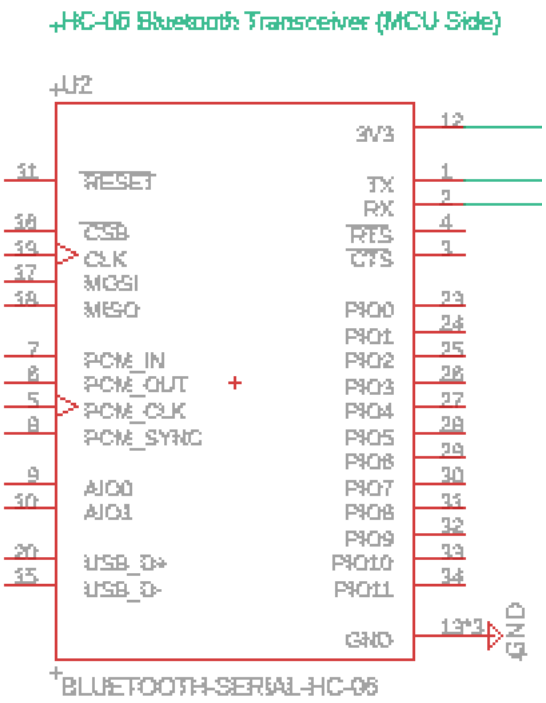


Figure 24: Circuit schematic HC-06 pin specifications.

HC-06 Module:

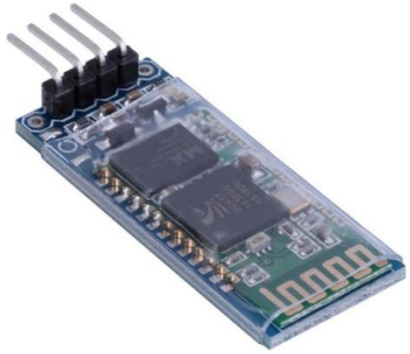


Figure 25: HC-06 module as sold in-market.

As is visible from the above image, the HC-06 module differs slightly from the module's footprint. In application, only four pins will be programmed and interfaced with. These pins, according to the device's datasheet, are as follows:

Pin	Name	Function
1	Key	The pin state determines whether the module works in AT command mode or normal mode [High=AT commands receiving mode(Commands response mode), Low or NC= Bluetooth module normally working]
2	Vcc	+5V Positive supply needs to be given to this pin for powering the module
3	Gnd	Connect to ground
4	TXD	Serial data is transmitted by module through this pin (at 9600bps by default), 3.3V logic
5	RXD	Serial data is received by module through this pin (at 9600bps by default),3.3V logic
6	State	The pin is connected to the LED on the board to represent the state of the module

Figure 26: HC-06 documentation of pin functions as seen in datasheet.

The four pins to be programmed are TXD, RXD, Vcc, and GND. Tx and Rx are connected to pins 4.3 and 4.2 respectively, the UART receive and transmit pins for module A0. GND is connected to ground, and V_{cc} is connected to the voltage output of the 3.6-5V converter. In this configuration, the MSP430 can send and receive data from the transceiver in real time.

6.2.5 Battery Molex In

The battery to be used on the AutoCaddie architecture is not depicted in the PCB design as it will be external to the physical board. It is to be connected to the hardware via a 2-pin Molex connector, enabling the sturdiness and ease of access which Molex boasts.

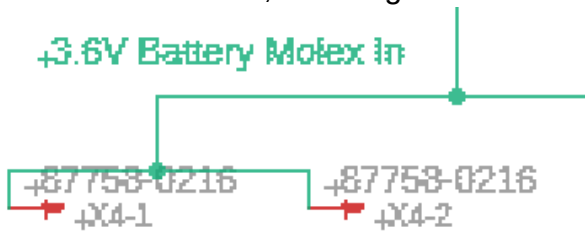


Figure 27: Circuit schematic of battery connection through molex connectors.

The battery will be connected directly to the power pins of the MSP430 and to the voltage input of the 3.6-5V voltage converter.

6.2.6 BNO080 Molex In

The BNO080 Inertial Measurement Units will be external to the PCB as well, being connected via 5-pin Molex connectors directly to GPIO pins on the MSP430. This is done

such that the IMUs can be treated as peripherals, attached to a to-be-designed apparatus which secures them about the player's elbow, connected safely and unobtrusively while measuring quaternion data.

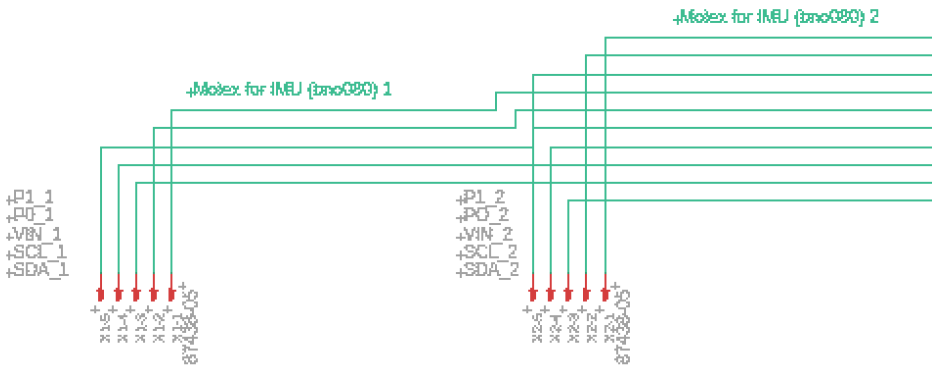


Figure 28: Circuit schematic of IMU connections through Molex connectors.

The connections are as follows (as per the datasheet):
SCL and SDA are connected to the MSP430 RX and TX UART pins.

UART Logic Pins

- **SCL** - UART TX- Connect to your **microcontroller RX** pin
- **SDA - UART RX-** Connect to your **microcontroller TX** pin

Figure 29: Documentation of UART logic pin equivalence as seen in unit datasheets.

P0 and P1 are connected to GPIO pins, programmed to select the operating mode of the transceiver:

- **P0/P1 Pins** and **Solder Jumpers -** Mode select. Use these pins to set the BNO085's operating mode according to the table below. Both pins are pulled low by default, defaulting to I2C

Figure 30: Documentation of mode selection pins as seen in unit datasheets.

PS1	PS0	Mode
Low	Low	I2C
Low	High	UART-RVC
High	Low	UART
High	High	SPI

Figure 31: Documentation of mode selection pins as seen in unit datasheets.

V_{in} is connected directly to the battery, thus as the battery is turned on the IMUs will also be active.
The first BNO080 is connected as follows:

BNO080 Pin	Connected Pin
Vin	3.6V Battery
SCL	P2.1 (UCA0RXD)
SDA	P2.0 (UCA0TXD)
P0	P8.8 (GPIO)
P1	P8.7 (GPIO)

Table 13: Connections of the first IMU to the MCU's pin I/O.

The second BNO080 is connected as follows:

BNO080 Pin	Connected Pin
Vin	3.6V Battery
SCL	P3.5 (UCA1RXD)
SDA	P3.4 (UCA1TXD)
P0	P7.6 (GPIO)
P1	P7.5 (GPIO)

Table 14: Connections of the second IMU to the MCU's pin I/O.

6.2.7 Buzzer Speaker

The SMT-0540-S-R is the intended mode of audio feedback for the user. Connected to a GPIO pin, it can be programmed to turn on whenever the hardware designers intend (still under consideration).

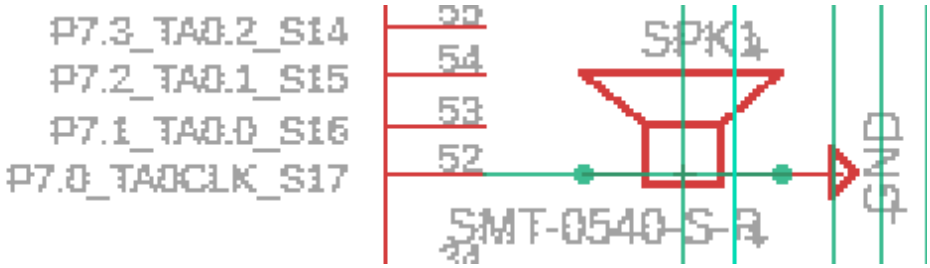


Figure 32: Circuit schematic of buzzer speaker connection to MCU.

The speaker is connected to P7.0, a GPIO pin and tied to a clock, allowing for periodic actuation. The second pin is connected directly to ground, as shown in the diagram.

6.2.8 MSP430FR6989IPZ

The MSP430FR6989IPZ is the most important component present in the PCB. It is the microcontroller which controls all other hardware components present, as well as performing simple arithmetic on the collected data, formatting it into easily read files (likely CSV). The majority of the MSP430's connections have already been detailed

under the other component sections. Below are all the MSP430FR6989IPZ's connections.

MSP430FR6989IPZ Pin	Connected Pin
ESIDVSS	GND
DVSS3	GND
DVSS2	GND
DVSS1	GND
AVSS3	GND
AVSS2	GND
AVSS1	GND
ESIDVCC	3.6V Battery
DVCC3	3.6V Battery
DVCC2	3.6V Battery
DVCC1	3.6V Battery
AVCC1	3.6V Battery
P2.1	SCL (IMU 1)
P2.0	SDA (IMU 1)
P8.8	P0 (IMU 1)
P8.7	P1 (IMU 1)
P3.5	SCL (IMU 2)
P3.4	SDA (IMU 2)
P7.6	P0 (IMU 2)
P7.5	P1 (IMU 2)
P7.0	SMT-0540-S-R Vin
P4.3	HC-06 TXD
P4.2	HC-06 RXD

Table 15: Overall pin connections of the MSP430.

6.3 Peripheral Hardware Integration

6.3.1 IMU System Design and Integration

The IMU sensor system data serves as a critical reference of real, direct-environment data that serves as an anchor for data analysis of the full AutoCaddie system. The primary reference frame that the IMU sensor system data provides is joint angle data for the user's driving arm. As arm straightness is a common point of feedback for golfers during swinging, the IMU sensors can provide direct data that models the linearity of the user's arm. This data can be used as its own condition for feedback, as well as used to further supplement the AI's models. The main types of data that are desired from the IMU sensors are absolute orientation quaternion vectors, as well as linear acceleration vectors.

The absolute orientation quaternion vector data serves as the primary key in the calculation of joint angles of the user's arm. Due to limits of sensor technology, relational position data cannot be directly detected or determined via instrument measurements without extensive data integration and estimation. As such, orientation data will be used to estimate rotational angles of a soft-joint model. At a high level, the quaternion rotation similarities are compared using quaternion dot product or inner product manipulations (as listed below). These rotational similarities are used to determine the overall projection difference of the vectors, thus allowing a calculation of a relative difference in angle. Quaternion vectors are preferred over Euler orientation vectors, as Euler orientation vectors suffer from singularity errors. Quaternions do not suffer from these singularity errors but come at the cost of more complex calculation requirements. The IMUs and quaternion calculations are not perfectly stable, however, so calibrations will be required between each use session of the AutoCaddie system.

$$\theta = 2 * a\tan 2\left(|q1 - q2|, |q1 + q2|\right)$$

Equation 9: Quaternion angle difference using arctan2.

$$\theta = 2 * a\cos(|q1 \cdot q2|)$$

Equation 10: Quaternion angle difference using arccos.

$$\theta = \cos^{-1}(2\langle q1, q2\rangle^2 - 1)$$

Equation 11: Quaternion angle difference using inverse cosine.

Equations 9, 10, and 11 describe several options for estimating joint angles. Equations 9 and 10, though simpler in terms of calculations requirements, do suffer from the "double cover issue", where **q** and **–q** describe the same quaternion rotation. Generally, though, this should not pose a major issue in-use, as the human elbow joint has an average maximum flexion range from 0° to 180°, thus crossover into mirror vectors should not be generally possible. Equation 11 is generally understood to be a more stable and complete description of quaternion angle separations, describing the required rotation to achieve one quaternion rotation to get another. Though it is more computationally complex, Equation 11 will be chosen for preliminary testing and integrations.

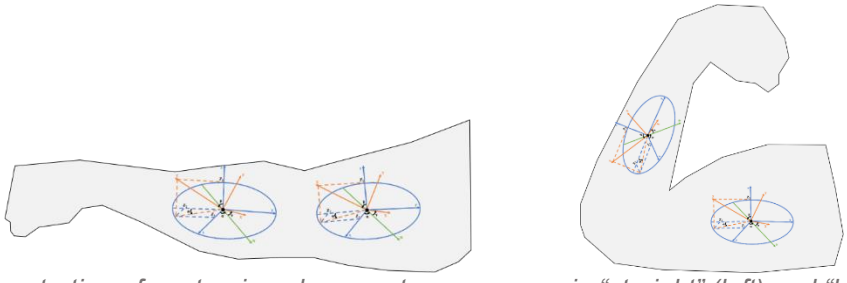


Figure 33: Demonstration of quaternion placement on user arm, in "straight" (left) and "bent" (right) arm states.

Of course, due to issues with IMU sensors systems, such as drift, calibration is required. As the quaternion angle difference calculations are not perfect representations of limb transpositions, errors, including those induced by drift, the required calibrations should be performed between each use of the AutoCaddie system. In order to reduce

unwanted variation in calibration results, a standardized procedure should be used to perform the calibration. For example, the user may initiate calibration and hold out their driving arm, which the IMU system is mounted on, at a 45° angle and keep the arm as straight as possible for a given period of time. With this pose during the calibration sequence, the AutoCaddie system can take calibration measurements to set an arm linearity threshold value, as well as “zero” in the reference quaternions, so that the necessary calculations are as accurate as possible with respect to the true position and rotations of the user’s arm.

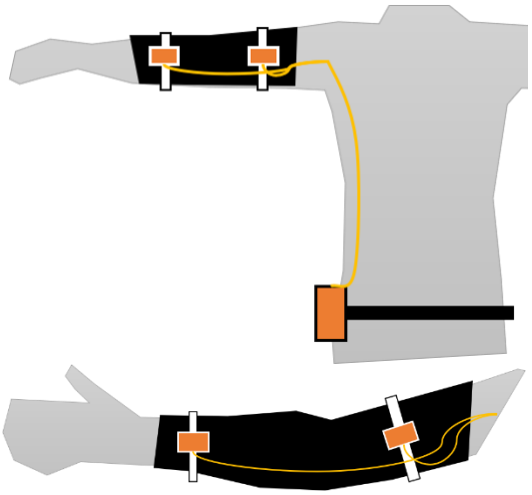


Figure 34: Demonstration of IMU system mounting on user.

As the IMU sensor data is relevant to the user’s driving arm, the IMUs must be securely placed on the user’s arm in a manner such that the IMUs maintain their relative position on the arm, while maintaining user mobility. For this purpose, the IMUs will be secured to an elastic sleeve worn by the user. This will allow for the system to maintain a relatively secure position, while not overly impeding user movement. The given wires of the IMUs will be fed through a flexible sheath, which will contain enough slack as to not catch or pull on the user during swing action. The IMU wires will feed into the PCB enclosure box, from where the data is wirelessly transmitted to the computer for calculation. The PCB enclosure is secured on the user’s waist for unobtrusive placement, as extra weight on the user’s arm or shoulders will impede user’s swings due to the extra inertial weight.

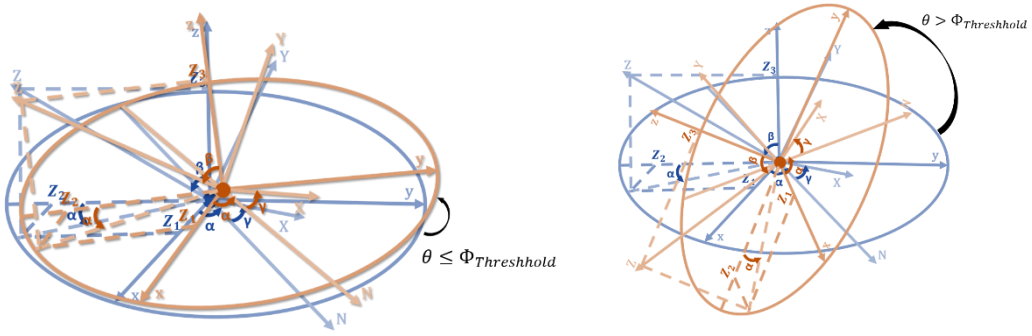


Figure 35: Demonstration of quaternion rotation difference calculation. Low dissimilarity of rotation (left) suggests arm linearity, whereas high dissimilarity suggests nonlinearity of the user's arm.

The IMU systems will collect data throughout the swing action following a signal to prompt the user to begin their swing. Following the swing, the collected data will be formatted into a package, and the package will be wirelessly transmitted to the central computer for processing. The calculation processing will be done on the central computer and not on the PCB MCU to save processing resources on the MCU system, as well as allowing the AI to interface with the pre-processed data. From here, feedback from the quaternion calculations can be generated, and the AI can use the data and calculation results as necessary. As discussed earlier, equations such as Equation 11 can be used to determine arm linearity from the measured quaternion vectors. The given angle calculation of the quaternion rotation difference can be compared to a given threshold value determined during calibration. If the calculated angle is less than the threshold, the arm is deemed straight, and if the calculated angle is greater than the threshold, the arm is deemed bent, and feedback to straighten should be given to the user.

6.3.2 Camera System and Placement

Overall, the camera setup for the AutoCaddie system is fairly simple. The cameras used in the system will interface with the central computer via USB connections, and due to the portable nature of the selected cameras, they can be placed and have their positions adjusted as necessary. The positions and orientations of the cameras must be placed in such a way that they fully capture the entire figure of the user. To better assist in the placement and orientation of the cameras, tripods can be used as necessary. Furthermore, if the reach of the USB cables is not sufficient, length extension adapters can be utilized.

The first camera should be positioned to face the front of the user while they are postured for a swing. From this angle, the camera can capture visual data of the user such the stance posturing of the user, as well as their general swing path and hip rotation. The second camera should be positioned to face the side of the user while they are postured for a swing. From this additional angle, the camera can capture more visual data of the user, such as the overall back posture of the user, as well as the swing plane of the golf club. Together, these camera angles provide a complete set of possible data that can be analyzed for the central computer's artificial intelligence.

6.4 PCB and Peripheral Control

6.4.1 MCU Control

The MCU is the central unit of the PCB and IMU subsystems. The microcontroller manages the I2C communications with the IMUs and oversees the requests to and collection of data from the IMUs. Furthermore, the MCU manages the data collection phase initiation through an action trigger, such as a dedicated button, and interfaces with a wireless communication module to wirelessly transmit the data collected during the collection phase. The data transmission protocols will be discussed in **Section 5.5.**

As the IMUs use I2C communication protocols, the MCU must be programmed with this communication protocol in mind. During the “zeroing” calibration of the IMU systems, the status of the magnetometers, accelerometers, and gyroscopes can be determined, and appropriate calibrations or adjustments can be made. Once the IMU system is ready for data collection, the MCU can access the I2C IMU devices during the data collection phase. Once the data collection phase is initiated, the MCU will repeatedly request and collect data from the IMUs at a frequency the IMUs are capable of producing (≤100Hz). While the MCU is collecting the IMU data, the MCU will construct a data package that will be transmitted to the central computer. The collected data will be formatted in a CSV (comma-separated value) format, where each element from the quaternion and acceleration vectors is a unique entry in the CSV package, and each instance of data is separated by a newline character. This simple data formatting method will reduce data packaging overhead and will be simple to parse. Furthermore, a header with the expected number of data entries will be provided, in order for the central computer to know if the data is a “start” or “data” signal, and know how much data is to be expected. The basic CSV format pattern for the data package is as follows:

```
HEADER X
q_x1,q_y1,q_z1,q_w1,q_x2,q_y2,q_z2,q_w2,a_x,a_y,a_z
q_x1,q_y1,q_z1,q_w1,q_x2,q_y2,q_z2,q_w2,a_x,a_y,a_z
q_x1,q_y1,q_z1,q_w1,q_x2,q_y2,q_z2,q_w2,a_x,a_y,a_z
… //Etc
q_x1,q_y1,q_z1,q_w1,q_x2,q_y2,q_z2,q_w2,a_x,a_y,a_z
```

Following the completion of the data collection phase, the MCU must transmit the data package to the central computer using the wireless transceiver module. To do this, the MCU will interface with the wireless transceiver module using UART data transmission standards, as the chosen HC-06 module uses UART Bluetooth communications. Before transmission, the module will be enabled, and then configured to the appropriate settings, such as setting the appropriate baud rate for the wireless transmission. Once the module is enabled and configured, the data package is then relayed to the wireless transceiver module, from which the Bluetooth communications to the central computer will begin. Once the data package is completely sent, the wireless transceiver module will be disabled until further use in order to reserve power.

6.4.2 IMU Component control

The Inertial Measurement Units (IMUs) will be controlled via the MSP430FR6989 MCU through the pins listed in Table 15 and code written in Code Composer Studio. The principal components that will interact with the IMUs are the UART modules present in the MCU, which will be responsible for bidirectional communication (receiving, sending data). In the code to be described, the UART modules must be initialized, ensuring that particular characteristics are actuated in the communication modules. Those characteristics are the following: No parity, 8-bit data, 1 stop bit, SMCLK, 9600 baud, modulation 1. Below is the UART initialization code:

```c
#include <msp430.h>

#include <stdio.h>

int i;

void UART0_Init() {
    // Configure UART0 (USCI_A0)

    UCA0CTL1 = UCSWRST;                     // Disable USCI_A0 during initialization

    UCA0CTL0 = 0;                           // No parity, 8-bit data, 1 stop bit

    UCA0CTL1 |= UCSSEL_2;             // Use SMCLK as the clock source

    UCA0BR0 = 52;                       // 9600 Baud rate, assuming SMCLK is 1048576 Hz

    UCA0BR1 = 0;                            // High byte of the baud rate

    UCA0MCTLW = UCBRS1;                     // Modulation UCBRSx = 1

    UCA0CTL1 &= ~UCSWRST;                   // Enable USCI_A0
}

void UART1_Init() {

    // Configure UART1 (USCI_A1)

    UCA1CTL1 = UCSWRST;                     // Disable USCI_A1 during initialization

    UCA1CTL0 = 0;                           // No parity, 8-bit data, 1 stop bit

    UCA1CTL1 |= UCSSEL_2;             // Use SMCLK as the clock source

    UCA1BR0 = 52;                       // 9600 Baud rate, assuming SMCLK is 1048576 Hz

    UCA1BR1 = 0;                            // High byte of the baud rate

    UCA1MCTLW = UCBRS1;                     // Modulation UCBRSx = 1

    UCA1CTL1 &= ~UCSWRST;                   // Enable USCI_A1

}

void UART0_Receive(char *buffer, int length) {

    for (i = 0; i < length; i++) {

        while (!(UCA0IFG & UCRXIFG));       // Wait until data is received

        buffer[i] = UCA0RXBUF;              // Read the received data

    }
}

void UART1_Receive(char *buffer, int length) {

    for (i = 0; i < length; i++) {

        while (!(UCA1IFG & UCRXIFG));       // Wait until data is received

        buffer[i] = UCA1RXBUF;              // Read the received data

    }

}
```

The communication is accomplished through flag polling, a technique taught in Dr. Zakhia Abichar's EEL4772 Embedded Systems course. The code waits until the UART stop flag is enabled, which signifies that a message has been completed. The code is then read, and the next message will be treated in the same fashion. Next, the code will be compiled into a CSV file, which is easy to read and transfer to the HC-06 transceiver module.

6.5 Data Transmission Design

Once received, the data from the IMUs will be compiled into CSV files, which are compact and easily read. These files will be transferred via UART to the HC-06 transceiver, which will then transmit the data to a paired device, likely a laptop. Below is the function which will send the compiled CSV file to the HC-06 module via UART:

```
void SendCSVDataViaUART(const char *filename) {

    FILE *file = fopen(filename, "r");

    if (file) {

        char data;

        while (fread(&data, sizeof(char), 1, file)) {

            while (!(UCA1IFG & UCTXIFG));   // Wait until UART1 buffer is ready

            UCA1TXBUF = data;               // Send data

        }

        fclose(file);

    }
}
```

The function passes a pointer to a file, reading each bit of the file into the UART buffer, and sending the data as the transmission buffer is ready. Afterwards, the file is closed, and the function is ready to send another file to the HC-06 transceiver.

Following the definition of these functions, the main function will be called. This function first initializes both UART modules and defines two arrays of size 10 to hold the data received from the IMUs. Next, the function will create a CSV file of name "collected_data.csv" in write mode. This file will first receive the data from the first UART module, writing it to the file. Next, it will receive the data from the second UART module, writing to it. The file is then closed. Next, the function will send the CSV file to the HC-06 transceiver via UART using the SendCSVDataViaUART function defined previously. Finally, the MSP430 will enter Low Power Mode 0, saving energy and increasing the battery life of the device. Below is the code:

```c
int main(void) {

    WDTCTL = WDTPW | WDTHOLD;               // Stop the Watchdog Timer

    UART0_Init();                           // Initialize UART0

    UART1_Init();                           // Initialize UART1

    char dataFromUART0[10];

    char dataFromUART1[10];

    // Receive data from UART0

    UART0_Receive(dataFromUART0, sizeof(dataFromUART0));

    // Receive data from UART1

    UART1_Receive(dataFromUART1, sizeof(dataFromUART1));

    // Create and open a CSV file for the collected data
    FILE *csvFile = fopen("collected_data.csv", "w");

    if (csvFile) {

        fprintf(csvFile, "UART0 Data\n");

        fprintf(csvFile, "Time,Value\n");

        for (i = 0; i < sizeof(dataFromUART0); i++) {

            fprintf(csvFile, "%d,%c\n", i, dataFromUART0[i]);

        }

        fprintf(csvFile, "\nUART1 Data\n");

        fprintf(csvFile, "Time,Value\n");

        for (i = 0; i < sizeof(dataFromUART1); i++) {

            fprintf(csvFile, "%d,%c\n", i, dataFromUART1[i]);
        }

        fclose(csvFile);

        // Send the CSV file via UART

        SendCSVDataViaUART("collected_data.csv");
    }


    __bis_SR_register(LPM0_bits);   |       // Enter Low-Power Mode
}
```

The above code is responsible for all communication between the MSP430 and the BNO080 modules, as well as the file transmission between the MSP430 and the HC-06 wireless transceiver. It is HIGHLY subject to change in the future.

6.6 Summary

The PCB design and the firmware code work in conjunction to facilitate effective, timely communication between the hardware and the software responsible for real-time analysis of the player's golf swing. The PCB design was such that all connectors will be easily interfaced with, allowing for the user to simply and quickly connect the battery, the IMUs, and, for development purposes, the JTAG connections to allow for further programming. The hardware devices above are what set AutoCaddie apart from its competitors, opening the door to an entirely separate avenue of feedback from what other platforms can offer, something which can be expanded upon simply in the future. The technologies employed are in a preliminary stage of implementation, and their functionalities and connectivity are likely to change significantly through the remainder of this project's duration. Next, the software component of AutoCaddie will be described in detail, illustrating the final and most complex facet of the project.

Chapter 7: Project Software Design Details

7.1 General Overview

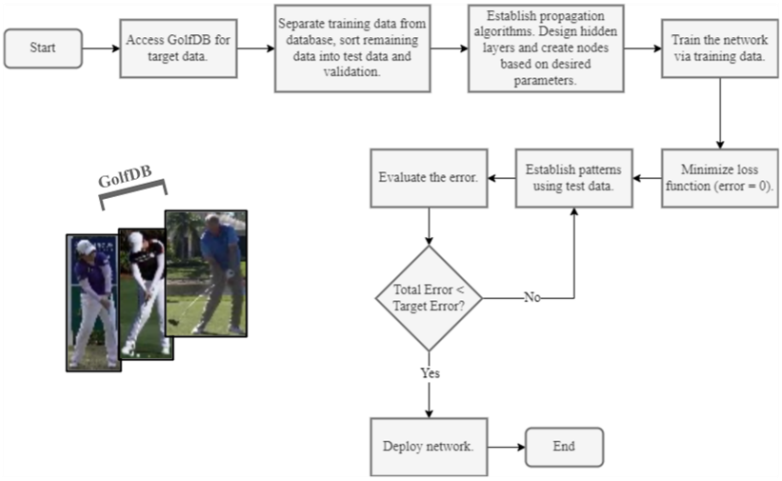


Figure 36: Block diagram outlining the machine learning training model. Accessed via [1] .

This diagram represents a high-level breakdown of the training process for the neural network. First, videos from GolfDB will be referenced, with a large quantity (not all) of the data separated and designated as “training data.” Next, internal mapping networks will be designed to reflect the hyperparameters being studied by the user. These make up a series of “internal layers” for the network and will utilize backward propagation to map actions within the swing data to their respective parameters. Then, through iteration, the system will reference training data, and try to predict the correct feedback with a calculated error rate. If the error is small enough, it can be concluded that the system is successful with analyzing golf swings, and the network can be deployed.

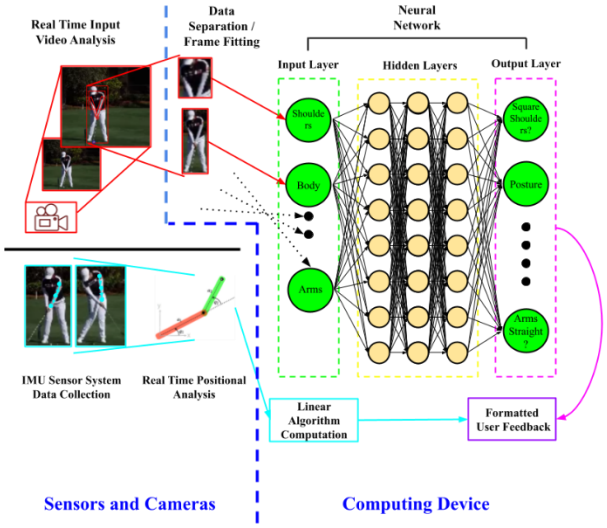


Figure 37: Diagram depicting a high-level overview of the Artificial Intelligence subsystem using a machine learning model. Accessed via [61] .

The associated diagram represents a low-level breakdown of the data process. There are two separate systems operating under the same supervision: the video system and physical sensor system.

The video system records the user's swing across a short duration and uploads it via a standardized package to the computing device. From there, the video is preprocessed, including separating actions into frame sequences, establishing bounding boxes around the user, and matching the dimensions to the training data. Then the data is fed into the trained neural network, which compares the input layer of data to hyperparameters via advanced feature matrix mapping in the hidden layers, then produces similarity measures in the output layer. Finally, the results are fed as formatted user feedback to be displayed.

Similarly, the sensor system starts acquiring data from two IMUs which record quaternion data. From there, we can send the data, packaged with the video feed, to the computing device, which observes the linearity of the two IMU locations throughout the swing. This data is also fed as formatted user feedback to be displayed.

7.2 Machine Learning Model

In the development of AutoCaddie, a key component is the integration of a bespoke machine learning model that synergizes the capabilities of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). This model is crafted to meticulously analyze and interpret the complexities of golf swings, thus providing a cornerstone for the project's innovative approach to sports training.

The CNN portion of our model, employing MobileNetV2, is judiciously selected for its proficiency in processing visual data with remarkable efficiency. This aspect is pivotal for a mobile-based application like AutoCaddie. MobileNetV2's architecture, featuring an inverted residual structure coupled with lightweight depthwise convolutions, offers an optimal blend of speed and accuracy. In the realm of our application, it is tasked with the crucial role of discerning spatial features from video frames of golf swings. This involves a detailed examination of a golfer's posture, grip, and swing mechanics, ensuring a granular understanding of each swing's visual elements.

For the temporal aspect, we incorporate a Bidirectional Long Short-Term Memory (LSTM) network into our RNN segment. This selection is instrumental in grasping the nuanced sequential data inherent in golf swings. The LSTM network excels in identifying and interpreting the intricate patterns over time, which is indispensable for analyzing the progression and coordination of a golfer's swing, especially during critical phases like the backswing, downswing, and follow-through.

Integrating these CNN and RNN layers, our model embarks on a comprehensive analysis of golf swings. Initially, the CNN layers scrutinize the video frames, extracting pivotal spatial features. Subsequently, these features are methodically fed into the Bidirectional LSTM layers, which assess the temporal relationships across the swing sequence. This

dual-faceted approach empowers our model to holistically interpret both the static and dynamic elements of the golf swing.

The model is meticulously tailored to align with the software architecture of AutoCaddie, ensuring a harmonious interaction with its various subsystems. Video frames undergo preprocessing to accentuate relevant spatial characteristics, and we leverage pre-trained weights on ImageNet to enhance the model's proficiency in domain-specific tasks. Optimizing the model involves utilizing the Adam optimizer, with an initial learning rate set at 0.001. This process includes fine-tuning various hyperparameters, such as input size and sequence length, to cultivate the most effective and efficient model configuration.

In the context of AutoCaddie, this machine learning model is not merely a technical component; it is the crux of a revolutionary coaching system. It is designed to provide immediate, tailored feedback to golfers, identifying key improvement areas and offering insights to refine their technique. This AI-driven approach, combining advanced machine learning techniques with a user-centric design, promises to significantly enhance the training process and overall experience for golfers. Below is an example of a hybrid approach for our model.

```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, LSTM, Dense, Flatten, TimeDistributed, Dropout

def create_hybrid_cnn_lstm_model(input_shape, num_classes):
    model = Sequential()

    # CNN layers - TimeDistributed wrapper to process each frame
    model.add(TimeDistributed(Conv2D(32, (3, 3), activation='relu'), input_shape=input_shape))
    model.add(TimeDistributed(MaxPooling2D((2, 2))))
    model.add(TimeDistributed(Conv2D(64, (3, 3), activation='relu')))
    model.add(TimeDistributed(MaxPooling2D((2, 2))))
    model.add(TimeDistributed(Conv2D(128, (3, 3), activation='relu')))
    model.add(TimeDistributed(Flatten()))

    # LSTM layers
    model.add(LSTM(50, return_sequences=True))
    model.add(Dropout(0.5))
    model.add(LSTM(50))

    # Dense layer for classification
    model.add(Dense(num_classes, activation='softmax'))

    return model

# Example: assuming the input is a sequence of 5 frames, each of size 64x64 with 3 channels (RGB)
input_shape = (5, 64, 64, 3)
num_classes = 8  # Example: 8 different events in a golf swing

model = create_hybrid_cnn_lstm_model(input_shape, num_classes)
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model.summary()
```

In conclusion, the machine learning model we are developing for AutoCaddie represents a pivotal advancement in the application of artificial intelligence to sports training. By integrating Convolutional Neural Networks (CNNs) with MobileNetV2 architecture and Recurrent Neural Networks (RNNs) using Bidirectional Long Short-Term Memory (LSTM) networks, our model is meticulously engineered to dissect and comprehend the complexities of golf swings. This integration enables a detailed analysis of both spatial and temporal aspects of the swing, offering insights into posture, grip, swing mechanics, and movement sequences.

7.3 Software Organization

The software implementation in AutoCaddie will be encompassed entirely within a laptop, or other computing device. It essentially acts as the main processor and feedback controller of the system. For each of the data acquisition subsystems, the software needs to be able to receive the results, apply preprocessing algorithms, feed it through either linear algorithms or the machine learning model, then display it back to the user. Additionally, the software needs to be packaged as a finalized product, including proper user design, additional features, and extensive testing. Each of these topics will be elaborated upon in this section.

7.3.1 Software Design Overview

The software design of the AutoCaddie project encompasses a comprehensive approach to developing an intelligent system that provides real-time coaching feedback for golfers. This overview outlines the key components, methodologies, and considerations involved in the software design process, aiming to create a seamless and user-friendly experience for athletes seeking to improve their golf swings.

The primary objective of the software system is to create a sophisticated, yet intuitive, AI-driven coaching system capable of analyzing golf swings in real time. The software aims to provide personalized feedback to users, helping them identify areas for improvement and refine their techniques. To achieve this, the software integrates data from two separate systems, processes it through machine learning and linear calculations, and presents feedback to users through a GUI.

The first section of the software design is the integration of data streams from IMUs and video cameras. These data streams provide real-time information about the user's swing, including arm position, hip movement, head stability, shoulder rotation, hip rotation, and swing arc. These are features defined in a previous section. The software processes this data concurrently, utilizing algorithms to extract relevant features and patterns.

At this point, the machine learning component is employed, which plays a crucial role in this project. These machine learning algorithms are used to compare the user's swing data to reference videos from a comprehensive database (GolfDB). Specifically, these comparisons identify discrepancies and deviations, allowing the system to provide precise and actionable feedback to the user.

The software design coordinates closely with the hardware components, which creates the effect of seamless integration and communication. The software receives data from the IMUs to obtain precise sensor data, and uninterruptedly streams data from two video cameras to capture video information.

After the algorithms generate similarity data, it is formatted and sent to a GUI display for the user to interpret. These will be targeted directly at the features in question given by the machine learning model features it has been trained on. The design of the system allows for large replay value, where an infinite number of iterations can be performed as each output gives feedback for that specific instance of a swing.

The system undergoes rigorous testing, including unit testing, integration testing, user-experience testing, and accessibility testing. Unit testing validates individual software modules, ensuring their functionality. Integration testing assesses the seamless interaction between software and hardware components. User experience testing evaluates the effectiveness of feedback mechanisms and the comfortability of the layout. Many of the processes have been outlined in the standards of validation and user-experience, where online tools can assist in the refinement of the user program.

Overall, the software design of AutoCaddie is a meticulous process that integrates cutting-edge technology, machine learning algorithms, and user-centered design principles. By seamlessly combining data integration, machine learning, intuitive user interfaces, and efficient hardware communication, the software aims to revolutionize golf training. Through continuous refinement and testing, the software design ensures that AutoCaddie provides golfers with personalized, real-time feedback, enhancing their skills and overall golfing experience.

7.3.2 Low-Level Software Flow

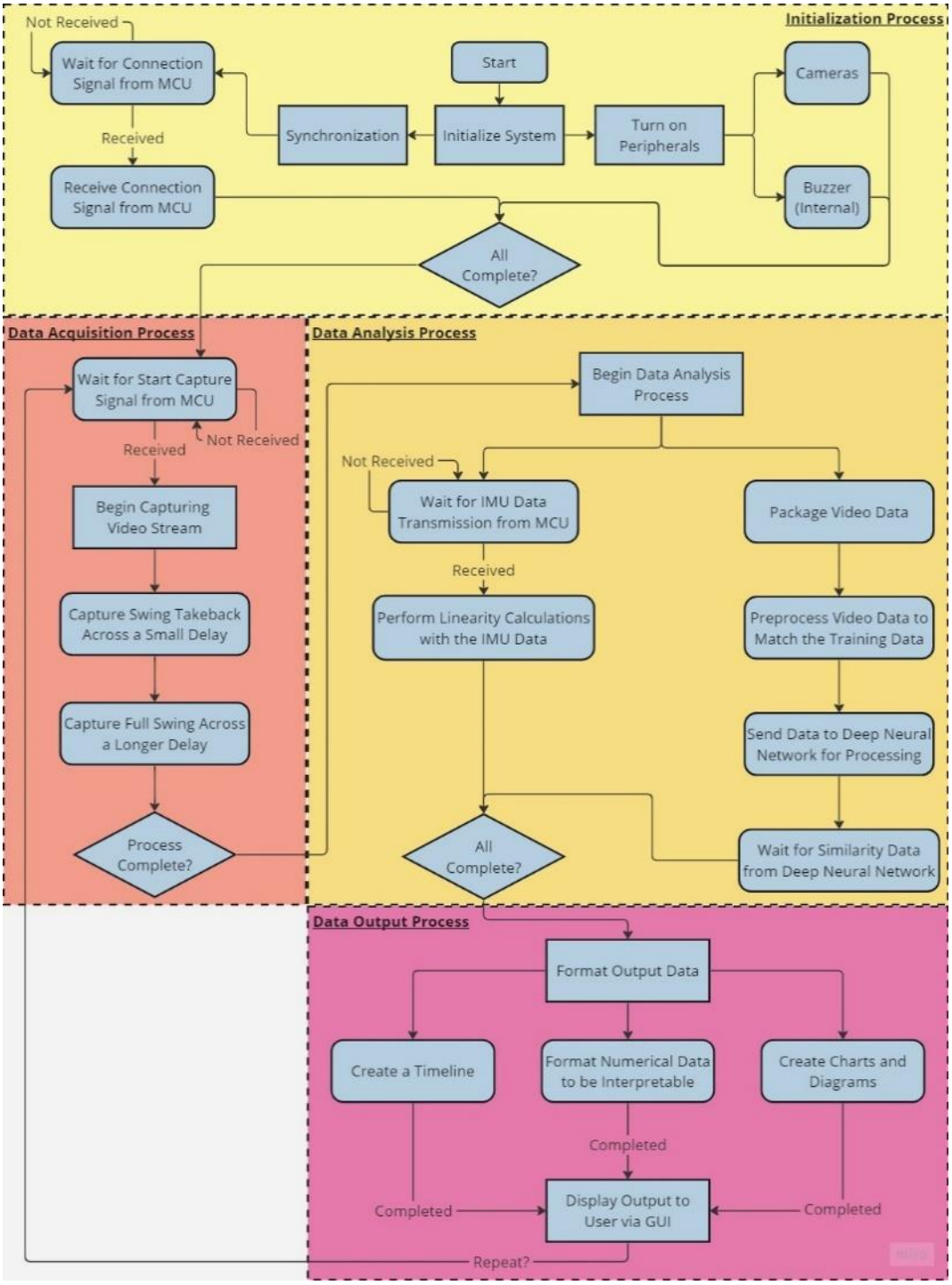


Figure 38: General software flow diagram.

7.3.3 Development Components

In this section, we explore the key components essential for building and deploying AutoCaddie as a robust local software solution. From the choice of programming languages and frameworks optimized for AI and machine learning tasks to the selection of powerful Integrated Development Environments (IDEs) that facilitate efficient coding

and debugging, every aspect is tailored to ensure the system's seamless operation within a local environment. Version control systems are employed to track changes and maintain code integrity, while rigorous testing and debugging tools guarantee the system's reliability and accuracy. Additionally, robust documentation practices are essential for comprehensive insights into the system's architecture and functionality.

7.3.3.a Machine Learning Model Programming Language

For the specific software domain of AutoCaddie, utilizing specific programming languages is necessary for performance. However, it is wise to reference the open-source community and understand commonly used languages for the tasks being tackled by this project. Specifically, for developing the Machine Learning model, Python is the most widely used language for this purpose. Therefore, for development, Python is the correct choice.

For further elaboration, Python is revered for its simplicity and versatility. For example, when comparing the popular language Java [79] to Python, the same task can be accomplished in significantly less lines. Here is the necessary code required in Java to display text to the user in console, generated via ChatGPT.

```java
public class HelloWorld {
    public static void main(String[] args) {
        System.out.println("Hello, World!");
    }
}
```

Similarly, here is the necessary code to accomplish the same task in Python, generated via ChatGPT.

```python
print("Hello, World!")
```

Apparently, Python provides a simpler approach to development. There are more examples of simplification of programs, but overall Python allows for an intuitive development process. This clean syntax can allow for development in AutoCaddie to be swiftly completed and translated for debugging purposes.

Additionally, with the inclusion of NumPy, complex mathematical functions can be encoded as simple algorithms. Both the IMU system and the Machine Learning model will incorporate matrix operations, which – depending on the number of variables – can quickly become resource intensive. For the IMU sensor data, quaternion data is being recorded, which provides a 4-dimensional vector at every instance of time. Thus, for each of these calculations, the linearity can be determined using matrix operations, which each matrix can be defined and manipulated using a single variable in NumPy. For example, the equation below Quaternion angle difference, which was defined as Equation 11.

$$\theta = \cos^{-1}(2\langle q1, q1\rangle^2 - 1)$$

Here is the Python integration using NumPy, generated via ChatGPT.

```python
import numpy as np

# Calculate the Quaternion Angle Difference
# Precondition:
#   q1 and q2 are defined as vectors of size [4,1]
def calculate_quaternion_angle_difference(q1, q2):
    return np.arccos(2 * np.dot(q1,q2) ** 2 - 1)

# Define Quaternion Data
q1 = np.array([w1, x1, y1, z1])
q2 = np.array([w2, x2, y2, z2])

# Find the Quaternion Angle Difference
theta = calculate_quaternion_angle_difference(q1, q2)
```

As shown by the function defined in the code example above, the quaternion angle difference calculation can be defined by a single line of code, and each quaternion data point can also be represented by a singular variable. Being able to simplify complex equations into a readable form in combination with both linear algebra techniques and NumPy allows for the development process to be easily readable and translatable for debugging.

Moreover, every image collected by AutoCaddie can be represented by a 2D matrix of pixels. Each pixel, furthermore, can be swiftly compared using matrix operations defined by NumPy. This streamlined approach not only ensures accuracy in assessing similarities but also optimizes the entire process, making AutoCaddie's feedback system astoundingly efficient and precise. This is the rationale behind why utilizing Python for machine learning model development is as important as it is.

7.3.3.b Graphical User Interface

Moving forward, since the machine learning model utilizes Python, it falls into place that Python will be the language for software development. Specifically, the software needs to be capable of understanding user logic, interpreting data in accordance with the software flow diagram, and present information in a GUI.

Python is revered for its large community support, including many open-source libraries for everything. In terms of GUI design, wxPython [54] is one of the most popular.

wxPython simplifies the complex task of displaying the swing analysis data generated via both the linear calculations and machine learning algorithms. Its extensive set of features allows for the creation of clear and intuitive graphical elements, which ensures that the user can easily interpret the real-time coaching feedback. As discussed by the standards, having a comfortable and intuitive GUI can help the user maximize their experience with AutoCaddie.

7.3.3.c Integrated Development Environment (IDE)

To follow the economic pattern of the project, there is no necessity to extend the budget of the project to an IDE when polished software is readily available. Whether the project

is employed on Virtual Studio Code (VS Code), Google Colab, Spyder, or any other IDE, there are no major benefits outside of the comfortability to the programmer and the convenience of deploying a machine learning model. As a final decision, VS Code is the preferred choice due to the local nature of the software application, as well as the extensive community support with plugins that can improve the efficiency of the development process.

Visual Studio Code, commonly known as VS Code, is a free and open-source code editor developed by Microsoft. It offers a lightweight yet powerful platform for software development, providing features like syntax highlighting, debugging, Git integration, and extensions support. VS Code is highly customizable, allowing developers to tailor their environment with various extensions and themes. Its versatility and user-friendly interface make it a popular choice among programmers for a wide range of programming languages and frameworks. For the integration in AutoCaddie, it can serve as an optimal choice for developing both the machine learning model and software application.

7.3.3.d Version Control

In the context of AutoCaddie's software development, version control is paramount. It allows multiple developers to work collaboratively, ensuring a systematic and organized approach to coding. With the project being coded in VS Code, version control becomes even more crucial. VS Code simplifies coding tasks and integrates seamlessly with version control systems, streamlining the process of tracking changes and managing codebase modifications.

GitHub, a web-based hosting service for version control using Git, emerges as an ideal platform for AutoCaddie's version control needs. Git is a distributed version control system that allows developers to collaborate efficiently while maintaining a complete history of code changes. GitHub enhances Git's functionality by providing a user-friendly web interface, making it easier to manage repositories, track issues, and merge code changes. Its collaborative features, including pull requests and code reviews, enable seamless teamwork and facilitate efficient communication among developers. GitHub's robust ecosystem of tools and integrations, combined with its accessibility and reliability, makes it a perfect choice for version control in the AutoCaddie project. With GitHub, developers can ensure code integrity, collaborate effectively, and maintain a well-organized codebase, contributing significantly to the project's success and streamlined development process.

A diagram of the source control flow as moderated by GitHub is shown below. Each developer can work on independent sections of the program, and push the changes to the overall project repository. So long as communication is maintained, and frequent pushing and pulling is employed, the version control is efficient using this system.

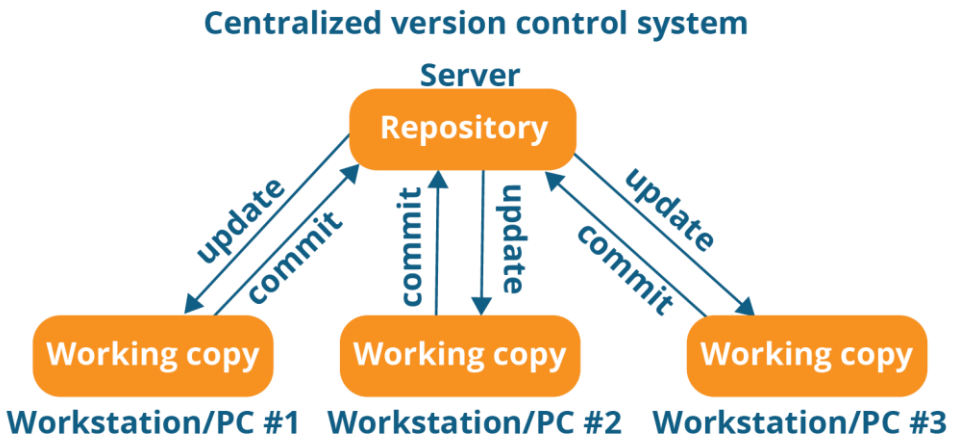


Figure 39: Version control diagram of GitHub. Each workstation can update (pull) from the main repository, then commit and push any changes back. Referenced via [80] .

7.3.3.e Documentation

Overall, clear and thorough documentation is indispensable. Documentation stands at the core of AutoCaddie's neural network and software application, offering vital insights for developers, users, and investors. It functions as a comprehensive reference, ensuring that everyone involved comprehends the project's intricacies and functions.

In the context of AutoCaddie, well-documented neural networks help simplify the extensive algorithms at a high level. It facilitates an understanding of the model between developers as changes are made or debugging is employed. Additionally, documentation accelerates the onboarding process for future expansions, enabling swift integration into the project. For end-users, documentation serves as a manual, guiding them through AutoCaddie's functionalities, from capturing golf swings to interpreting feedback effectively.

Markdown, a lightweight markup language, will be the language used for AutoCaddie's documentation. Its simplicity ensures clear and organized content, which can boost productivity during its creation. Headers, subtext, sections, graphics, and other features can easily be introduced using a short character sequence. An example of this is shown below.

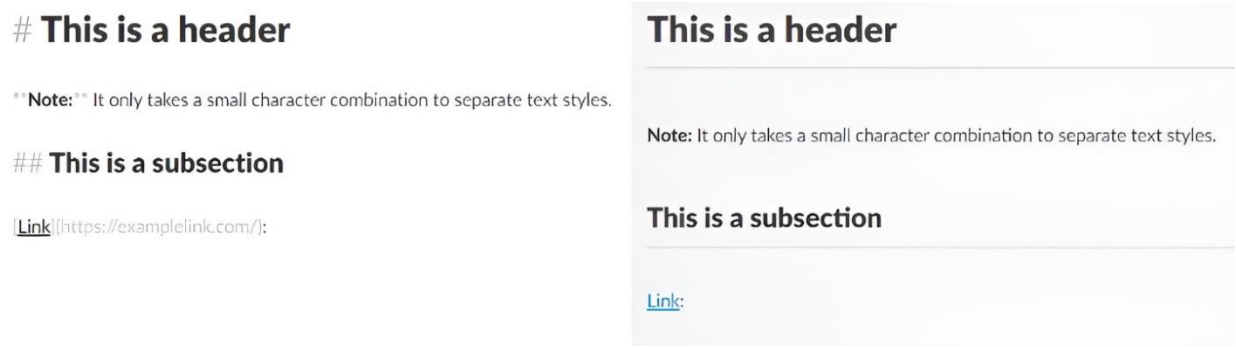


Figure 40: On the left is the source code for the markdown file. On the right is the resultant text displayed to the user. Created via [81] .

Markdown files are easily version-controlled using GitHub, enabling seamless collaboration among the developer team. Visual Studio Code, with its built-in Markdown support, becomes the primary tool for crafting AutoCaddie's documentation. Its intuitive interface allows developers to write and preview content in real-time, ensuring accuracy before publication.

By harnessing Markdown and Visual Studio Code, AutoCaddie can grow its documentation as a dynamic resource. This documentation becomes the source of knowledge for development by guiding users and contributing to AutoCaddie's success.

7.4 Communication

In the context of AutoCaddie, seamless communication between all its components is essential for its functionality. The communication pathways are structured to ensure data flow is smooth and uninterrupted. Utilizing standardized protocols and APIs, AutoCaddie establishes connections between its key elements: the Microcontroller Unit (MCU), cameras, neural network, intercommunication modules, GUI, and the end-user.

7.4.1 MCU

The MCU plays a pivotal role in data processing and exchange. It interfaces with IMUs, gathers input data, and communicates this information to the computer. AutoCaddie's MCU relies on Bluetooth technology to facilitate wireless communication. Bluetooth offers a balance between low power consumption and efficient data transfer, enabling real-time interaction with the cameras and the neural network.

During the swing recording process, the computer system will remain in a state of readiness, anticipating the reception of Bluetooth packets. The MCU will transmit three distinct signals: one indicating the beginning of the swing, another denoting the conclusion of the swing, and a third signaling readiness for a subsequent swing. The initial and final signals will serve as notifications, prompting the program to prepare for data acquisition. Conversely, the signal at the end of the swing will transmit packets of quaternion data to the computer for processing. Each transmitted packet will include a header, indicating the specific type of signal that has been sent.

Examples of code snippets that can anticipate Bluetooth packets over a socket connection are shown below. It utilizes the PyBluez library to establish the port connection. First, to establish a server configuration between the MCU and the computer, the code below can initialize a socket over a designated RFCOMM port, generated via ChatGPT.

```
# Bluetooth server configuration
server_socket = bluetooth.BluetoothSocket(bluetooth.RFCOMM)
port = 1  # RFCOMM port number
server_socket.bind(("", port))
server_socket.listen(1)
```

There are several important pieces of information to gather from this code. The server socket is established via Bluetooth RFCOMM. Then the socket is bound to a specific port number, which will be the transmitting port of the MCU.

Additionally, waiting for data from the MCU can be demonstrated by the code below, generated via ChatGPT. The system can infinitely wait for data to be received, and, once valid data is received, the result can be used for processing.

```
# Receive data from the MCU
try:
    while True:
        data = client_socket.recv(1024)  # Receive data
        if not data:
            break
        print("Received data:", data.decode("utf-8"))  # Decode the received data
except Exception as e:
    print("Error:", str(e))
```

In this code, data is infinitely trying to be received by the system. If the data received is not a valid package sent by the MCU, the system retries. If it is valid, then the data is stored into a data variable.

7.4.2 Cameras

AutoCaddie's camera system captures all the necessary visual data of the golfer's swing. The system will consist of two cameras, one positioned behind the user, and another to the side of the user. By capturing both perspectives of the golfer, the hyperparameters in question can be comprehensively tracked throughout the swing process. In addition, both perspectives are supported by GolfDB's video collection.

Each camera can record at 30 frames per second, which provides ample data for attributing every action within the swing sequence. Additionally, it corresponds to the provided video framerate of GolfDB. The cameras will be tethered to the computer via USB, which will allow for rapid transmission of data without reliance on signal receiving. Additionally, since the data will be stored as it is captured, there is no direct need for ensuring synchronization between the two streams, especially when the data preprocessing algorithms will attribute the actions between the two independently.

In terms of coding implementation, we can utilize OpenCV [45] a popular computer vision library in Python. Below is an example code snippet demonstrating capturing video frames from two cameras simultaneously, generated via ChatGPT.

```
# Initialize camera objects using distinct indices
camera_1 = cv2.VideoCapture(0)
camera_2 = cv2.VideoCapture(1)

# Arrays to store frames
frames_camera_1 = []
frames_camera_2 = []

while True:
    # Capture frames from both cameras
    ret_1, frame_1 = camera_1.read()
    ret_2, frame_2 = camera_2.read()

    # Check if frames are successfully captured
    if not ret_1 or not ret_2:
        break

    # Store frames in arrays
    frames_camera_1.append(frame_1)
    frames_camera_2.append(frame_2)
```

In this code, the camera objects are initialized to separate indices representative of the USB ordering. From there, each camera is read, and if valid frame data is captured, it is stored in the array of frames. If one of the cameras does not record frame data, that instance of time is skipped. That way, both cameras capture the same sequence of frames.

7.4.3 Neural Network

The neural network serves as the core analytical engine within AutoCaddie's framework. Its primary function is to process data obtained from the cameras, extracting all of the necessary details of the golfer's swing. The neural network employs complex algorithms to decipher this information, identifying specific patterns within the golfer's movements. These patterns are crucial to the output data, as the swing's score is ranked against GolfDB's video collection of proper swings. The similarity of each feature of the swing is mapped to the database to be analyzed, then presented to the user in a readable format.

The neural network relies on effective communication with the cameras. This data is sent through preprocessing algorithms before being read, which helps format the data to match the database and boost the accuracy of the system. From here, due to the nature of a neural network, the entirety of the communication process can be encapsulated by a single function call. Similar to how Java creates classes, the complex analysis of the neural network can be abstracted to a separate section and called via a function. Therefore, data communication with the network is simple.

An example of this is shown below. The function is defined separately from the main body of code, generated via ChatGPT, and will send the camera data to be analyzed and return float data representative of the score of each feature.

```
# Function to analyze swing using neural network
def analyze_swing(frames_camera_1, frames_camera_2):
    # Define the neural network logic here
    # Call neural network model to process frame data and compare to the database
    # Return a list of floats representing the score of swing features

# Example function call
swing_analysis_object = analyze_swing(frames_camera_1, frames_camera_2)
```

7.4.4 Internal Communication

Beyond the neural network, the primary internal communication involves the MCU transmitting data for processing. This process mirrors the neural network setup, where the core logic is isolated from the main code, and outcomes are relayed through a function. The primary distinction lies in verifying that the data from the MCU corresponds to the correct signal before entering the interpretation algorithms. As detailed in Section 5.4, the MCU data is tagged with a header, indicating the specific signal, ensuring accurate data examination and understanding.

An example of deciphering the MCU data in csv format is shown below, generated via ChatGPT. In this case, the header “data” signifies the end of the swing sequence.

```
# Gather the csv data from the MCU
header, csv_data = data.split(",", 1)
if header.strip() == "data":
    # Call the analyze_quaternion_data function with quaternion data
    analyze_quaternion_data(csv_data.strip())
```

7.4.5 GUI

AutoCaddie’s GUI server as the user’s window into the analysis. It receives the processed data after the swing has been completed and both the quaternion data analysis and neural network systems have completed.

This interface acts as the means of communication for conveying the swing data from the system to the user. The effectiveness of AutoCaddie lies upon the complete and coherent presentation of this information. Unlike needing to engage with peripherals, the GUI's role lies in transforming the data into visually comprehensible graphics such as timelines, plots, and similarity scores. This transformative process, detailed further in **Section 7.7 Graphical User Interface**, is a pivotal step, ensuring that users receive a rich, meaningful, and insightful overview of their swing performance.

7.5 Data Processing Algorithmic Integration

Moreover, the exact data processing algorithms can be integrated into AutoCaddie’s software to ensure the seamless transfer of data throughout the system. Specifically, this refers to frame extraction, bounding box annotation, image standardization, zero-padding, action detection, and kinematic equation algorithmic integration. The implementation strategy involves segregating these algorithms into discrete logic units, thereby delineating them from the overarching software design. This approach facilitates a modular and object-oriented execution of the software, allowing for efficient referencing and utilization of specific algorithms as required in different components of the system.

7.5.1 Algorithmic Structure

AutoCaddie leverages the wxPython framework, which is a cross-platform GUI toolkit for the Python programming language. It has been referenced that this project will utilize Python for all software development, and thus, through thorough research outlined by Section 3.5.7, wxPython provides enough support for intricate data formatting while also providing portability and not demanding a large learning curve for development. As a brief overview, wxPython is based on the native GUI toolkit wxWidgets. WxPython not only provides a logical integration of GUI elements, but also aligns with the principles of modularity and extensibility. By utilizing these tools, which will be highlighted in **Section 7.8**, AutoCaddie will be capable of providing the best possible user experience.

By utilizing the wxPython framework, it follows the modularity design principles that every algorithm is extracted into its own container of logic. In other words, each algorithm is encapsulated into separate .py files. This organizational strategy enhances code readability, facilitates testing and maintenance, and provides simpler integration into the entire system.

An example of the software hierarchy is shown below. Every Python (*.py*) file contains logic critical to execute the program, whereas *main.py* contains the primary controls. Through file referencing rooting back to *main.py*, it is possible to utilize code through abstracted files, such as each algorithm being implemented.

```
AutoCaddie/
|-- main.py
|-- algorithms/
|   |-- __init__.py
|   |-- frame_extraction.py
|   |-- bounding_box_annotation.py
|   |-- image_standardization.py
|   |-- zero_padding.py
|   |-- action_detection.py
|   |-- kinematic_equation_algorithm.py
```

Figure 41: A folder representation of the AutoCaddie software. Every indent is equivalent to the number of folders containing each file, where the algorithms/ folder contains every algorithm Python script. The controlling logic is contained within main.py.

As shown by Figure 41, the AutoCaddie software hierarchy can be explained through abstraction principles. The *algorithms/* folder contains the Python scripts containing each algorithm that has been mentioned prior. Additionally, the *__init__.py* file signifies the *algorithms/* directory as a Python package, which enables imports between algorithm modules. By utilizing these design principles, it is possible to modularize the logic of each algorithm.

A primary consequence of separating every algorithm into separate files is to enhance unit testing. Unit testing is critical to ensure the reliability of each algorithm implemented, as it is the process of implementing software checks within specific sections of code to ensure overall functionality. With every algorithm residing in its dedicated *.py* file, unit

testing becomes a streamlined process, allowing for the meticulous examination of individual components in isolation. This approach, overall, expedites the development lifecycle and reduces the burden of debugging. By subjecting each algorithm to rigorous unit tests, we can verify its conformity to expected behavior and promptly address any deviations.

By utilizing wxPython, the Python framework unittest [82] allows for direct integration of unit testing with modularized code. By referencing Figure 41, it can be observed that the project hierarchy has the controlling logic at the parent folder, with algorithms abstracted down a directory into an algorithms package. It is possible to modify this structure to create a tests package, where each *.py* file within this package tests the behavior of a corresponding algorithm.

```
AutoCaddie/
|-- main.py
|-- algorithms/
|   |-- __init__.py
|   |-- frame_extraction.py
|   |-- bounding_box_annotation.py
|   |-- image_standardization.py
|   |-- zero_padding.py
|   |-- action_detection.py
|   |-- kinematic_equation_algorithm.py
|-- tests/
|   |-- __init__.py
|   |-- test_frame_extraction.py
|   |-- test_bounding_box_annotation.py
|   |-- test_image_standardization.py
|   |-- test_zero_padding.py
|   |-- test_action_detection.py
|   |-- test_kinematic_equation_algorithm.py
```

Figure 42: A folder representation of the AutoCaddie software with the unittest module. For every test file within the tests package, there is a corresponding algorithm in the algorithms package.

As shown by Figure 42, the *tests* package contains Python scripts for testing the functionality of each algorithm defined within the *algorithms* package. More specifically, each test module is prefixed with “test_” to adhere to the unit test naming convention. Once again, the *__init__.py* file signifies the directory as a Python package.
On a separate note, code invocation can be defined from the *main.py* file. The integration of these algorithms is straightforward because wxPython facilitates the instantiation of GUIs and their interactions with underlying algorithms. Below is an illustrative example of calling the frame extraction algorithm.

```python
import wx
from algorithms import frame_extraction

class AutoCaddieApp(wx.App):
    def OnInit(self):
        # Call the frame extraction algorithm
        frames = frame_extraction.extract_frames("video_file.mp4")
```

As demonstrated by the code, the *algorithms* package can be imported through a simple import statement. This package contains the scripts necessary to run each algorithm, where *frame_extraction* contains the logic of converting a video file to a list of frames. This logic is defined within the *main.py* file of the software. This example showcases the seamless integration of these data processing algorithms into the wxPython-based application. Similar calls can be used for each algorithm, following this structured pattern, and ensuring a clean separation of code.

Moreover, unittest also provides seamless integration into the software development of AutoCaddie. The following example below showcases code that can be utilized within "test_frame_extraction.py" to unit test the functionality of the frame extraction algorithm.

```
import unittest
from algorithms.frame_extraction import extract_frames

class TestFrameExtraction(unittest.TestCase):
    def test_extract_frames_single_video(self):
        # Test extracting frames from a single video
        video_path = "path/to/single_video.mp4"
        frames = extract_frames(video_path)
        self.assertEqual(len(frames), expected_number_of_frames)

if __name__ == '__main__':
    unittest.main()
```

This Python class contains a test method for ensuring that the number of frames contained within a video is exactly equal to a specified amount. For the purpose of AutoCaddie, this would be to ensure that a video can be extracted to exactly 150 frames. Similar to before, the *frame_extraction* logic can be imported with a simple import statement. In terms of new code, the *self.assertEqual()* call is used to execute the unit test, and the *unittest.main()* call is used to run the logic from this Python class.

Overall, utilizing these two Python libraries allows for robust software development with AutoCaddie. The algorithmic structure follows a modularized design, where each algorithm is abstracted to separate scripts contained within a single algorithms package. Similarly, testing can be abstracted to a tests package, where there is an equivalent number of testing scripts as there are number of algorithms. By following these design principles, the development of AutoCaddie can be streamlined, and the resulting software will be optimized.

7.5.2 Frame Extraction

Frame extraction is the first step in image data preprocessing for usage within AutoCaddie's CNN. This process involves breaking down a continuous video feed into distinct images, each representing a specific moment in time. The extracted frames serve as snapshots for precise examination of the golfer's movement.

Each frame can be represented as a 2D matrix of pixels, where each pixel is equivalent to a 3-channel number (24-bits), each channel composing a red, green, and blue value. This matrix format allows for algorithms to manipulate video data effectively. This representation provides a comprehensive understanding of color intensities, which is essential for image processing.

As described by Section 7.4.2, OpenCV allows the software to create the illusion of downloading and extracting a video by live parsing frames from a video feed. The implementation below showcases this relationship, where the function defines the behavior of parsing two separate camera streams.

```
import cv2

def extract_frames(camera_indices=[0, 1]):
    cameras = [cv2.VideoCapture(idx) for idx in camera_indices]
    frames = [[] for _ in camera_indices]
    while True:
        ret_frames = [camera.read() for camera in cameras]
        if not all(ret_frames):
            break
        for i, (ret, frame) in enumerate(ret_frames):
            if ret:
                frames[i].append(frame)
    for camera in cameras:
        camera.release()
    return frames
```

In this structure, the frame extraction logic is encapsulated in a separate module, *frame_extraction.py*. The script, when *extract_frames()* is called, reference predefined cameras connected to the computing device, and initializes empty lists of 2D matrices for each camera. It then iterates through the live camera streams and extracts the current frame as it is presented. If there an error from either device, the current moment of time is skipped, and the next frame is checked. After the video feed duration, the camera streams are released to avoid unwanted memory clogging, and the two lists of frames are returned. This frames object can next be utilized by the bounding box annotation algorithm.

7.5.3 Bounding Box Annotation

After the frames have been collected from the live video feeds, AutoCaddie employs computer vision to annotate bounding boxes around the golfer and golf club during the swing motion. This technology is important to initiate the process of reducing the computational cost of presenting data to AutoCaddie's CNN. As researched by **Section 3.3.2**, MobileNetV2 is a network that is tasked with object detection, and has been selected for this project due to its efficiency with less performant devices, which aligns with AutoCaddie's diverse computational environments.

In short, MobileNetV2 is a lightweight and efficient convolution neural network architecture suitable for mobile applications. It utilizes TensorFlow, which is the Python library selected for the development of AutoCaddie's analytical CNN. TensorFlow provides an easy-to-use API through Keras applications, allowing developers to leverage pre-trained models such as MobileNetV2.

The implementation details are shown in the visualization below. MobileNetV2 can be referenced through the "MobileNetV2" class from the *tensorflow.keras.applications* module. This class provides a pre-trained MobileNetV2 model with weights from ImageNet, making it suitable for various computer vision tasks, including object detection.

```
import cv2
import numpy as np
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.applications.mobilenet_v2 import preprocess_input

def annotate_bounding_boxes(frames):
    # Load pre-trained MobileNetV2 model
    model = MobileNetV2(weights='imagenet')

    # Bounding box annotation process
    annotated_frames = []
    for frame in frames:
        # Preprocess frame for MobileNetV2
        img = preprocess_input(frame)
        img = cv2.resize(img, (224, 224))
        img = np.expand_dims(img, axis=0)

        # Run MobileNetV2 model
        predictions = model.predict(img)

        # Extract bounding box coordinates from prediction
        bounding_box = extract_bounding_box(predictions)

        # Draw bounding box on the frame
        annotated_frame = draw_bounding_box(frame, bounding_box)
        annotated_frames.append(annotated_frame)

    return annotated_frames
```

The code can be explained as follows. First, the MobileNetV2 model is loaded using *MobileNetV2(weights='imagenet')*. This model is pretrained on the ImageNet dataset, making it capable of recognizing golfers within images. Second, each frame is lightly preprocessed using imported functions from within MobileNetV2's documentation. This descales the image to a smaller size. Third, the model is run through *model.predict(img)*, which is the most computationally expensive step in this process. Fourth, the bounding

box coordinates are extracted and drawn onto the image, which concludes the automatic bounding box annotation process.

This is significant for easy integration of object detection into AutoCaddie. This code can be adapted to adhere to specific requirements and performance constraints, which will be thoroughly tested throughout testing. Moreover, the lightweight nature of MobileNetV2 makes it suitable for deployment on various computing devices, including those with limited resources. This also reduces the burden of running a prediction algorithm, ad the model does not employ large computations.

7.5.4 Image Standardization

As the next step in the procedural preprocessing of video data, ensuring that input data for a CNN maintains consistent dimensions is crucial for effective analysis. In the context of AutoCaddie, frame standardization involves cropping an image to follow an annotated bounding box surrounding the golfer and club, as well as applying zero-padding to match the dimensions of the image to the correct scale as GolfDB's training data.

First, each image needs to be cropped to the region of interest. This has already been defined by the MobileNetV2 network, which returns a list of a coordinate point, width, and height relevant to the bounding box's dimensions. A visual integration of this is shown below.

```
for frame in frames:
    x, y, width, height = bounding_box
    cropped_frame = frame[y:y+height, x:x+width]
```

In this code, *x* and *y* represent the bottom-left-most pixel of the bounding box location. *Width* and *height* represent the number of pixels the box stretches to the left and upward, which can be used to surround the region of interest. At this point, a cropped frame can be created by extracting a subsection of the 2D array containing the contents from the bottom, top, left, and right pixel locations.

At this point, the image dimensions will be smaller than that of GolfDB's training data, particularly from both the MobileNetV2 preprocessing and this cropping process. Therefore, zero-padding will be employed to standardize the dimensions for the CNN model. The code below visualizes a zero-padding script that can be imported into the image padding Python file.

```
import cv2

def zero_pad_frame(frame, target_size):
    height, width, _ = frame.shape
    pad_height = (target_size - height) // 2
    pad_width = (target_size - width) // 2

    # Applying zero-padding
    padded_frame = cv2.copyMakeBorder(frame, pad_height, pad_height, pad_width,
pad_width, cv2.BORDER_CONSTANT, value=[0, 0, 0])
    return padded_frame
```

In this code, the *zero_pad_frame()* function takes in an input frame, and the target size of the training data dimensions from GolfDB. First, the image height and width are extracted, and the amount of padding for each dimensions of the border are calculated. Then, using the OpenCV library, a border of zeros can be applied to the image data, which standardizes its dimensions.

7.5.5 Action Detection

The last stage of image data preprocessing within AutoCaddie is action detection, which is synonymous with feature extraction. While presenting data accurately to the neural network is important, providing specific insights into each phase of the golf swing is equally crucial. Action detections covers the computer vision topics of identifying specific motions, sequences, and patterns across a series of frames indicative of a particular action. For AutoCaddie, there are eight separate actions composing an entire swing, including: the address, toe-up, mid-backswing, top, mid-downswing, impact, mid-follow-through, and finish.

Classification in the context of the golf swing involves labeling specific instances of time, which is representative of the order of the frames collected by the frame extraction algorithm. LinearSVM is the most effective classification model for this context, exhibiting high accuracy across diverse experiments, which aligns with nuanced nature of golf swing events. Scikit-learn's LinearSVC, a faster implementation of Support Vector Classification, is utilized for its efficiency in linear kernel applications like golf swing event spotting. This library, along with Keras for deep learning operations, provides the essential tools for implementing these algorithms into AutoCaddie.

However, like any traditional classification model, LinearSVC also needs to be trained. This can be done through a similar procedure to **Section 7.2**. First, the GolfDB collection can be utilized, as it provides a comprehensive golf swing dataset. Next, each frame corresponding to the one of the eight golf swing actions needs to be labeled. This can be represented by an array of eight integers, each representative of the beginning of the next action. By performing this annotation, LinearSVC is given a direction on what to identify with testing data. Furthermore, for the model training (fitting), only the eight starting action frames will be used per swing to create patterns. This will simplify the computation of

training the model while also maintaining accuracy, as LinearSVC will focus on finding the best fit frames to the eight presented.

From this point, like other neural network training procedures, the dataset is split into a training and validation set. The validation set consists of 30% of the original GolfDB database to ensure thorough accuracy measurement. The model will predict the annotated frames of which each event starts, and the accuracy can be measured by how different the frame selected is compared to the actual annotated frame in terms of the frame index. By using hyperparameter tuning methods, such as grid search, which is demonstrated by Figure 43, this model can be refined so that maximum accuracy can be achieved by the LinearSVC model.

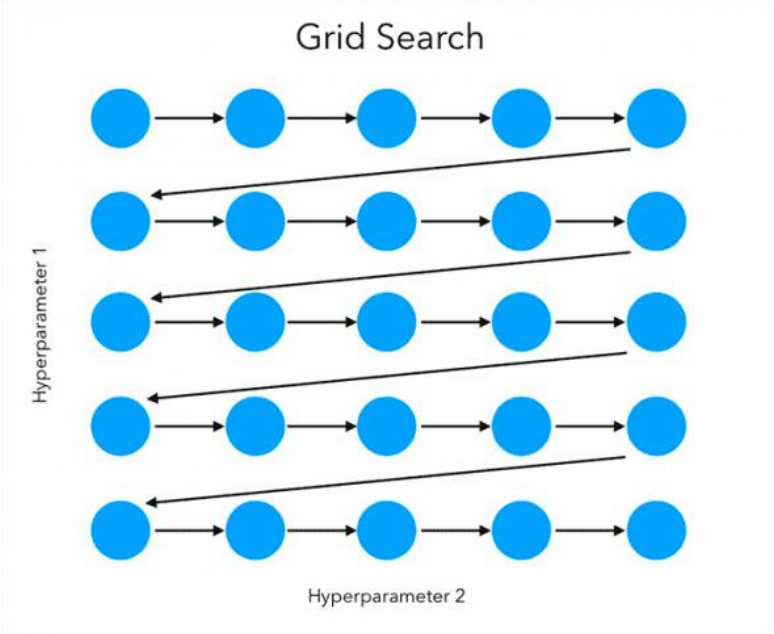


Figure 43: A visual representation of the grid search algorithm. This algorithm evaluates every possible combination of model hyperparameters and returns the combination with the highest accuracy through the validation test. Referenced via [83] .

A visual representation of the code implementation for training the LinearSVC model is shown below. Once this model is trained, it can be implemented algorithmically into the AutoCaddie project for event prediction.

```
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.svm import LinearSVC
from sklearn.metrics import accuracy_score

# Create a LinearSVC model
model = LinearSVC()

# Define the hyperparameters to tune
param_grid = {'C': [0.001, 0.01, 0.1, 1, 10]}

# Perform GridSearchCV for hyperparameter tuning
grid_search = GridSearchCV(model, param_grid, cv=5, scoring='accuracy')
grid_search.fit(X_train, y_train)

# Train the model with the best hyperparameters
best_model = LinearSVC(C=grid_search.best_params_['C'])
best_model.fit(X_train, y_train)
```

The code can be explained as follows. First, the model and hyperparameters to be tested are defined, and a grid search is performed to determine the highest performing hyperparameters utilizing sklearn's *accuracy* metric. Next, the LinearSVC model is trained using the training data and the optimal hyperparameters to determine the best performing LinearSVC model. At this point, the model is completed, and can be deployed into the software. The figure below represents the process completed by this model. Throughout a collection of frames presented to LinearSVC, it determines a list of probabilities that a particular frame begins the action sequence, and, relative to location, predicts which frames are the correct starting frames for each event.

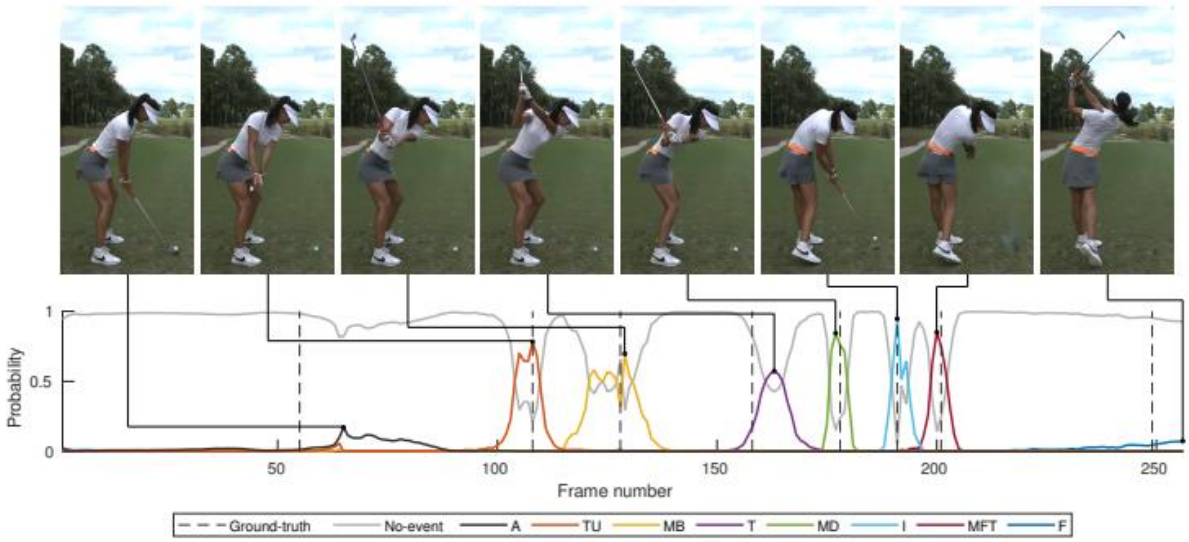


Figure 44: A visual representation of image classification throughout the golf swing. The probability of a current frame being the start of an action, sequentially, is represented by the probability chart. The frames

with the highest probability of starting each event are selected, and the accuracy of the model is assessed through a validation dataset. Referenced via [1] .

Once the model is trained, it can be saved to a file using joblib. [84] Then, like the *algorithms* package, it can be imported to the file currently referencing it. In this case, in regard to Figure 42, *action_detection.py* will call the model. joblib includes a *load()* function, which searches for an existing model file and allows for sklearn operations to be executed externally, specifically with respect to predicting event frames. The visualization below showcases the structure of *action_detection.py*.

```
from sklearn.externals import joblib
import numpy as np

def load_model():
    try:
        # Load the saved model if it exists
        model = joblib.load('linear_svc_model.pkl')
        return model
    except FileNotFoundError:
        return None

def determine_action_frames(input_frames):
    model = load_model()

    if model is not None:
        predicted_actions = model.predict(input_frames)

        # Access the probability scores for each event
        action_probabilities = model.decision_function(input_frames)

        # Select the frame with the highest probability for each predicted action
        selected_frames = [np.argmax(probabilities) for probabilities in
action_probabilities]
        return selected_frames
    else:
        return None
```

The code above provides two functions, *load_model()* and *determine_action_frames().* The purpose of *load_model()* is to import the LinearSVC model that has been trained previously. Once the code has access to that model, it can run the action detection algorithm by calling *model.predict()* and *model.decision_function()*. Finally, the eight frames with the highest probabilities are selected and used as the beginning frames for each action.

By extracting the key frames within the golf sequence, it is possible to present classification information to the user for insightful feedback. The actions can be

referenced for timing purposes, as well as attributing swing errors to particular events within a swing. By utilizing LinearSVM, a second, smaller scale neural network is trained for the purpose of finding eight events within a golf swing and storing them for analysis.

7.5.6 Kinematics

Lastly, quaternion data stores spatial data throughout the swing process of the user's inner arm. There are two IMUs positioned throughout the arm, one on the forearm and one on the upper arm. By referencing *Equation 11*, which is reshown below, it is possible to determine the angle between the two quaternion data points for every instance of time during the swing.

$$\theta = \cos^{-1}(2\langle q1, q2\rangle^2 - 1)$$

Equation 11: Quaternion angle difference using inverse cosine.

It has been established that NumPy will be used to implement matrices operations. Each quaternion data point can also be represented by a four-value vector, and the composition of 10 data points per second for five seconds eludes to a $50x4$ dimension matrix for each IMU. Therefore, it is possible to determine θ by the code shown below.

```
import numpy as np

def calculate_angles(Q1, Q2):
    dot_products = np.sum(Q1 * Q2, axis=1)
    squared_terms = 2 * dot_products**2 - 1
    theta = np.arccos(squared_terms)
    return theta
```

In this code, Q1 and Q2 contain all the quaternion data points stored as matrices. The function *calculate_angle(Q1, Q2)* returns a vector of the angle between the two IMUs for every instance of time recorded.

7.5.7 Summary

The integration of these processing algorithms into AutoCaddie's software design is facilitated through their abstraction into distinct scripts. While the majority of these algorithms exhibit a straightforward design, both bounding box annotation and action detection necessitate the utilization of neural networks to ensure precise assessment. However, it has been researched that both implementations are not computationally expensive, allowing for AutoCaddie to be runnable through diverse computing devices. The systematic abstraction of these algorithmic implementations is organized within an *algorithms* package, where each Python file encapsulates a specific data manipulation method. This modular structure enhances the maintainability and extensibility of the software, allowing for streamlined development and integration of additional functionalities.

7.6 Data Management

AutoCaddie is composed of complex systems, each responsible for managing the transformative flow of data. The process initiates with thorough data collection, which is completed through camera and IMU peripherals. Once the data is gathered, it is augmented in different methods. For the IMU data, data is sent via packet data with a specified header which denotes the role of the specific package sent. The camera data is extracted into frames, where preprocessing algorithms will be applied. Therefore, this data finds a home in storage, where AutoCaddie's efficient data storage mechanisms are employed to organize and manage information systematically.

7.6.1 Data Collection and Storage Requirements

Overall, there are two avenues of data collection through the AutoCaddie system: through the cameras, and through the IMUs. Both of these devices provide valuable information for the AI to analyze, and each data type is managed separately to assess different topics within the user's golf swing technique.

First, there are two cameras tethered to AutoCaddie's computing device. The responsibility of each camera is to provide a video stream of the entire swing motion so that it may be analyzed. However, the beginning of the video sequence is initiated by the "Start" packet and can be implemented via the code referenced by OpenCV in **Section 7.3.4.b**. In short, frames are continuously connected for a short duration, and appended to a list. We know that, for the HP 320 FHD camera to be used in project, it records at 30 frames per second and 1080p resolution, which is equivalent to $1920x1080 = 2076300$ pixels. By multiplying this across 5 seconds, with 30 frames captured per second, with each pixel representing 3 channels (24 bits), and converting to megabytes, there are *0.869* megabytes of storage necessary for each swing. Finally, there are two cameras, so for every swing, there will need to be *1.738* megabytes available. This is a temporary requirement, as every video will be deleted after being analyzed.

Similarly, the IMU records quaternion data over time. The research for quaternion data analyzed that, for the processing algorithm, two quaternion matrices of data are necessary, each of size one less than what is transmitted. The BNO055, the selected IMU unit, can capture quaternion data during the golf swing action. Each quaternion data point consists of 4 axes, each axis containing a 32-bit number. For measuring 10 data points every second for five seconds, it requires $32 \cdot 4 \cdot 10 \cdot 5 = 6400$ bits of data. Moreover, to record acceleration data, it requires 3 axes of measurements, which is equivalent to another *4800* bits*. Multiply that by two IMU sensors, and the overall storage* required to receive the input data is *2800* bytes of data.

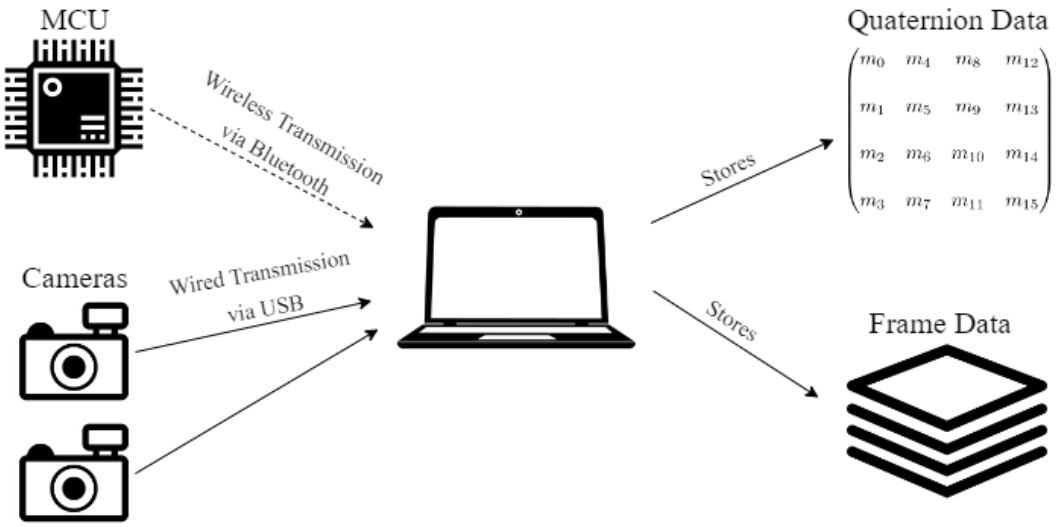


Figure 45: Figure representing the data flow of the peripherals to the computing device. Quaternion data is packaged and transmitted from the MCU via Bluetooth, and video data is transmitted from the cameras via USB.

7.6.2 Video Data Augmentation

Once the data has been received by the computing device, the next step is to process it. Both the camera data and quaternion data experiences manipulation before being directly analyzed, which allows for complete analysis throughout the entire swing process.

First, the camera data undergoes preprocessing algorithms, which reduces the storage requirements necessary in the system. As established earlier, there are several steps to the preprocessing system. First, the frame data is annotated with bounding boxes to isolate the golfer and club. Next, the frame is cropped so that the width and height border the boundary around the golfer and club. Then the boundaries are extended with zero data to match the exact dimensions of that provided by GolfDB. Finally, eight specific actions are cut from the entire frame list, so only eight subsets of the original data remain. In short, these operations reduce the storage necessity on the system. It is still a requirement for AutoCaddie to be able to support the resource demands of acquiring the original data, but understanding the scalability of these operations, as well as the management of augmented data is crucial for understanding the design of the software.

It is important to mention that the ordering of the frame collection is by time instance. Each frame is collected in the order in which they occurred, thus, by iterating over the list, the same time ordering is maintained. During the bounding box annotation process, the region of interest is encapsulated, and the coordinate list is stored as annotation data. This data can be stored in 4 separate arrays, $x, y, width,$ and $height$ which represent the bottom left-corner of the boundary box at a specified instance of time, and the exact number of pixels the width and height from that corner covers. From this point, it is simple to crop the image to the specified width and height dimensions using an exact pixel reference point. An example of this is shown below.

Figure 46: On the left, the golfer is isolated by a bounding box. On the right, the image is cropped, creating a new image of resolution 90 pixels by 120 pixels. Referenced via [85] .

In Figure 46, a golfer is isolated by the annotations of a bounding box created by MobileNetV2. The new dimensions of the frame are 90 pixels by 120 pixels, which is a reduced version of the original image, storing less pixels. Therefore, to reference the exact coordinates to crop the image, the width and height vectors would output 90 and 120, which encompasses a smaller area of *32,400* bytes.

Next, the data is standardized through zero-padding, which is the technique of expanding an image's dimensions by applying an equal border to both the width and height of it and setting those new values as zero. In terms of GolfDB's video collection, each training video has the dimensions of 160 pixels by 160 pixels. Therefore, for every frame that has fully been linearly transformed, each can be stored within *76,800* bytes. Thus, for five seconds of recording through two cameras recording at 30 frames per second, the new storage requirement for the frame data is *22,500* MB.

Figure 47: Applying zero-padding to an image. The black background represents pixels stored with a value of 0. Now the image matches the resolution of GolfDB's training dataset. Referenced via [85] .

Lastly, after transforming every frame within the dataset, the LinearSVM algorithm can traverse the collection and determine starting frames and the finishing frame for action sequences. Each starting frame signifies the start of a specific action, such as the address or mid-backswing. For implementation purposes, assume an array $actions$ contains a list of eight integers, where the first eight integers represent the beginning of a specific swing action sequence, and the last integer represents the final frame of the swing. Using the code below, we can reference a specific action sequence.

```
action = frames[actions[i] : actions[i + 1] - 1]
```

Knowing this, it is apparent that the frames before the first action (the address) and the frames after the last action (the finish) are removed before analyzing the data. Therefore, the final storage demands, depending on the exact speed of the swing, will be smaller than the original *22,500* MB requirement.

7.6.3 Quaternion Data Augmentation

The other data augmentation system within AutoCaddie is through the quaternion data collected by two separate IMU units. It has been established that storing this data initially requires *2800* bytes of data. Therefore, each quaternion matrix can be represented using *1400* bytes of data. Referencing Equation 11, we can determine the additional data requirement necessary for the solution vector θ storing the angle between each quaternion matrix at every instance of time. Specifically, the IMU sensors are each recording 10 data points per second for five seconds, a total of 50 data points each. Therefore, the output vector θ will only contain 50 angles, which can be represented by the float primitive, totaling 100 bytes.

Moreover, at this point, the original data is no longer needed for further analysis, so it can be removed from the system to increase available storage.

7.7 Neural Network and Kinematic Algorithm Interpretation

The previous sections have discussed the implementation of AutoCaddie's neural network, preprocessing algorithms, and kinematic equations. This section covers the next step in the software flow: interpreting the results gathered from both the neural network and kinematic processing.

7.7.1 Neural Network Output Interpretation

The neural network employed in our AutoCaddie system, outputs a detailed and nuanced interpretation of a golf swing. This is achieved by analyzing video data and identifying key events in a golf swing sequence. These events include Address, Toe-up, Mid-backswing, Top, Mid-downswing, Impact, Mid-follow-through, and Finish. For each frame of the swing, our model assigns a probability to these events, thereby identifying the most likely phase of the swing the golfer is in at any given frame.

Interpreting these outputs involves understanding the spatial and temporal dynamics of a golf swing. For instance, detection of the 'Impact' event involves pinpointing the exact frame where the clubhead contacts the ball. This precise moment is crucial for analyzing

the effectiveness and efficiency of the swing. Similarly, the identification of the 'Top' event, which is the transition from backswing to downswing, gives insights into the golfer's technique, such as the backswing length and transition smoothness.

The output probabilities offer a frame-by-frame analysis, akin to the quaternion data's detailed arm movement tracking. However, while quaternion data provides spatial and rotational coordinates, the model's output gives a temporal sequence of swing events. This sequential data can be visualized as a timeline, showing the progression of the swing and highlighting areas where the swing deviates from an ideal model.

Thresholding techniques, similar to those used in quaternion data analysis, can also be applied to our models outputs. By setting specific thresholds for event probabilities, we can flag critical moments in the swing, such as an unusually long backswing or a delayed impact. This method allows for a detailed examination of the swing, identifying not just what happens, but also when it happens relative to the rest of the swing sequence. An example of what the extraction of event probabilities could look like is as follows along with an example of thresholding analysis.

```python
import numpy as np

# Assume model_output is an array of probabilities from our neural network model for each frame
# Each row represents a frame, and each column represents a probability for an event

# Define the events for readability
events = ["Address", "Toe-up", "Mid-backswing", "Top", "Mid-downswing", "Impact", "Mid-follow-through", "Finish"]

def extract_event_probabilities(model_output):
    # Find the index of the maximum probability for each frame
    max_event_indices = np.argmax(model_output, axis=1)

    # Translate indices to event names
    identified_events = [events[index] for index in max_event_indices]
    return identified_events

# Example usage
model_output = np.random.rand(100, len(events))  # Sample output
identified_events = extract_event_probabilities(model_output)
print("Identified Events per Frame:", identified_events)

def thresholding_analysis(model_output, threshold=0.7):
    # Thresholding to identify significant event probabilities
    significant_events = model_output > threshold

    # Mapping to event names
    for frame_index, events in enumerate(significant_events):
        print(f"Frame {frame_index}: ", end="")
        for event_index, is_significant in enumerate(events):
            if is_significant:
                print(events[event_index], end=" ")
        print()

# Example usage
thresholding_analysis(model_output)
```

Moreover, combining the output with quaternion data enriches the analysis for the user. For instance, if the model identifies an issue at the 'Impact' event and quaternion data shows unusual forearm rotation at the same moment, the user can infer that there was an issue with their arm posture. With all this data we will be able to infer a great amount

about the user's swing that would be very difficult for a human to interpret. For a human trying to analyze all these aspects of a user's swing simultaneously would be a fruitless endeavor. While our model would be able to process and interpret this information.

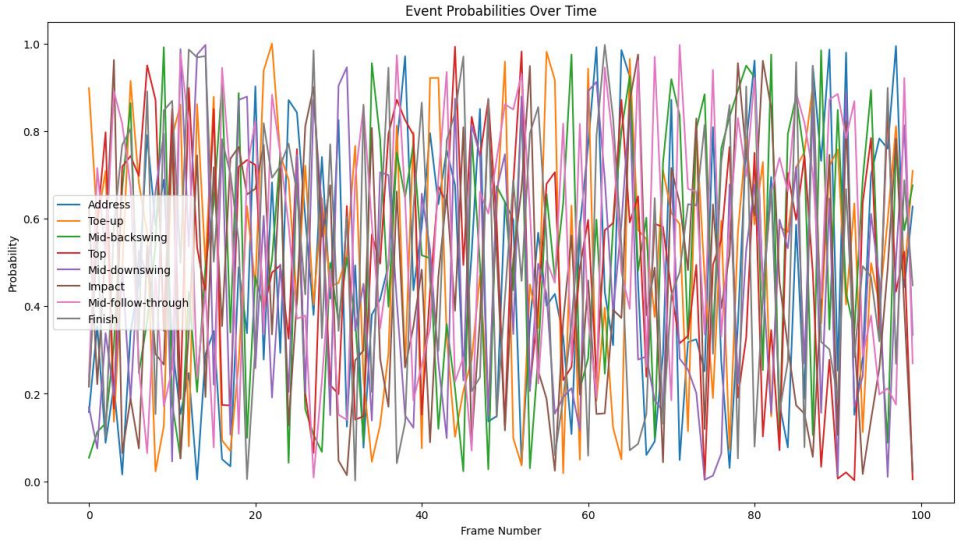


Figure 48: Event probabilities over time per frame number.

In summary, the interpretation of the model's output is a complex process that requires a nuanced understanding of the golf swing's biomechanics. By integrating this output with kinematic data, AutoCaddie offers comprehensive insights into each swing, allowing for a more informed approach to golf training and technique refinement.

7.7.2 Quaternion Data Output Interpretation

The quaternion data that is given to the computing device is representative of spatial and rotational coordinates, as well as general acceleration information. Specifically, through the IMUs, there are 10 quaternion data points captured every second, which shows the orientation of the least-dominant arm's upper arm and forearm. By having an IMU on each section of the arm, the angle between the two can be calculated, and if the arm is not hyperextended, there will be results that can justify this.

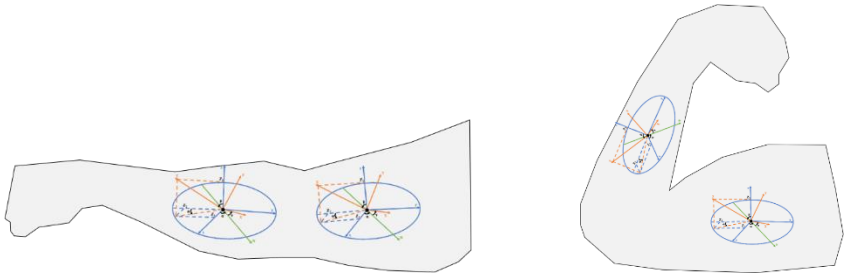


Figure 49: Demonstration of quaternion placement on user arm, in "straight" (left) and "bent" (right) arm states. This figure was reinserted for convenience.

Furthermore, *Equation 11* defines a vector, θ, that contains every resultant angle from the quaternion processing. This vector can be iterated over, and numerically analyzed. There

are two direct ways that will be employed to analyze this behavior: thresholding and visualization.

Thresholding refers to defining a specific value and comparing the angle to determine if it is less than the thresholder amount. If there exists an angle or group of angles such that the resultant value is larger than the threshold, then the system marks a flag at this location. For every point that falls above the threshold, the flag will signify the GUI to explicitly mention where in the swing the arm broke its straightness in respect to the action sequences. If the instance of time, listed as the order of the quaternion data points, falls within the same index range as the frames representing a specific action sequence, then the system can infer that the faulter occurred at that specific action.

Formally, let's define the address of the swing to indices $i \in [x, y]$. Both the video streams and quaternion data points were captured in respect to the same starting point in time, which has been ensured through MCU transmitting a "Start" package that the user triggers via button. If θ contains an index, *j*, such that $\theta_j > \theta_{threshold}$, and $i < j < k$, then the system can define an error within the address action of the swing. However, this threshold value will be discovered through testing, which is outlined in **Chapter 9**.

The visualization of this process refers to creating a timeline and plotting the magnitude of the angle at every instance of time. There will be, at maximum, 50 data points, each separated by $\frac{1}{10}th$ of a second. This way, for the swing duration, any deviations from the expected hyperextended angle behavior can be transparently viewed.

Also, for creating this visualization, it is important to label each action of the swing, like thresholding's methodology. By combining the visualization with the thresholding, it is possible to observe an entire script of the user's swing and make educated conclusions about the arm straightness using kinematic data.

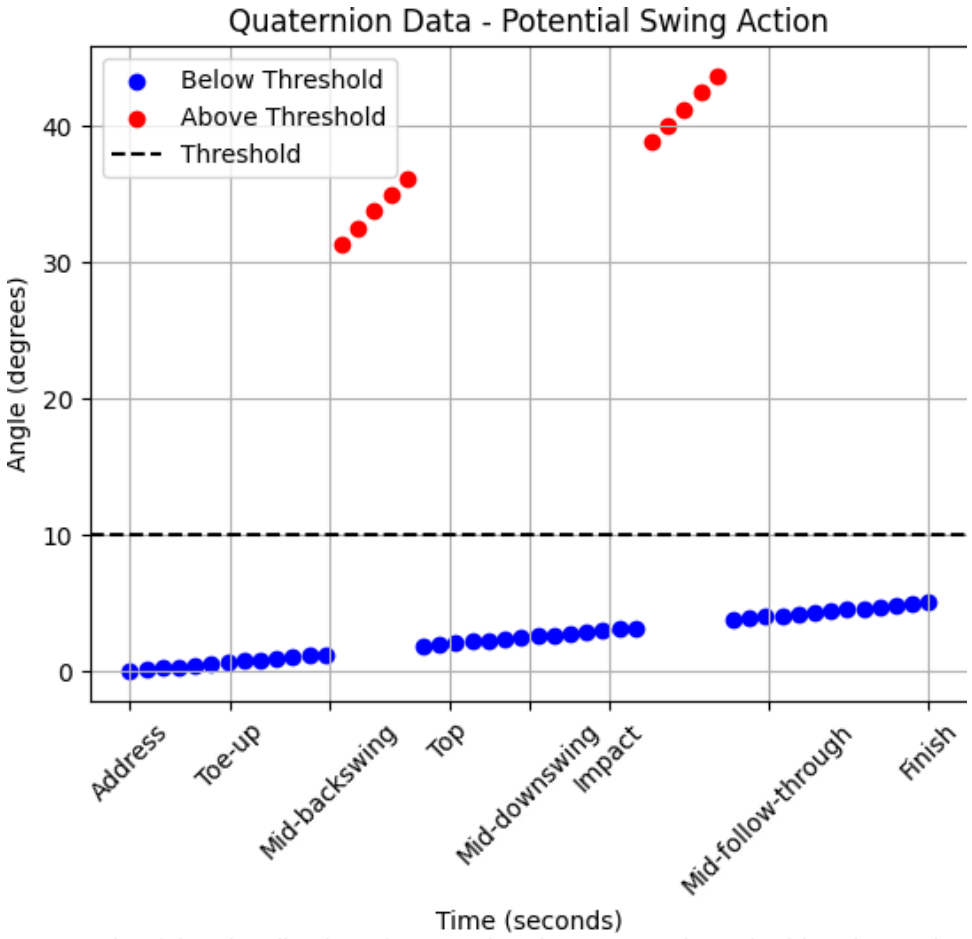


Figure 50: An example of the visualization of quaternion data processing. The blue data points represent instances of time where the angle between the two IMUs is less than the defined threshold, and the red data points represent instances of time where the angle is larger than the threshold. Each action is labeled along the x-axis, so the user can attribute specific errors to the exact segment of the swing. Referenced via [69] .

7.8 Graphical User Interface

7.8.1 Framework Selection: wxPython

The graphical user interface, or GUI, of AutoCaddie will be representative of the output mechanism of providing feedback to the user. The GUI will be responsible for displaying formatted statistics pertaining to the user's previous golf swing technique and analyzing it using the pre-established data analysis methods. Through the mediums of charts, graphs, and percentages with respect to time and swing actions, the user can gain insightful feedback from AutoCaddie's AI.

As researched in **Section 3.5.6**, the selection of a particular GUI library is a critical decision in AutoCaddie's development. Numerous libraries have been considered such that the selected one needs to contain integration with NumPy, OpenCV, sklearn, Keras, and Tensorflow. Among those reviewed, wxPython emerged as the strongest choice. It serves as a cross-platform GUI toolkit for Python and can interface the wxWidgets library

written in C++ for optimization. One significant advantage that wxPython presents is its compatability with different operating systems, allowing it to be run within Windows, MacOS, and Linux. Plus, with the design choices of data processing, it can be deployed on a diverse background of computing devices.

It is worth mentioning one of the drawbacks of wxPython as well. The installation process on macOS has been reported to be challenging, which can undermine some of these cross-platform compatibility claims. AutoCaddie boasts accessibility, so being able to ensure ease-of-access is a must for deployment purposes.

Overall, wxPython is the most suitable choice for this project. Its portability, native appearance, and comprehensive set of widgets allow for this tool to act powerfully without demanding a large load of resources. Additionally, on most platforms, its ease-of-use aligns with this project's goals. Overall, wxPython will be utilized because it provides the right balance of features, ease-of-development, and cross-platform compatibility.

7.8.2 GUI Structure

7.8.2.a Starting a New Project

To fully understand the software design of the GUI application within AutoCaddie, it is important to reference the full design process of wxPython. Moreover, when initiating a new project, it's essential to follow a structured approach to maintain code organization and modularity.

To begin the development for AutoCaddie's GUI, a *main.py* Python file must be declared at the root of the project folder. This file is essential for maintaining GUI control. The executable application can be controlled using the code logic below.

```
import wx
from gui_module import AutoCaddieGUI

if __name__ == '__main__':
    app = wx.App()
    AutoCaddieGUI(None, title='AutoCaddie GUI')
    app.MainLoop()
```

In this code, there are several important takeaways. First, importing 'wx' allows for the utilization of wxPython. Next, the 'if' condition checks that, once the program is running, if this specific section of text defines the main control. From this point, any code provided within this code will be used as the primary operation.

Moreover, the call *AutoCaddieGUI()* is used to reference the GUI module of the software application. By creating directories within the project folders, it is possible to create separate packages that can be imported through higher level Python files. An example of the AutoCaddie project folder would look like, at a barebone level, is shown below.

```
AutoCaddie/
|-- main.py
|-- gui_module/
|   |-- __init__.py
|   |-- autocaddie_gui.py
|   |-- other_gui_components.py
|-- algorithms/
|   |-- __init__.py
|   |-- frame_extraction.py
|   |-- bounding_box_annotation.py
|   |-- image_standardization.py
|   |-- zero_padding.py
|   |-- action_detection.py
|   |-- kinematic_equation_algorithm.py
|-- tests/
|   |-- __init__.py
|   |-- test_frame_extraction.py
|   |-- test_bounding_box_annotation.py
|   |-- test_image_standardization.py
|   |-- test_zero_padding.py
|   |-- test_action_detection.py
|   |-- test_kinematic_equation_algorithm.py
```

Figure 51: A folder representation of the AutoCaddie software containing a GUI module.

In Figure 51, there are several takeaways. First, the hierarchy of each file is determined by the indentation. In other words, each indent represents files being contained within a parent folder. The algorithms and tests packages have previously been explained in **Section 7.5**. The *gui_module* package pertains to the *gui_module/* parent folder containing three independent *.py* files. The *__init__.py* file is necessary for the program to recognize the GUI module as an independent package that can be imported into other files such as *main.py*. Moreover, the two remaining *.py* files contain the logic that defines a proper GUI for the user, encapsulating widgets, events, and other design aspects. This organization not only is important for functionality but enhances readability and maintainability.

Overall, it is possible to define GUI modules using this pattern. By creating a parent folder within the main directory, it is possible to establish packages that can be imported and initialized within the main controlling logic. By doing this, it is possible to integrate data processing algorithms with the GUI and facilitate a streamlined user experience.

7.8.2.b wxPython Primary Programming Concepts

Moreover, by utilizing this project structure as prior mentioned, it is possible to prototype an early edition of AutoCaddie. However, there are still missing components from this project hierarchy, including the incorporation of the following key components.

- wx.App: Initialization of the wxPython application.
- wx.Frame: Representation of the main window of the application.
- Event Handling: Connecting user actions (events) to specific functions (event handlers).

First, the role of ‘wx.App’ is to initialize a wxPython application. It acts as the entry point for the application and sets up necessary resources. Before creating the GUI elements,

an instance of ‘wx.App’ must be created, which is typically done at the beginning of a script or application via the following code.

```
app = wx.App()
```

Second, the role of ‘wx.Frame’ is to represent the main window of the application. It serves as the container for other GUI elements such as buttons, text boxes, and panels. To create a main window, ‘wx.Frame’ is subclassed and overwritten by an ‘__init__’ method. This is the specific point in the code to define the main characteristics of the window, such as its title, size, and initial layout. An example of this is shown below.

```
class MyFrame(wx.Frame):
    def __init__(self, parent, title):
        super(MyFrame, self).__init__(parent, title=title, size=(400, 300))
```

This code displays a parent-child relationship, which is reflective of modularization and is important to consider during development. The ‘parent’ parameter of *__init__()* refers to the parent window or frame. If a window has no parent, it is considered a top-level window.

Third, event handling is a broad term given to connecting user actions to event handlers. This can be in the context of selecting specific pieces of data, pushing buttons to swap GUI screens, and other actions. As a generic definition, event handling is the process of connection user interactions to specific functions, known as event handlers.

The ‘Bind’ method is used to associate an event with a function. This is typically done within the frame’s ‘__init__’ method. An example of this is shown below.

```
class MyFrame(wx.Frame):
    def __init__(self, parent, title):
        super(MyFrame, self).__init__(parent, title=title, size=(400, 300))

        # Creating a button
        btn = wx.Button(self, label='Click me')

        # Binding button click event to the on_button_click function
        btn.Bind(wx.EVT_BUTTON, self.on_button_click)

    def on_button_click(self, event):
        print("Button clicked!")
```

When an event occurs, an event object is usually passed to the associated function. This object contains information about the event, such as the widget generating the event.

By utilizing the flow of these three components, it is possible to design control flow within AutoCaddie’s software design.

7.8.2.c Widgets and Layout

Widgets are the building blocks of a GUI, and arranging them efficiently is crucial. wxPython provides a variety of events that can be bound to specific widgets. These events represent user actions, and are confined within the 'wx.EVT_Events' module. Some examples of useful widgets are: Buttons, Text Controls, Panels, and Menus.

An important topic within layout management is Sizers. It's essential to arrange widgets in a way that adapts to different screen sizes and orientations. By utilizing Sizers, it is possible to automatically create device-specific GUIs, which provides accessibility across a diverse range of computing devices. An example of a Sizer is shown below.

```
class AutoCaddieGUI(wx.Frame):
    def InitUI(self):
        panel = wx.Panel(self)
        hbox = wx.BoxSizer(wx.HORIZONTAL)
        # Insert code for attaching components to the Horizontal Box here.
        panel.SetSizer(hbox)
```

In this code, the 'wx.BoxSizer' represents the Sizer object. It is created with a specified orientation. At this point, the *SetSizer()* function call sets the box's sizer as the parent panel's sizer.

Additionally, menus are another important concept within GUI design. Menus provide a way to organize and group functionality. They are created using 'wx.MenuBar' and 'wx.Menu' classes. The code below showcases these objects.

```
menubar = wx.MenuBar()
fileMenu = wx.Menu()
fileMenu.Append(wx.ID_EXIT, 'Exit', 'Exit application')
menubar.Append(fileMenu, '&File')
self.SetMenuBar(menubar)
```

In this code, both the Menu bar and Menu objects are created, and an "Exit" item is appended to the File menu. The final line sets the menu to the main frame to be displayed to the user.

Furthermore, the implementation for event binding is shown below. This is reflective of menu objects and is attributed to particular actions.

```
self.Bind(wx.EVT_MENU, self.OnQuit, id=wx.ID_EXIT)
```

This line binds the "Exit" menu item to the *OnQuit()* method, specifying that it should be triggered when the exit menu item is selected. Thus, the *OnQuit()* method can be defined as below to close the GUI widget.

```
def OnQuit(self, event):
    self.Close()
```

Specifically, calling *self.Close()* closes a specific window designated as the main frame displayed to the user.

Overall, effective widget management and layout are achieved through the use of Sizers, which allow for dynamic adaptation to different screen sizes. Combining this with well-structured menus and event handling creates a comprehensive and user-friendly wxPython GUI.

7.8.3 Parameters and Data Output

The data processing algorithms are responsible for converting the user data into an interpretable form. These algorithms, encompassing frame extraction, bounding box annotation, image standardization, action detection, and kinematic equation processing, are systematically organized into a modular structure within the algorithms package. The integration of these algorithms into AutoCaddie's software design is intended for a smooth user experience with the GUI. Therefore, the results of these algorithms collectively contributes to a holistic representation of the golfer's swing. The algorithms package feeds data through both a CNN and kinematic equations to create the resulting output data to be formatted by this GUI program. These two subsystems provide a multitude of data that can assist the user with their golf swing with direct analyses of swing technique.

First, the CNN processes a series of frames, each corresponding to one of the eight predefined actions in a golf swing. The network compares these frames to a database of swings, specifically GolfDB, and computes similarity weights for key parameters, including back posture, leg position, hip position, and swing speed.

The integration of the CNN into the AutoCaddie GUI allows users to receive real-time feedback on their technique. The GUI dynamically displays similarity weights for each parameter at every frame, enabling golfers to assess and refine their performance. The implementation involves the following steps:

1. Frame Sequence Input: The GUI continuously feeds the CNN with a series of frames capturing different phases of the golf swing.
2. Parameter Similarity Calculation: The CNN evaluates the similarity between the input frames and the swings stored in the GolfDB database. Similarity weights are computed for back posture, leg position, hip position, swing speed, and overall swing technique.
3. Real-Time Display: The GUI dynamically showcases the computed similarity weights for each parameter as the user progresses through the swing. This real-time feedback allows golfers to make instant adjustments and better understand their strengths and areas for improvement.

The generic code for implementation is shown below. This is incomplete, as many more user widgets can be utilized to enhance the output format.

```python
# Neural Network Integration for GUI
def integrate_neural_network(frames, golfdb_database):
    similarity_weights = []

    for frame in frames:
        weights = cnn_process_frame(frame, golfdb_database)
        similarity_weights.append(weights)

    return similarity_weights
```

This is a generic call to the CNN model within AutoCaddie. The similarity weights contains a score for each swing, specifically for the overall swing analysis. Specific features can be extracted using methods of the same format.

Second, the quaternion data, representing arm orientation during the golf swing, undergoes two primary interpretation processes for GUI presentation: thresholding and visualization. These processes enhance the golfer's understanding of arm straightness and aid in correlating deviations with specific swing actions.

1. Thresholding: The GUI applies a defined angle threshold to identify instances of arm straightness deviation. Flags are raised at frames where the arm angle surpasses the threshold, allowing users to associate errors with specific swing actions.
2. Visualization: A graphical timeline of angle magnitudes at each instance of time is generated. This visual representation, combined with thresholding, enables users to transparently observe and correlate arm deviations with precise segments of the swing.

This methodology, including visualization of data points, has been demonstrated through Figure 50 in **Section 7.7.2**. But this allows for the GUI to dynamically display the threshold results and visual timeline.

Both of these systems incorporate real-time feedback mechanisms, providing golfers with a comprehensive view of both the CNN analysis of their swing technique and the spatial dynamics captured by quaternion data. Moreover, the modular design ensures that the GUI remains intuitive and user-friendly, fostering a valuable tool for golf improvement.

```python
# GUI Implementation
def update_gui(frames, golfdb_database, quaternion_data, threshold):
    # Neural Network Integration
    similarity_weights = integrate_neural_network(frames, golfdb_database)

    # Quaternion Data Visualization
    visualize_quaternion_data(quaternion_data, threshold)

    # Update GUI with real-time feedback
    gui_update(similarity_weights)
```

As shown by the code, the updating of this GUI frame is simply called by the *gui_update()* function call, utilizing the new data results from the previous algorithmic calls. Through this integrated approach, AutoCaddie provides golfers with a sophisticated, user-friendly platform for refining their golf swing technique based on both visual and neural network feedback.

7.8.4 Project Directory Structure

Compiling all this information, a prototype project directory is shown below.

```
AutoCaddie/
|-- main.py
|-- gui_module/
|   |-- __init__.py
|   |-- autocaddie_gui.py
|   |-- other_gui_components.py
|   |-- charts/
|   |   |-- __init__.py
|   |   |-- chart_module.py
|   |   |-- timeline_module.py
|   |   |-- other_chart_components.py
|   |-- plots/
|   |   |-- __init__.py
|   |   |-- plot_module.py
|   |   |-- other_plot_components.py
|-- algorithms/
|   |-- __init__.py
|   |-- frame_extraction.py
|   |-- bounding_box_annotation.py
|   |-- image_standardization.py
|   |-- zero_padding.py
|   |-- action_detection.py
|   |-- kinematic_equation_algorithm.py
|-- neural_network/
|   |-- __init__.py
|   |-- cnn_module.py
|   |-- linear_svc_module.py
|   |-- other_neural_network_components.py
|-- data_processing/
|   |-- __init__.py
|   |-- data_processing_module.py
|   |-- other_data_processing_components.py
|-- tests/
|   |-- __init__.py
|   |-- test_frame_extraction.py
|   |-- test_bounding_box_annotation.py
|   |-- test_image_standardization.py
|   |-- test_zero_padding.py
|   |-- test_action_detection.py
|   |-- test_kinematic_equation_algorithm.py
|   |-- test_cnn_module.py
|   |-- test_linear_svc_module.py
|   |-- test_data_processing_module.py
```

Figure 52: A prototype project directory structure for AutoCaddie.

As shown by Figure 52, the project can be divided into many different modules, each containing an abstracted responsibility of logic.

The ‘main.py’ file is responsible for controlling the main flow of the software. Depending on the state of the program, whether it be through calibration, data collection, or output presentation, this file will dictate which GUI window is displayed to the user. Thus, each subsequent module within the project can directly be imported into main.py, and used through single line calls. This enhances the readability of the program and allows for transparent readability. A key signifier of a package is the existence of the ‘__init__’.py file.

The ‘gui_module’ module contains necessary widgets and files for displaying a GUI to the user for AutoCaddie. It has a class declared for plots, which will be the output of the kinematic data, as well as a class declared charts, which can contain statistical data representative of the similarity scores from the CNN. Each of these output mediums contain their own package with individual logic, which can ide extraneous code from the developers.

The ‘algorithms’ module contains the necessary files for completing the data preprocessing algorithms. The procedural transition of video data to standardized frames and action sequences can be referenced minimally through the main code by using logic within this module. Not to mention, the kinematic data processing can also be referenced through here.

Similarly, the ‘data_processing’ module is used for calling necessary code for converting preprocessed data to readable output. This involves feeding frame data to AutoCaddie’s CNN, and IMU data to the kinematic equation.

The ‘neural_network’ module is the bulkiest section in this project, as it contains a trained CNN. This network is trained on a collection of 1400 compressed golf swing videos, and is constructed using extensive layer connections. That is why it is important to ensure this module is abstracted, as importing the model provides a significant improvement to code readability.

Lastly, the ‘testing’ module implements the unit tests for each algorithm implemented. By creating specific tests utilizing the ‘unittest’ library, the output of each defined function can be compared to expected values to ensure functionality. To follow proper naming conventions, each testing file follows the “test_[file name].py” syntax style.

7.9 System Integration and Optimization

7.9.1 Overall Integration

Overall, there is much to consider when integrating every subsystem into the overlaying software mechanism of AutoCaddie. It is important that this is performed seamlessly so that the system can perform without inconsistencies. At the scope of AutoCaddie’s accuracy, it is imperative that there are minimal factors that can negatively impact the performance of the software, so that the user feedback can be as truthful as possible.

Additionally, by providing successful integration, there will be efficient data flow, synchronization, and smoother operations throughout testing.

The components to be integrated are as follows. The two peripheral apparatuses, specifically the cameras and IMU sensors, should provide data in sync to the computing device. This device will contain the software of AutoCaddie, and will manage the data operations, as outlined in **Section 7.6**. Once the data has been received and run through both the computer vision preprocessing algorithms and the quaternion vectorization steps, the CNN and kinematic equations will compute. With the size of the data being manipulated, it is also important to emphasize optimizations within these algorithms to ensure the processes do not delay a final result. Then the results of these operations will be run through different analyses, where the output will be presented to the user. For AutoCaddie to align with its goals, it needs to be capable of real-time analysis. This stresses the importance of optimizing every internal algorithm to be as efficient as possible, while not jeopardizing overall accuracy.

Therefore, it is also important to highlight synchronization. For the user feedback to be comprehensive, certain statistics can reference both physical and video data at specific instances of time. Being able to manage an exact chronological order, which references specific instances of time, allows for AutoCaddie to perform a proper real-time breakdown of actions.

Lastly, the information presented to the user must also be comprehensive without jeopardizing processing speeds. It is important to ensure that the output does not facilitate long operations to generate graphics, extraneous information, or other expenditures. Thus, rigorous testing is a requirement before AutoCaddie can fulfill its goals.

Thus, the previous sections within this chapter discussed the implementation details. The following subsections explain optimizations and benefits for utilizing the design choices implemented.

7.9.2 Algorithmic Optimizations

7.9.2.a Modular Design Benefits

AutoCaddie embraces a modular and object-oriented approach to integrate each processing algorithm. This design philosophy is important for enhancing code maintainability and readability. The utilization of the wxPython framework for GUI development complements this modular structure, ensuring a robust and efficient software architecture.

In adhering to a modular design, AutoCaddie has segregated algorithms, such as frame extraction, bounding box annotation, and others, into discrete logic units. Each of these algorithms resides in its dedicated .py file, contributing to the clarity of code organization and simplifying the debugging and maintenance processes. This separation enables developers to focus on specific functionalities without the complexity of navigating through a monolithic codebase.

Additionally, AutoCaddie's software hierarchy is organized as a folder structure, providing a clear overview of the project's architecture:

- algorithms/ folder: Contains Python scripts, where each individual script is dedicated to a specific algorithm.
- init.py file: Signifies the parent directory as a Python package, enabling clean imports between modules.

This hierarchical arrangement ensures that each algorithm operates as an independent and reusable unit. Moreover, this transitions to the utilization of unit testing to ensure functionality before deployment.

The integration of wxPython and the Python framework unittest directly supports unit testing within this modularized code structure. By referencing Figure 52, the project hierarchy places the controlling logic at the parent folder, with algorithms extracted down to a subdirectory. Similarly, the introduction of a ‘tests’ package showcases a dedicated space for unit testing each algorithm individually. Therefore, the integration process of unit testing, which ensures program functionality and promotes debugging convenience, is streamlined.

7.9.2.b Frame Extraction Benefits

Frame extraction is the first step in the image data preprocessing pipeline for AutoCaddie's CNN. This process involves breaking down a continuous video feed into distinct images, each representing a specific moment in time. The frames, represented as 2D matrices of pixels, provide the fundamental building blocks for subsequent image processing within the AutoCaddie system. To achieve this, the OpenCV library is used to parse frames from live video feeds. OpenCV's capabilities enable AutoCaddie to create the illusion of downloading and extracting a video by live parsing frames from a video feed.

Within the implementation, there are many benefits for AutoCaddie:

- Real-time Processing: By extracting frame data from live video streams, AutoCaddie can operate in real-time without worrying about employing a video parsing algorithm after receiving the camera data. This saves processing speed, as there is no additional algorithm that needs to be used for this task after acquiring the data.
- Data Precision: The representation of frames as 2D matrices, where each matrix contains pixels representative of 3 color channels, ensures precise data to be maintained through subsequent image processing algorithms.
- Synchronization: Implemented error checking ensures that if one video does not properly capture an instance of time, neither frame is saved. This ensures continuity for the image processing, as both frame lists are representative of equal moments in time.

- Memory Optimization: By properly managing and releasing camera streams, there is less of a resource burden on the system.

7.9.2.c Bounding Box Annotation Benefits

Bounding box annotation is the next step in the image data processing pipeline to reduce the computational burden of AutoCaddie's CNN. The primary objective is to annotate bounding boxes around the golfer and golf club during the swing motion. This is implemented via the use of MobileNetV2, which is a CNN model used for object detection. MobileNetV2 is lightweight and efficient, which makes it well-suited for deployment in AutoCaddie.

The benefits of using an additional network for object detection are as follows:

- Computational Efficiency: Bounding box annotation strategically reduces the computational cost for AutoCaddie's CNN, optimizing resource utilization.
- Object Detection Accuracy: Leveraging MobileNetV2 enhances the accuracy of object detection, ensuring precise identification of the golfer and golf club.
- Adaptability to Diverse Environments: MobileNetV2's lightweight architecture enables AutoCaddie to operate efficiently across diverse environments, catering to the project's varied deployment scenarios.
- Streamlined Data Presentation: Annotated bounding boxes provide a clear and focused representation of the region of interest within each frame, allowing for image cropping to be optimized.

7.9.2.d Image Standardization Benefits

Image standardization assumes the next step in the image data processing pipeline. Its objective is to ensure uniformity within the image input dimensions when presented to the CNN. This process involves a dual approach – cropping images to annotated bounding boxes, and applying zero-padding.

Specifically, cropping to the region of interest is the first action. This refers to utilizing the coordinates of each image's bounding box, and removing all unnecessary pixels outside the border. Zero-padding refers to upscaling an image's dimensions to match those presented by the GolfDB training database by applying zero values outside the region of interest.

Therefore, by applying these two algorithms, the following benefits are achieved:

- Enhanced Analysis Accuracy: Consistent dimensions across all input data frames contribute to the accuracy of the CNN analysis. This standardization minimizes variability and ensures a reliable basis for identifying patterns and features.
- Optimal CNN Model Compatibility: The standardized images smoothly integrate with the CNN model's expectations. This compatibility is essential for maximizing the efficiency by reducing the variability of input, and boosting the performance overall.

- Precise Focus on Key Elements: By cropping images to the bounding boxes, the CNN is directed to focus specifically on the golfer and golf club. This precision enhances the system's ability to extract meaningful insights from the golf swing data.

7.9.2.e Action Detection Benefits

Another stage of the image processing pipeline is to extract specific events within the user's swing, and map them to predefined actions. By discerning and classifying these actions, AutoCaddie lays the foundation for comprehensive swing analysis and user feedback.

The implementation of action detection is performed through the training of a LinearSVC model. This choice was determined by efficiency of classification, as well as scalability of the model. Thus, to train this model, it needs to be provided annotated GolfDB training videos with exact action starting frames annotated. Additionally, by tuning the hyperparameters, it is possible to deploy a model that is efficient as possible.

The benefits for using a LinearSVC, as well as action detection in general, are as follows:

- Precision in Swing Phase Identification: Action detection enhances the precision with which different phases of the golf swing are identified, providing a detailed breakdown of the user's swing sequence.
- Nuanced Motion Recognition: The system excels in recognizing nuanced motions and patterns across frames due to the variety presented by the input data. This contributes to a comprehensive understanding of the user's swing dynamics.
- Efficient LinearSVC Classification: The choice of LinearSVC ensures efficiency in classifying the eight golf swing actions, striking a balance between accuracy and computational performance.
- Real-time Integration into AutoCaddie: The trained model easily integrates into AutoCaddie's architecture, enabling real-time action detection during golf swing analysis.

7.9.2.f Kinematics Benefits

As a separate but synchronous system within AutoCaddie, spatial data processing is computed through quaternion data points. Quaternion data serves as a valuable resource for storing the spatial information of the user's inner arm throughout the entirety of the swing. Specifically, quaternion data can represented by a 4-dimensional vector, which calls for the utilization of NumPy. In other words, the performance benefits of the kinematic equations running alongside the image processing data include boosted accuracy of calculations, as well as every mathematical optimization presented by the NumPy library. Formally, these benefits are as follows:

- Precision in Spatial Representation: By using quaternion data points over Euler angles, it is possible to track more dimensions of the input data without

jeopardizing storage requirements. Quaternion data is highly accurate, and allows for linearity calculations to be simplified into a single vector equation.

- Efficient Matrix Operations: Leveraging NumPy for matrix operations enhances computational efficiency, enabling swift and optimized calculations of quaternion angle differences.
- Dynamic Angle Calculation: The ability to calculate angles between quaternion data points for every instance recorded during the swing provides a comprehensive perspective of the arm's spatial orientation.
- Numerical Stability: NumPy's numerical stability ensures reliable and accurate results, crucial for maintaining the integrity of spatial data processing in kinematic analysis.

It is worth mentioning that the implementation libraries for the image data preprocessing algorithms utilize NumPy's matrix operations. It has been established that each frame is a 2D collection of integers, so when operated upon by NumPy's functions, the analysis process is simplified.

Specifically, NumPy's standout features in regards to image data and neural networks is its seamless integration with Singular Value Decomposition (SVD). SVD is a sophisticated technique utilized extensively in data analysis, signal processing, and, notably, in the image processing realm of AutoCaddie. With SVD, complex matrices are reduced into three concise matrices, capturing nuanced patterns and crucial relationships inherent in the data. A diagram of the SVD transformation of a matrix is shown below.

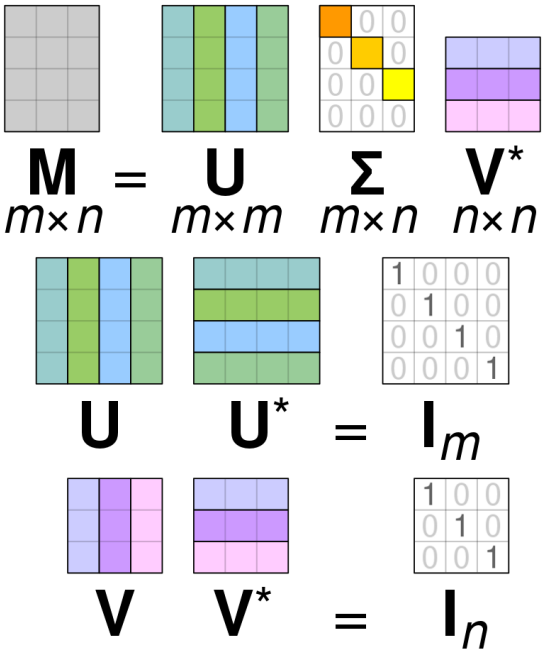


Figure 53: The Singular Value Decomposition of a Matrix. A matrix of dimensions mxn is reduced into three compact matrices. Matrix U contains orthogonal column vectors, and matrix V contains orthogonal row vectors. Matrix Σ is a diagonal matrix which contains the singular values of A. Many matrix operations can be completed using this reduced form of the original matrix A. Referenced via [86] .*

In the context of AutoCaddie, this translates into the processing of video data with strong precision. The live video feed, through the data preprocessing algorithms, can be dissected into a collection of frames, where certain segments map to exact actions within the golf swing sequence. Moreover, each frame can be represented as a matrix of pixels. Through SVD, these matrices are simplified, shedding redundant information, and eliminating noise while preserving the vital aspects. In essence, this reduction in dimensionality streamlines the data, making it more manageable and refining its quality.

7.9.2.g Summary

Overall, each of the implementation strategies for the data processing algorithms maintain the line between performance and resource demands. In optimizing these algorithms, a modular design philosophy is embraced, enhancing code maintainability and readability. The software hierarchy, organized into a folder structure, promotes algorithm independence, and streamlined unit testing. Frame extraction employs OpenCV, offering real-time processing, data precision, synchronization, and memory optimization. Bounding box annotation strategically reduces computational costs using MobileNetV2, ensuring computational efficiency, object detection accuracy, and adaptability to diverse environments. Image standardization, through cropping and zero-padding, ensures consistent input dimensions for effective CNN analysis, enhancing accuracy and model compatibility. Action detection, utilizing LinearSVC model training, enhances precision in identifying different swing phases, providing nuanced motion recognition and real-time integration into AutoCaddie. Kinematics, employing quaternion data and NumPy, ensures precise spatial representation with efficient matrix operations, dynamic angle calculation, and numerical stability, contributing to a comprehensive understanding of the user's arm dynamics during the golf swing. Overall, these optimizations lead to a robust and efficient system for golf swing analysis.

7.10 Summary

7.1 Introduction

AutoCaddie is a state-of-the-art system tailored for analyzing golf swings, integrating advanced machine learning models and software algorithms within a user-friendly interface. The system adeptly processes video and sensor data, providing real-time feedback to golfers. This feedback is crucial for players looking to enhance their skills, offering insights that would be challenging to obtain through traditional coaching methods. By leveraging the power of AI and machine learning, AutoCaddie stands at the forefront of technological innovation in sports training, offering a blend of accuracy, immediacy, and accessibility.

7.2 Machine Learning and AI Subsystems

AutoCaddie’s machine learning model is a cornerstone of its functionality, utilizing the expansive GolfDB database for robust training. This neural network-driven approach enables the system to map out intricate details of golf swings, linking specific actions to relevant parameters. The model iteratively refines its predictions, reducing errors and fine-tuning its accuracy. Complementing this, the AI subsystem is divided into two integral components: a video system and a physical sensor system. The video system

meticulously preprocesses and frames golf swings, extracting pivotal features for analysis. In parallel, the sensor system, equipped with IMUs, captures detailed quaternion data, enriching the swing analysis with a layer of depth and precision.

7.3 Software Implementation and Design

At the heart of AutoCaddie is its software, hosted on a computing device like a laptop, serving as the central hub for data processing and feedback dissemination. This software is engineered to handle data inputs from various sources, applying a series of preprocessing algorithms before funneling the data into the machine learning model. The design of the software is centered around creating an AI-driven, intuitive system that can analyze golf swings in real-time. It integrates data from both IMUs and video cameras, processing it through advanced machine learning algorithms and presenting the analyzed feedback through an interactive GUI.

7.4 Technical Aspects of Software

Python is the backbone of AutoCaddie's software development, chosen for its simplicity, versatility, and extensive support for relevant libraries like NumPy, crucial for handling complex mathematical operations. The GUI, crafted using wxPython, is designed to be user-friendly and efficient, presenting data in a manner that is both informative and easy to interpret. Development is carried out in Visual Studio Code, a versatile IDE supporting Git integration for streamlined version control. AutoCaddie's commitment to robustness and reliability is underscored by its comprehensive testing regimen, which includes unit testing and integration testing, ensuring the software's performance and reliability.

7.5 Communication and Data Processing

The communication framework within AutoCaddie ensures efficient and accurate data transmission between the microcontroller unit (MCU), cameras, neural network, and other internal components. Data processing algorithms like frame extraction, bounding box annotation, image standardization, and action detection are integrated into the system with a focus on modularity and maintainability. This modular approach not only facilitates ease of testing but also enhances the scalability and robustness of the software architecture.

7.6 Data Management and Analysis

AutoCaddie exhibits an adept strategy in managing and processing data from cameras and IMUs, emphasizing efficiency to enable real-time feedback. The system skillfully interprets neural network outputs and kinematic data, providing a comprehensive analysis of each golf swing. This integration of spatial-temporal data analysis ensures a detailed and holistic understanding of the swing mechanics, offering valuable insights to the user.

7.7 GUI and System Integration

The GUI, based on wxPython, is meticulously structured to offer a seamless and intuitive user experience. It effectively displays processed data, enhancing the user's understanding of their swing technique. The integration of the system is a testament to AutoCaddie's commitment to accuracy and efficiency. Algorithmic optimizations across

different components ensure a balance between performance and resource demands, augmenting the overall effectiveness of the system.

7.8 Optimization and Validation

Optimizing the neural network is a critical task, balancing model complexity with operational efficiency to enable real-time analysis. The system undergoes regular updates and refinements, based on a comprehensive validation process that includes cross-validation techniques and real-world testing. These processes ensure the model's effectiveness and reliability in practical scenarios, making it a dependable tool for golfers.

7.9 Conclusion

In conclusion, AutoCaddie represents a groundbreaking solution in the realm of golf swing analysis. Its fusion of advanced machine learning, sophisticated software engineering, and user-centered design results in a system that not only excels technologically but is also practical and user-friendly. AutoCaddie stands out as an exemplary innovation in sports technology, offering a valuable tool for golfers of various skill levels to enhance their performance.

Chapter 8: CAD Design and Fabrication

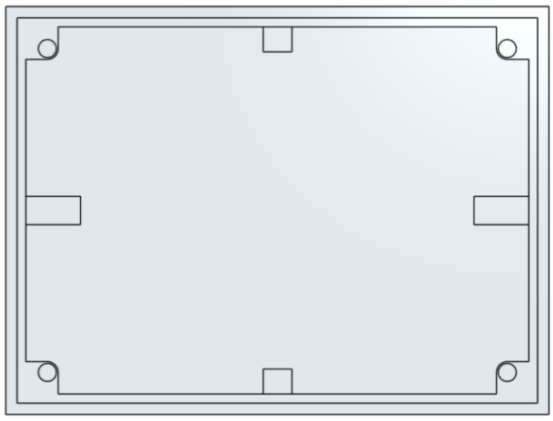
8.1 Kinematics system and hardware

8.1.1 Central PCB Fabrication

The central PCBs will be ordered and manufactured through JLPCB, following the specifications and design requirements. Post-acquisition, the assembly process entails soldering the essential components onto the PCB. Surface mount components undergo soldering using a reflow oven, ensuring precise and uniform attachment. The other components that use through holes can be hand-soldered onto the PCB. This approach in component attachment ensures the integrity and reliability of the central PCB, aligning with industry standards and best practices in electronic manufacturing.

Following the completion of the central PCB hardware, the MCU component of the programmed. The MSP430 is designed to interface with a JTAG (Joint Task Action Group). which supports in-circuit programming of flash and FRAM memory. The JTAG also supports testing program interconnects and improves debugging capabilities of the device. To allow the MSP430 to connect to an available JTAG, pin connections must be made available with a VCC and GND connection, as well as with the MSP430's TEST and RESET pins. Wiring these connections to a JTAG device will allow the MSP430 to be effectively programmed and tested.

8.1.2 PCB and IMU enclosures



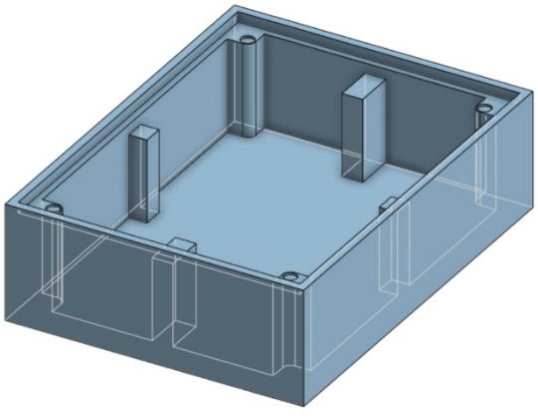


Figure 54 (LEFT): PCB mounting box; Top view.
Figure 55 (RIGHT): PCB Mounting Box; Isometric view.

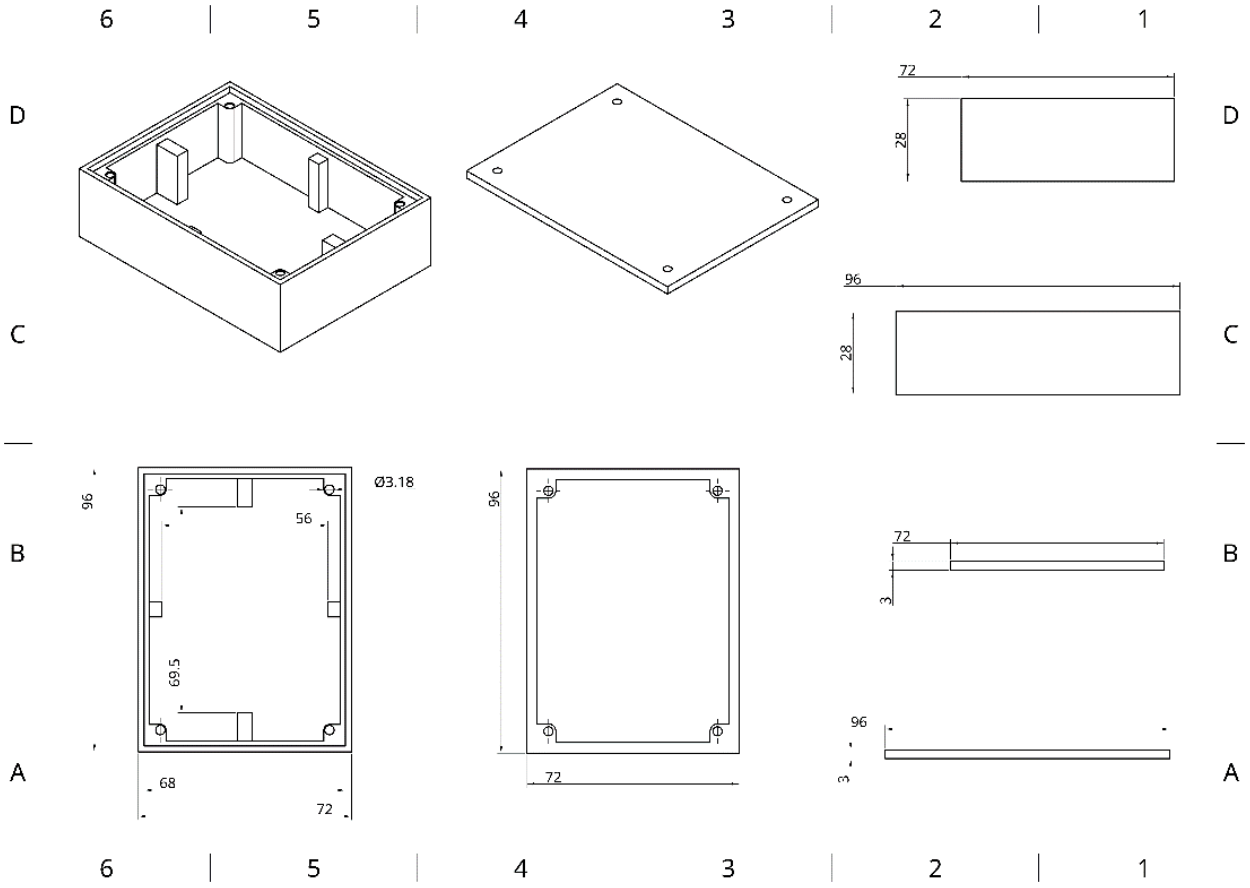


Figure 56: PCB mounting box engineering drawings.

Designing enclosures for both the central PCB and the IMUs is important for ensuring the protection and stability of these hardware components, particularly as they are wearable devices. The enclosures serve a dual purpose: shielding the components from environmental factors like dust, moisture, and physical impact, and providing a secure means of attachment to the wearer. The enclosures are designed as CAD models, where they can be 3D printed using PLA plastics, offering a decent balance between cost effectiveness, strength, and flexibility.

To facilitate the attachment of these enclosures onto a wearer, a practical approach involves incorporating Velcro straps into the design. These straps can be fed through designated slots or loops on the enclosures, allowing for adjustable and secure fastening around the user's body. To secure the IMUs and PCB within the enclosures, the components are securely fastened using screws. The design includes through holes placed on the PCB and IMU, which align with corresponding points on the enclosure. The enclosure is designed to allow the screws to cut their own threads as they are tightened. The points at which the screws engage with the enclosure have holes which diameters are slightly smaller than the diameters of the screws. As such, as the screws are tightened into the holes, they cut into the PLA, creating their own threads. This self-threading

mechanism ensures a robust connection, preventing the components from shifting during movement while maintaining the structural integrity of the wearable device.

8.1.3 Enclosure box mounting

As the IMU and MCU PCB units are worn by the user during the use of AutoCaddie, the enclosure boxes must be secured to the user. As mentioned in the prior section, Velcro straps can be used to secure the enclosures to the user. With the central PCB for the MCU, two Velcro straps can be fed through the enclosure. These Velcro straps can be used as a form of “belt”, where the enclosure box should be secured on the user’s waist.

The IMU enclosures will also utilize Velcro straps to secure the IMUs in a similar manner to that of the central PCB. Additionally, however, the IMU containers can also be further secured by using Velcro pads to lock the containers in place with respect to an elastic sleeve on the driving arm (Refer to Figure 34). These additional Velcro pads will ensure that the IMUs cannot shift around on the User’s arm, and will prevent positional drift errors. As the IMUs must be wired to the central PCB for optimal signal and data transmission stability, the wiring must be set in such a way that the wires do not interfere with the user’s movement. To do this, wire sheaths can be used to keep all of the wires together. The sheath can then also be attached to the elastic sleeve on he user’s arm, ensuring it does not fall into obtrusive spaces. Furthermore, enough slack must be given for the wires and sheath, such that any tightness does not interfere with the movement of the user. Additional attachment points can be placed on the user to secure the wires as necessary, should wire movement pose an issue.

Chapter 9: Testing Plan

9.1 Hardware Component Test and Verification

Hardware testing for the AutoCaddie architecture is characterized by constant referencing and re-referencing of component documentation as well as deliberation on the topic of best practices of IMU calibration, wireless transmission behaviors, and MCU component control. Below is a detailed description of how each component will be tested and verified:

9.1.1 MCU Wiring Verification

The wiring of the MSP430FR6989IPZ Microcontroller is central to the accuracy and performance of the AutoCaddie project. As was illustrated in Chapter 6, the traces connecting the MCU and the various I/O devices on the PCB are laid deliberately with consultation of each component's documentation.

Verification of the MCU's wiring configuration encompasses delivering power to the MCU on a breadboard, connecting the pins enumerated in Table 15 [REFERENCE] to the proper pins on each I/O device. The wiring configuration will be tested using jumper cables, a wired connection to a computer, and a breadboard. Using the code explained in Chapter 6, the MCU will either correctly receive data from the IMUs, or the wiring will be edited such that the pinout is correct. The connections to the HC-06 transceiver will tested through sending UART data and attempting to configure the transceiver into command reception mode and Bluetooth transmission mode. The light on the HC-06 module will change color depending on the mode it is set into and can therefore be verified through its use.

9.1.2 IMU Component Testing

The Inertial Measurement Units (IMUs) are the focal point which differentiates AutoCaddie from other golf-related machine learning projects. Using these hardware components, real-time hard data can be given to the user which details the straightness of their arm. Given the correlation between the straightness of one's arm and the quality of one's golf swing, this data will be used to vastly improve the form of one's golf swing.

The IMUs will be tested using a breadboard and an MSP430FR6989 development board. First, they will be powered and will send and receive data from/to the MSP430. Then, their locations and orientations will be edited using a goniometer. The goniometer is traditionally used to measure the angle between two points, for instance the angle of one's shin with respect to their femur about the knee. For the purposes of AutoCaddie, the goniometer will simulate the changing angle between the forearm and the humerus.

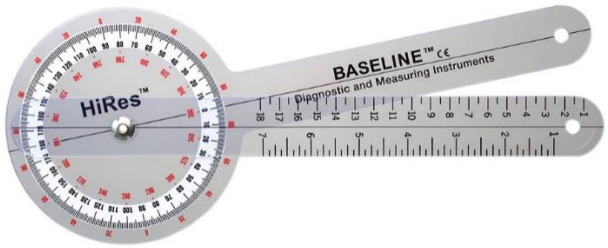


Figure 57: An example of a goniometer to be used in IMU angle testing.

Each IMU will be attached to one of two limbs of the goniometer, and the angle between them will be changed by moving the mobile limb to another location. Depending on the new vector returned, the IMU effectiveness can be proven or disproven.

9.1.3 IMU Calibration

Following the IMU quaternion data testing, the methodology for IMU calibration can be determined. For the IMU data and quaternion data to be accurate for the user of the AutoCaddie system, it must be ensured that it is robust against drift and inherent inaccuracies in placement. The natural drift that IMUs experience due to factors such as magnetic interference, as well as differences in natural orientation upon placement of the user can cause inaccuracies in the data and calculations originating from the IMUs

To address these issues, a calibration methodology must be defined and tested for the IMU systems. To calibrate the IMUs, the offset of the measurements from one IMU must be accounted for with respect to the other IMU by applying a calibration offset vector. To facilitate the calibration process and the determination of the calibration offset vector, the user should maintain a straightened arm during the calibration process.

In order to test the calibration process and its effectiveness, the proposed calibration process should be performed several times. Following each calibration process, the accounting for IMU orientation differences via the calibration offset vector can be analyzed, and the quaternion linearity calculation can be performed to determine the success of the calibration process. In order to validate the robustness of the calibration methodology, between each calibration test, the offset difference between each IMU can be manipulated to control the degree of the overall offset between the two IMU devices.

9.1.4 Wireless Transceiver Testing

The HC-06 Bluetooth Wireless Transceiver is the ligament which connects hardware to software on the AutoCaddie architecture. The data collected from the IMUs will be sent along traces to the MCU, where the data will be formatted for transmission. Finally, the MCU will send the formatted data to the HC-06 transceiver, where the paired device will receive a .CSV file containing the formatted IMU data.

The HC-06 module will be tested using a breadboard, jumper wires, and an MSP430FR6989 development board. The pins in Chapter 6 will be connected via jumper

wires. Once the device is powered, it will be set into command reception mode via UART control, pairing it with a separate device not running the control code. This device will open a Bluetooth Serial terminal, where it can receive any data sent by the HC-06. The HC-06 will be returned to Bluetooth operation mode. A sample .CSV file will be sent to the HC-06 for transmission, and reception of the file will be verified on the paired device. If the file data is untouched and received in a timely fashion, the HC-06 transceiver's effectiveness can be verified or disproven.

9.2 Neural Network Testing

9.2.1 Neural Network Optimization

Optimizing the neural network for the AutoCaddie project involves a comprehensive approach, encompassing various aspects from architecture design to real-time performance enhancement. Here's a detailed look at each key strategy:

The architecture of our neural network is fundamental to its success. For the complex task of analyzing golf swings, a hybrid architecture that marries the spatial analytical prowess of Convolutional Neural Networks (CNNs) with the temporal sequencing capabilities of Recurrent Neural Networks (RNNs) is recommended. CNNs can adeptly process and interpret the visual aspects of the golf swing, such as the position and movement of the golfer and club. On the other hand, RNNs, especially those with Long Short-Term Memory (LSTM) units, are well-suited for understanding the sequential nature of the swing, capturing nuances over time. This hybrid model aims to thoroughly analyze each phase of the swing, ensuring no critical component is overlooked.

Achieving a balance between the model's complexity and its operational efficiency is a delicate task. A highly complex model, while potentially more accurate, may require substantial computational resources, rendering it impractical for real-time analysis, which is crucial for immediate feedback during training sessions. Techniques like model pruning, which involves trimming non-critical neurons; quantization, reducing the precision of the numerical parameters; and leveraging depthwise separable convolutions, a more efficient form of convolution operation, can significantly enhance computational efficiency. These approaches aim to retain the model's accuracy while ensuring it remains lightweight and agile for real-time processing.

The input data's quality directly influences the model's performance. Effective preprocessing techniques are critical. These include frame normalization to maintain consistency across different lighting conditions and videos, alignment to ensure a standardized input, and background subtraction to reduce noise and focus the model on the golfer's movements. Additionally, augmenting the data by introducing variations like random cropping, rotations, and horizontal flipping can robustly train the model to recognize swings under various conditions and viewpoints, enhancing its ability to generalize.

Tuning hyperparameters is a crucial step in optimizing the neural network. Hyperparameters such as the learning rate determine how quickly or slowly the model learns; the batch size affects the memory usage and speed of training; and the configuration of layers and neurons impacts the model's ability to capture complex patterns. Employing methods like grid search, random search, or Bayesian optimization can systematically explore the hyperparameter space to find the most effective combination for our model, balancing learning efficiency with predictive accuracy.

Regularization techniques are essential in preventing the model from overfitting, particularly vital due to the possibly limited size of specialized golf swing datasets. Techniques like dropout, which randomly disables neurons during training, and L2 regularization, which penalizes large weights, help the model generalize better to unseen data. Early stopping, where training is halted once the model's performance on a validation set ceases to improve, also prevents overfitting. These methods ensure that the model learns the general patterns in the data, rather than memorizing the training set.

The loss function guides the model's learning process. In our context, a cross-entropy loss function is fitting as it effectively handles classification tasks, like identifying different phases in a golf swing. Complementing the loss function, evaluation metrics like accuracy, precision, recall, and the F1 score offer a multifaceted view of the model's performance. These metrics help assess not just the model's overall accuracy, but also its ability to balance false positives and false negatives, providing a nuanced understanding of its predictive capabilities.

Transfer learning can be an invaluable strategy given the challenges of acquiring extensive labeled golf swing data. By pre-training the model on a larger, related dataset and then fine-tuning it on our specific golf swing data, we can jump-start the learning process, benefiting from learned patterns that can be applied to our task. This approach can lead to significant improvements in model performance, especially in terms of learning speed and final accuracy.

For applications requiring real-time analysis, like swing feedback during practice, optimizing the model for quick inference is crucial. Techniques such as model quantization, which reduces the model's precision, and knowledge distillation, where a smaller, faster model is trained to replicate the behavior of a larger, more accurate one, can be explored. These techniques aim to reduce the computational load, enabling the model to analyze swings swiftly without substantial loss in accuracy, a critical factor for real-time applications.

The following Python code snippet exemplifies the approach discussed. It showcases a hybrid architecture where time-distributed CNN layers are employed to extract and analyze spatial features from each frame of the golf swing video. These features are then

sequentially processed by LSTM layers, capturing the temporal dynamics and transitions of the golf swing. This combination aims to harness the strengths of both CNNs and LSTMs, making the model adept at understanding the intricate spatial-temporal patterns of golf swings. The code is a representative example of how such a hybrid model could be structured, providing a foundation that can be further tailored and refined to meet the specific demands of our golf swing analysis task.

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, LSTM, Dense, Flatten, TimeDistributed, Dropout

def create_hybrid_cnn_lstm_model(input_shape, num_classes):
    model = Sequential()

    # CNN layers - TimeDistributed wrapper to process each frame
    model.add(TimeDistributed(Conv2D(32, (3, 3), activation='relu'), input_shape=input_shape))
    model.add(TimeDistributed(MaxPooling2D((2, 2))))
    model.add(TimeDistributed(Conv2D(64, (3, 3), activation='relu')))
    model.add(TimeDistributed(MaxPooling2D((2, 2))))
    model.add(TimeDistributed(Conv2D(128, (3, 3), activation='relu')))
    model.add(TimeDistributed(Flatten()))

    # LSTM layers
    model.add(LSTM(50, return_sequences=True))
    model.add(Dropout(0.5))
    model.add(LSTM(50))

    # Dense layer for classification
    model.add(Dense(num_classes, activation='softmax'))

    return model

# Example: assuming the input is a sequence of 5 frames, each of size 64x64 with 3 channels (RGB)
input_shape = (5, 64, 64, 3)
num_classes = 8  # Example: 8 different events in a golf swing

model = create_hybrid_cnn_lstm_model(input_shape, num_classes)
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model.summary()
```

In conclusion, optimizing our neural network encompasses a comprehensive strategy involving architectural decisions, data processing, computational efficiency, and ongoing learning and adaptation. These strategies are designed to develop a model that is not only robust and accurate but also efficient and adaptable, aligning with the specific challenges and demands of golf swing analysis in the AutoCaddie project.

9.2.2 Neural Network Validation

The process of validating our neural network in the AutoCaddie project is as crucial as its development and optimization. Validation involves a comprehensive set of methodologies and practices designed to rigorously assess the performance and reliability of the model under varied conditions, ensuring its effectiveness in real-world golf swing analysis scenarios. Here is an example of how you would prepare a validation set.

```
from sklearn.model_selection import train_test_split
import numpy as np

# Assuming 'data' is your dataset and 'labels' are the corresponding labels
data = np.load('golf_swing_data.npy')
labels = np.load('golf_swing_labels.npy')

# Splitting the dataset into training and validation sets
train_data, val_data, train_labels, val_labels = train_test_split(data, labels, test_size=0.2, random_state=42)

# Now, 'val_data' and 'val_labels' can be used as your validation dataset
```

The foundation of a robust validation process is the preparation of an extensive and representative validation dataset. This dataset, distinct from the training data, should encompass a broad spectrum of golf swings, capturing variations in player techniques, environmental conditions, and camera angles. A diverse dataset is instrumental in evaluating the model's generalization capabilities, ensuring that it performs consistently across different scenarios and player styles.

Incorporating cross-validation techniques, such as k-fold cross-validation, is pivotal in thoroughly testing the model's performance. This approach, where the dataset is split into several subsets with the model trained and validated on different combinations of these subsets, offers a detailed and holistic view of the model's performance. It helps identify any specific data segments where the model might underperform, allowing for targeted improvements. An example of what k-fold cross-validation would look like is as follows.

```
from sklearn.model_selection import KFold
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Define a simple model for demonstration purposes
def create_model():
    model = Sequential([Dense(10, input_shape=(input_shape,), activation='relu'),
                        Dense(num_classes, activation='softmax')])
    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
    return model

# k-Fold Cross-Validation
kfold = KFold(n_splits=5, shuffle=True, random_state=42)
scores = []

for train, test in kfold.split(data, labels):
    model = create_model()
    model.fit(data[train], labels[train], epochs=10, batch_size=32, verbose=0)
    score = model.evaluate(data[test], labels[test], verbose=0)
    scores.append(score)

# 'scores' contains the evaluation results for each fold
```

Analyzing key performance metrics is an integral part of the validation process. Metrics such as accuracy, precision, recall, F1-score, and confusion matrices provide a multi-dimensional view of the model's performance. While accuracy gives an overall effectiveness measure, precision and recall focus on the model's capability to correctly classify specific events in the golf swing. The F1-score harmonizes these two metrics, offering a balanced view, and confusion matrices present a detailed breakdown of the model’s performance across all categories. Below is an example of what the code could look like to calculate key performance metrics.

```python
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix

# Assume 'predictions' and 'true_labels' are the model's predictions and the true labels, respectively
predictions = model.predict(val_data)
predicted_classes = np.argmax(predictions, axis=1)
true_classes = np.argmax(val_labels, axis=1)

# Calculating various performance metrics
accuracy = accuracy_score(true_classes, predicted_classes)
precision = precision_score(true_classes, predicted_classes, average='weighted')
recall = recall_score(true_classes, predicted_classes, average='weighted')
f1 = f1_score(true_classes, predicted_classes, average='weighted')
conf_matrix = confusion_matrix(true_classes, predicted_classes)

# Print the performance metrics
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
print("Confusion Matrix:\n", conf_matrix)
```

Conducting a thorough error analysis is essential to understand where and why the model may falter. By scrutinizing misclassifications and errors, we can gain insights into the model's limitations and areas needing refinement. This analysis is crucial for iterative improvements and for fine-tuning the model to better handle challenging scenarios. Below is an example of calculating error.

```python
# Analyzing where the model predictions go wrong
error_indices = np.where(predicted_classes != true_classes)[0]

# Analyzing errors
for index in error_indices[:10]:  # Just looking at the first 10 errors
    print(f"Data Index: {index}, Predicted: {predicted_classes[index]}, True: {true_classes[index]}")

# Further analysis can be conducted to understand the nature of these errors
```

Testing the model in real-world conditions is critical to ensure its practical applicability. This step involves evaluating the model with live or recorded golf swings in various uncontrolled environments. Such real-world testing is vital to confirm the model's reliability and effectiveness outside laboratory conditions.

Sensitivity and specificity analysis further enriches our validation process. These metrics are particularly important in tasks like golf swing analysis where false positives and false negatives carry significant implications. They help us understand the model's effectiveness in correctly identifying true positives (actual events) and true negatives (non-events), ensuring reliability in its practical applications.

Finally, user testing with players offers invaluable insights. Feedback from end-users about the model’s utility, user experience, and practical applicability in real-world settings is critical. This feedback not only validates the model's technical performance but also its usability and effectiveness in meeting the users' actual needs.
In summary, validating our neural network model is a comprehensive and continuous process that encompasses a wide range of methodologies, from technical performance assessments to practical usability checks. Through rigorous and multifaceted validation, we aim to ensure that our model is not just a technological achievement but a reliable, effective, and user-friendly tool for golf swing analysis.

9.3 Software Integration Testing

9.3.1 Introduction

The algorithmic structure of AutoCaddie showcases a modular design philosophy. It fosters an organized and scalable approach to software development, as showcased by **Chapter 7**. Each processing algorithm within AutoCaddie is encapsulated within its dedicated logical unit, which promotes maintainability and reusability. This is particularly advantageous for debugging and maintenance by allowing developers to concentrate on specific functionalities without having to navigate through a complex, monolithic codebase. The software hierarchy is represented as a folder structure, where different logical groupings are separated into modules.

wxPython is utilized within AutoCaddie for the development of the project's GUI. The cross-platform compatability and extensive capabilities of wxPython align with the software's modular design. The organizational overview of AutoCaddie's software hierarchy, represented as a folder structure, ensures that each algorithm functions as an independent and reusable unit, allowing for streamlined testing.

9.3.2 Unit Testing with wxPython and Python unittest

Overall, unit testing is an important facet of software development. The process of unit testing ensures the reliability and functionality of individual components within a system. This testing method involves subjecting discrete units of code to different tests to ascertain their conformity to expected behavior. In the context of AutoCaddie, where data processing algorithms form the backbone of the system, robust unit testing facilitates maintainability.

The implementation strategy for unit testing in AutoCaddie revolves around the modularized code structure. The software allows for separate pieces of functionality to operate as their own files. This allows for the creation of a dedicated 'tests' package within the project, containing individual testing modules corresponding to each algorithm. An example of this is shown in the figure below. By utilizing unittest's library, a testing Python file can be created to analyze the functionality of a specific algorithm.

```
AutoCaddie/
|-- main.py
|-- algorithms/
|   |-- __init__.py
|   |-- frame_extraction.py
|-- tests/
|   |-- __init__.py
|   |-- test_frame_extraction.py
```

Figure 58: An example of implementing a testing Python file for the frame extraction algorithm. By using the naming convention "test_[FILE NAME].py", wxPython recognizes this as a testing file.

The Python unittest module integrates smoothly within AutoCaddie, allowing for an efficient means of conducting unit tests. The integration is straightforward, with testing

modules referencing their corresponding algorithms through import statements. In Figure 58, the frame extraction algorithm, named as “frame_extraction.py,” is tested by “test_frame_extraction.py.” Similarly, the naming convention of testing files follows this convention: “test_[FILE NAME].py.” This direct integration allows developers to execute highly specific tests and analyze overall precision and functionality.

The unittest module is setup directly within the project resources. It allows for direct testing during development of the project and ensure that the data presented by the GUI is accurate before deployment.

For every testing file, there are criteria that need to be ensured to be accurate. The following list comprehensively covers the structure of each testing file within the “testing” package in AutoCaddie.

1. Is the input data collected as expected?
    1.1. This serves as a prerequisite check for the parameters of interest for the algorithm. Each data processing method requires a specific combination of input data, an example being that the zero-padding algorithm expects an image of lesser or equal to dimensions of the GolfDB training data.
    1.2. This test checks the input data, and assesses the format in respect to the expected format.
2. Does the function handle empty data?
    2.1. In every live system, there is the expectation that empty data is collected during idle time or errors. Therefore, it is the responsibility of each program to ensure that the data being used is not empty to not forward an invalid data point.
3. Is the initialization process functional?
    3.1. For objects or variables needed for the algorithm, does the Python file set them up correctly?
4. Does the algorithm provide the correct functionality?
    4.1. This stage consists of several parts. These tests are as follows:
        4.1.1. For a normal data point, is the outcome the same as expected?
        4.1.2. For an extreme data point (outlier), does the algorithm still work as expected?
        4.1.3. For data points that are expected to produce errors, does the algorithm assess invalid data?
5. Does the algorithm invoke correctly?
    5.1. When calling the algorithm, ensure the correct function is referenced when given specific parameters.
6. How performant is the algorithm?
    6.1. During execution, it is important to analyze the execution time of each algorithm. This is imperative to ensure real-time data analysis within AutoCaddie.

6.2. First, the execution time of the algorithm needs to be observed. Using manual analysis or Python benchmarking, determine if the execution time is acceptable.
6.3. Second, ensure that the memory and resource consumption is not overbearing on the system.

7. Does the algorithm perform cleanup correctly?
   7.1. If the algorithm involves resource allocation, ensure that it is properly released after execution.
   7.2. Ensure that the algorithm is cyclic, or that all conditions return to their original state (unless static calling is used).

For each of the data processing algorithms involved in AutoCaddie, each of these tests will be executed. Overall, the testing process ensures correct data input, handling of empty data scenarios, and accurate initialization of objects. Functionality tests cover normal and extreme data points, error-handling capabilities, and proper algorithmic invocation. Performance assessments focus on execution time and resource usage for real-time data analysis. The evaluation also ensures correct cleanup processes, emphasizing resource release and the return to original conditions, crucial for algorithmic cyclic operations.

9.3.3 MobileNetV2 Model Testing

In AutoCaddie's image data processing workflow, the introduction of bounding box annotation is important to alleviate the computational load on the system's CNN. MobileNetV2 is a lightweight CNN architecture that can perform object recognition. It is integrated through TensorFlow's Keras applications and is pretrained on the ImageNet database to provide the capability of recognizing golfers within images.

Validation testing plays a critical role in ensuring the efficacy of MobileNetV2's implementation. While the model comes pretrained on the ImageNet dataset, fine-tuning becomes important to align the model with the requirements of AutoCaddie. This process involves optimizing hyperparameters and model parameters to enhance accuracy and responsiveness. Specific hyperparameters for MobileNetV2's model are given below.

- **Learning Rate:** The learning rate determines the size of the steps taken during optimization. It is a crucial hyperparameter that influences how quickly a neural network learns. A suitable learning rate is essential for preventing the model from converging too quickly.
- **Batch Size:** This hyperparameter defines the number of training samples utilized in one iteration. A balance must be struck, as a larger batch size can speed up training but might lead to increased memory requirements. Conversely, a smaller batch size may result in a more stable convergence.
- **Optimization Algorithm:** MobileNetV2 can use various optimization algorithms, such as Stochastic Gradient Descent (SGD), Adam, or RMSprop. The choice of the optimization algorithm can impact the convergence speed and overall performance of the model.

- **Number of Training Epochs:** An epoch refers to one complete pass through the entire training dataset. The number of training epochs is a hyperparameter that defines how many times the learning algorithm will work through the entire training dataset. Too few epochs may result in underfitting, while too many may lead to overfitting.
- **Weight Initialization:** The initial weights of the neural network play a crucial role in the learning process. Hyperparameters related to weight initialization, such as the choice of a specific initialization method, can impact the convergence and generalization of the model.
- **Dropout Rate:** Dropout is a regularization technique used to prevent overfitting. It randomly sets a fraction of input units to zero at each update during training, which helps prevent complex co-adaptations on training data.
- **Architecture-Specific Hyperparameters:** Depending on the architecture of MobileNetV2, there may be additional hyperparameters related to the network's depth, width, and expansion ratio. These parameters influence the overall architecture and computational efficiency of the model.

Fine-tuning these hyperparameters involves a nuanced exploration of combinations of these values. The learning rate plays an important role in balancing the model's ability to adapt to new data without overfitting or underfitting. A grid search algorithm, as depicted in Figure 43, can be employed to systematically evaluate every possible combination of hyperparameter values and select the configuration that yields optimal results during validation. This configuration will be deployed to the AutoCaddie project as the final model, which means that MobileNetV2's testing is derived through an automatic validation process. In other words, the testing of this model will be the result of the total processing speed.

9.3.4 LinearSVC Model Testing

Within AutoCaddie, action detection is the process of focusing on extracting features to identify specific motions within a golf swing. LinearSVM, specifically implemented through scikit-learn's LinearSVC, proves highly effective in classifying eight distinct actions of a golf swing. This classification model is pivotal for providing detailed insights into each phase of the swing, including the address, toe-up, mid-backswing, top, mid-downswing, impact, mid-follow-through, and finish.

To train the LinearSVC model, a process outlined by **Section 7.2** is followed. The GolfDB dataset serves as a comprehensive source, and each frame corresponding to the eight golf swing actions is labeled. Training involves using only the starting frames of each action, simplifying the computational burden while retaining the same information. Subsequently, the dataset is split into training and validation datasets, with 30% of the database being allocated for validation. For the purpose of the testing plan, the validation process comprehensively covers this topic.

Validation is a critical step, ensuring that the hyperparameters utilized by this model are accurate. Similar to MobileNetV2, the LinearSVC model will perform validation through a grid search algorithm. This involves comparing every possible combination of

hyperparameters to each other, selecting the model with the best overall accuracy. This accuracy is measured in terms of the proximity of the selection of each action to the actual starting frame index. A list of hyperparameters to be compared are shown below.

- **Penalty:** Specifies the norm used in penalization during model training. The choice influences the characteristics of the learned coefficients. “L2” is the standard penalty used, while “L1” leads to sparce coefficient vectors.
- **Loss:** Specifies the loss function used in the training process. “Hinge” is the standard SVM loss function.
- **Tolerance:** Tolerance is a value set for stopping criteria during the optimization process. It determines the acceptable level of change in the objective function before considering the optimization as converged.
- **Regularization Parameter:** The regularization parameter determines the strength of regularization of the model. A large regularization parameter implies less overall regularization. This parameter balances the desire to fit the training data well against the goal of keeping the model simple and avoiding overfitting.
- **Random State:** This parameter controls the random number generation for shuffling data. This helps ensure reproducibility of results when shuffling data is involved.
- **Max Iterations:** This specifies the maximum number of iterations to be run during optimization. Specifically, it sets an upper limit on the number of iterations to prevent the optimization process from running indefinitely.

The benefits of action detection are substantial. It ensures precision in identifying swing phases, excels in recognizing motions, and offers efficient classification of golf swing actions. Therefore, by deploying the strongest model through validation testing, the LinearSVC model can detect actions with the highest possible accuracy through the GolfDB dataset.

9.4 Summary

The above was an in-depth analysis of how each of the core components of the AutoCaddie project will function and be implemented. The software components, those being the machine learning neural network and the GUI to be designed, and the hardware components, those being the IMUs, MCU, and transceiver as well as their designed enclosures, were all thoroughly explored. The testing plans for each of these components are laid out in their entirety, defining how the minutiae of the project will be individually verified. As the testing plans are meant to ensure that all components work with their wiring orientation, enclosures, and code, this necessitates that the forms that the hardware currently takes are highly subject to change in the future, as well as the software components. Going forward, the operation of the project from a user’s view will be explored, detailing exactly how AutoCaddie will feel and be used in the hands of an aspiring golf master.

Chapter 10: Project Operation

<Is this necessary>

Chapter 11: Administrative Content

11.1 Estimated Budget

Estimated Budget

Item	Amount	Cost (Individual)	Cost (Total)
IMU [BNO055/80]	2	$ 34.95	$ 69.90
MCU [MSP430]	1	$ 12.01	$ 12.01
PCB Order (EST)	1	$ 30.00	$ 30.00
Wireless transceiver module [HC-06 RF]	1	$ 9.99	$ 9.99
3.7V 4.4Ah Li-ion battery	1	$ 19.95	$ 19.95
HP 320 FHD Camera	2	$ 28.51	$ 57.02
Wearable mount setup (EST MAX)	1	$ 75.00	$ 75.00
Electrical wire	1	$ 8.00	$ 8.00
Device Enclosures	1 (Full sys)	$ 20.00	$ 20.00
TOTAL			**$ 301.87**

Table 16: Estimated costs of AutoCaddie project.

11.2 Semester Milestones

11.2.1 First Semester

September 4th

- Database resources found

October 1st

- Artificial Intelligence methodology researched

October 16th

- Artificial Intelligence methodology defined

October 1st

- Hardware resourced and validated

October 30th

- Hardware systems designed

11.2.2 Second Semester

Third Week

- Direct linearity calculation systems complete

Fourth Week

- Hardware systems integrated

Third Week

- Artificial Intelligence vision system completed

Fifth Week

- Complete Artificial Intelligence trained

Sixth Week

- Feedback systems integrated

Eighth Week

- Testing results gathered

Twelfth Week

- Final product completed

References

[1] W. Mcnally, K. Vats, T. Pinto, C. Dulhanty, J. Mcphee, and A. Wong, “GolfDB: A Video Database for Golf Swing Sequencing.” Accessed: Sep. 27, 2023. [Online]. Available: https://arxiv.org/pdf/1903.06528.pdf

[2] P. Cintia, “Coach2vec: autoencoding the playing style of soccer coaches.” Accessed: Sep. 26, 2023. [Online]. Available: https://arxiv.org/ftp/arxiv/papers/2106/2106.15444.pdf

[3] G. Searle, “Singlearity: Using A Neural Network to Predict the Outcome of Plate Appearances,” *Baseball Prospectus*, Jul. 09, 2020. https://www.baseballprospectus.com/news/article/59993/singlearity-using-a-neural-network-to-predict-the-outcome-of-plate-appearances/ (accessed Sep. 26, 2023).

[4] “Home,” *www.alfaswing.ai*. https://www.alfaswing.ai/ (accessed Sep. 26, 2023).

[5] “AI Coach | 18Birdies,” *18birdies.com*. https://18birdies.com/aicoach/ (accessed Sep. 26, 2023).

[6] “Sportsbox AI,” *SB*. https://www.sportsbox.ai/ (accessed Sep. 26, 2023).

[7] P. Carroll, “Apple iPhone XR camera review: Top-ranked single-lens phone,” *DXOMARK*, Dec. 06, 2018. https://www.dxomark.com/apple-iphone-xr-camera-review/

[8] C.-C. Liao, D.-H. Hwang, and H. Koike, “AI Golf: Golf Swing Analysis Tool for Self-Training,” *IEEE Access*, vol. 10, pp. 106286–106295, 2022, doi: https://doi.org/10.1109/access.2022.3210261.

[9] “SMARTGOLF AI Coach | SMARTGOLF,” Jun. 28, 2022. https://smartgolf.biz/en/product/smartgolf-aix/

[10] X. Zhu, Q. Wang, and W. D. Lu, “Memristor networks for real-time neural activity analysis,” *Nature Communications*, vol. 11, no. 1, May 2020, doi: https://doi.org/10.1038/s41467-020-16261-1.

[11] A. Wright, E.-P. Damskägg, L. Juvela, and V. Välimäki, “Real-Time Guitar Amplifier Emulation with Deep Learning,” *Applied Sciences*, vol. 10, no. 3, p. 766, Jan. 2020, doi: https://doi.org/10.3390/app10030766.

[12] “DeepMind - What if solving one problem could unlock solutions to thousands more?”, *Deepmind*. https://www.deepmind.com/

[13] H. Dong *et al.*, “A deep convolutional neural network for real-time full profile analysis of big powder diffraction data,” *npj Computational Materials*, vol. 7, no. 1, pp. 1–9, May 2021, doi: https://doi.org/10.1038/s41524-021-00542-4.

[14] M. Versteyhe, H. De Vroey, F. Debrouwere, H. Hallez, and K. Claeys, “A novel method to estimate the full knee joint kinematics using low cost IMU sensors for easy to implement low cost diagnostics,” Sensors, vol. 20, no. 6, p. 1683, 2020. doi:10.3390/s20061683

[15] J. H. Challis, “Quaternions as a solution to determining the angular kinematics of human movement,” BMC Biomedical Engineering, vol. 2, no. 1, 2020. doi:10.1186/s42490-020-00039-z

[16] Md. M. Rahman, K. B. Gan, N. A. Aziz, A. Huong, and H. W. You, “Upper Limb Joint Angle Estimation Using Wearable Imus and personalized calibration algorithm,” Mathematics, vol. 11, no. 4, p. 970, 2023. d10.3390/math11040970

[17] Leo J. Roberts, Mervyn S Jackson, Ian H. Grundy. "The effects of cognitive interference during the preparation and execution of the golf swing," International Journal of Sport and Exercise Psychology, pp. 413-428, 2021.
[18] Timothy Fulton, Josiah Ertz, Abraham Rohler, Fabio Fontana, Mickey Mack. "The Effects of a Visual Distraction," International Journal of Golf Science, no. 3, pp. 26-34, 2014.
[19] Saba M Hoesseini, David Fukada, Joon-Hyuk Park. “Optimal Multi-Modal Sensory Feedback to Maximize Motor Learning Efficiency,” Department of Mechanical and Aerospace Engineering, University of Central Florida.
[20] G. Oppy and D. Dowe, “The Turing Test (Stanford Encyclopedia of Philosophy),” Stanford.edu, Apr. 09, 2003. https://plato.stanford.edu/entries/turing-test/
[21] H. Singh, “How are Images Stored on a Computer | Grayscale & RGB Image Formats,” Analytics Vidhya, Mar. 16, 2021. https://www.analyticsvidhya.com/blog/2021/03/grayscale-and-rgb-format-for-storing-images/
[22] Krizhevsky, A., Sutskever, I., Hinton, G. ImageNet Classification with Deep Convolutional Neural Networks. Advances in Neural Information Processing Systems,2012, 25: 1097-1105.
[23] A. Voulodimos, N. Doulamis, A. Doulamis, and E. Protopapadakis, “Deep Learning for Computer Vision: A Brief Review,” Computational Intelligence and Neuroscience, vol. 2018, pp. 1–13, 2018, doi: https://doi.org/10.1155/2018/7068349.
[24] “Papers with Code - SDAE Explained,” paperswithcode.com. https://paperswithcode.com/method/sdae (accessed Nov. 12, 2023).
[25] S. Park, J. Chang, H. Jeong, J.-H. Lee, and J.-Y. Park, “Accurate and Efficient 3D Human Pose Estimation Algorithm using Single Depth Images for Pose Analysis in Golf.” Accessed: Sep. 27, 2023. [Online]. Available: https://openaccess.thecvf.com/content_cvpr_2017_workshops/w2/papers/Park_Accurate_and_Efficient_CVPR_2017_paper.pdf
[26] B. Tian and W. Wei, “Research Overview on Edge Detection Algorithms Based on Deep Learning and Image Fusion,” Security and Communication Networks, vol. 2022, pp. 1–11, Sep. 2022, doi: https://doi.org/10.1155/2022/1155814.
[27] “Can we trust bounding box annotations for object detection? | IEEE Conference Publication | IEEE Xplore,” ieeexplore.ieee.org. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9857206 (accessed Nov. 12, 2023).
[28] M. Hashemi, “Enlarging smaller images before inputting into convolutional neural network: zero-padding vs. interpolation,” Journal of Big Data, vol. 6, no. 1, Nov. 2019, doi: https://doi.org/10.1186/s40537-019-0263-7.
[29] Hashemi, Mahdi. (2019). Enlarging smaller images before inputting into convolutional neural network: zero-padding vs. interpolation. Journal of Big Data. 6. 10.1186/s40537-019-0263-7.
[30] Marais, Marc. (2021). Golf Swing Sequencing using Computer Vision. 10.13140/RG.2.2.14864.48641.
[31] K. Simonyan and A. Zisserman, “Two-Stream Convolutional Networks for Action Recognition in Videos.” Available:

https://papers.nips.cc/paper_files/paper/2014/file/00ec53c4682d36f5c4359f4ae7bd7ba1-Paper.pdf
[32] A. Karpathy, G. Toderici, S. Shetty, T. Leung, R. Sukthankar, and L. Fei-Fei, "Large-scale Video Classification with Convolutional Neural Networks." Available: https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/42455.pdf
[33] "MobileNet V2 — Torchvision main documentation," pytorch.org. https://pytorch.org/vision/main/models/mobilenetv2.html (accessed Sep. 27, 2023).
[34] J. Diebel, "Representing Attitude: Euler Angles, Unit Quaternions, and Rotation Vectors," 2006. Available: https://www.astro.rug.nl/software/kapteyn-beta/_downloads/attitude.pdf
[35] "Euler angles - Knowino," www.tau.ac.il. https://www.tau.ac.il/~tsirel/dump/Static/knowino.org/wiki/Euler_angles.html (accessed Nov. 12, 2023).
[36] "Trilinear interpolation," Wikipedia, Jan. 08, 2023. https://en.wikipedia.org/wiki/Trilinear_interpolation (accessed Nov. 12, 2023).
[37] J. H. Challis, "Quaternions as a solution to determining the angular kinematics of human movement," BMC Biomedical Engineering, vol. 2, no. 1, Mar. 2020, doi: https://doi.org/10.1186/s42490-020-00039-z.
[38] J. Novotny, "A Programmers' Guide to Python: Advantages & Disadvantages," Linode Guides & Tutorials, Mar. 09, 2023. https://www.linode.com/docs/guides/pros-and-cons-of-python/
[39] Javatpoint, "Advantages and disadvantages of Java - Javatpoint," www.javatpoint.com. https://www.javatpoint.com/advantages-and-disadvantages-of-java
[40] "Advantages and Disadvantages of C++ Programming Language - Javatpoint," www.javatpoint.com. https://www.javatpoint.com/advantages-and-disadvantages-of-cpp-language
[41] "Python vs JavaScript - Javatpoint," www.javatpoint.com. https://www.javatpoint.com/python-vs-javascript
[42] A. Saxena, "Introduction to NumPy," Medium, Jun. 01, 2020. https://medium.com/analytics-vidhya/introduction-to-numpy-279bbc88c615
[43] "Introduction — SciPy v1.9.0 Manual," docs.scipy.org. https://docs.scipy.org/doc/scipy-1.9.0/tutorial/general.html (accessed Nov. 12, 2023)
[44] "Pandas Vs NumPy: What's The Difference? [2023]," InterviewBit, Oct. 22, 2021. https://www.interviewbit.com/blog/pandas-vs-numpy/
[45] OpenCV, "OpenCV library," Opencv.org, 2019. https://opencv.org/
[46] K. Kroening, "ffmpeg-python: Python bindings for FFmpeg," GitHub, Nov. 12, 2023. https://github.com/kkroening/ffmpeg-python (accessed Nov. 12, 2023).
[47] A. C. Salian, "video2images: Video 2 Image converter," PyPI. https://pypi.org/project/video2images/ (accessed Nov. 12, 2023).
[48] Keras, "Home - Keras Documentation," Keras.io, 2019. https://keras.io/
[49] scikit learn, "1.4. Support Vector Machines — scikit-learn 0.20.3 documentation," Scikit-learn.org, 2018. https://scikit-learn.org/stable/modules/svm.html

[50] “Models & datasets,” TensorFlow. https://www.tensorflow.org/resources/models-datasets
[51] “torchvision.models — Torchvision 0.10.0 documentation,” pytorch.org. https://pytorch.org/vision/stable/models.html
[52] R. C. Limited, “PyQt5: Python bindings for the Qt cross platform application toolkit,” PyPI. https://pypi.org/project/PyQt5/#:~:text=PyQt5%205.15.10&text=PyQt5%20is%20a%20comprehensive%20set (accessed Nov. 12, 2023).
[53] Python Software Foundation, “tkinter — Python interface to Tcl/Tk — Python 3.7.2 documentation,” python.org, 2019. https://docs.python.org/3/library/tkinter.html
[54] T. wxPython Team, “Welcome to wxPython!,” wxPython, Aug. 02, 2021.https://wxpython.org/index.html
[55] “Kivy: Cross-platform Python Framework for NUI,” kivy.org. https://kivy.org/
[56] “PySimpleGUI,” www.pysimplegui.org. https://www.pysimplegui.org/en/latest/
[57] “American National Standards Institute - ANSI Home.” *American National Standards Institute - ANSI*, ansi.org/. Accessed 30 Oct. 2023.
[58] “PyTorch Benchmark — PyTorch Tutorials 2.1.0+Cu121 Documentation.” Pytorch.org, pytorch.org/tutorials/recipes/recipes/benchmark.html. Accessed 30 Oct. 2023.
[59] van Rossum, Guido, et al. “PEP 8 – Style Guide for Python Code | Peps.python.org.” Peps.python.org, 5 July 2001, peps.python.org/pep-0008/.
[60] “Rules of Machine Learning: | ML Universal Guides.” Google Developers, developers.google.com/machine-learning/guides/rules-of-ml.
[61] Network Architecture of SwingNet. 2019. Accessed: Sep. 26, 2023. [Online]. Available: https://arxiv.org/pdf/1903.06528.pdf https://arxiv.org/pdf/1412.6980.pdf
[62] "IEEE/EIA - Standard for Information Technology - Software Life Cycle Processes," in IEEE/EIA 12207.0-1996 , vol., no., pp.1-88, 31 March 1998, doi: 10.1109/IEEESTD.1998.88083.
[63] Darrah, Marjorie. “Verification and Validation of Neural Networks: a Sampling of Research in Progress.” SPIE Proceedings, 2003.
[64] “User Experience Design (UX) Standards and Guidelines | Enterprise Brand and Marketing Guide.” Brandguide.asu.edu, brandguide.asu.edu/execution-guidelines/web/ux-design.
[65] U.S. Access Board. “Section508.Gov.” Www.section508.Gov, Sept. 2023, www.section508.gov/test/web-software/. Accessed 29 Oct. 2023.
[66] “ANDI - Accessibility Testing Tool - Install.” Www.ssa.gov, www.ssa.gov/accessibility/andi/help/install.html.
[67] Lauke, Patrick. “Release CCA 2.5.0 · ThePacielloGroup/CCA-Win.” GitHub, 3 June 2017, github.com/ThePacielloGroup/CCA-Win/releases/tag/2.5.0. Accessed 30 Oct. 2023.
[68] “Section508.Gov.” Www.section508.Gov, Aug. 2023, www.section508.gov/develop/universal-design/.
[69] OpenAI. "ChatGPT: Revolutionizing Research and Writing," 2023. [Online]. Available: https://www.openai.com/research/chatgpt. Accessed: Oct. 29 2023.

[70] hix.ai. “HIX.AI: All-In-One ChatGPT Copilot for Web.” Chrome.google.com, 13 Oct. 2023, chrome.google.com/webstore/detail/hixai-all-in-one-chatgpt/njggknpmkjapgklcfhaiigafiiebpchm. Accessed 30 Oct. 2023.
[71] “ChatSonic - like ChatGPT but with Superpowers.” Writesonic.com, writesonic.com/chat. Accessed 29 Oct. 2023.
[72] “Your AI-Powered Copilot for the Web.” Www.microsoft.com, Feb. 2023, www.microsoft.com/en-us/bing?form=MA13FV. Accessed 29 Oct. 2023.
[73] Demo, GPT-3. “YouChat | Discover AI Use Cases.” Gpt3demo.com, 23 Dec. 2022, gpt3demo.com/apps/youchat. Accessed 30 Oct. 2023.
[74] “Claude.” Claude.ai, July 2023, claude.ai/. Accessed 29 Oct. 2023.
[75] “Bard - Chat Based AI Tool from Google, Powered by PaLM 2.” Bard.google.com, 21 Mar. 2023, bard.google.com/chat. Accessed 29 Oct. 2023.
[76] “AutoGPT Official.” AutoGPT Official, 16 Aug. 2023, autogpt.net/.
[77] “CopyAI: Create Marketing Copy in Seconds.” Www.copy.ai, www.copy.ai/. Accessed 29 Oct. 2023.
[78] “WEBENCH-CIRCUIT-DESIGNER Design tool | TI.com,” www.ti.com. https://www.ti.com/tool/WEBENCH-CIRCUIT-DESIGNER
[79] Oracle. “Java Documentation.” Oracle Help Center, 23 Jan. 1996, docs.oracle.com/en/java/.
[80] Ahmed, Reshma. “What Is Git ? – Explore a Distributed Version Control Tool.” Edureka, Edureka, 16 Nov. 2016, www.edureka.co/blog/what-is-git/. Accessed 29 Oct. 2023.
[81] “StackEdit.” Stackedit.io, stackedit.io/app. Accessed 30 Oct. 2023.
[82] “unittest — Unit testing framework — Python 3.8.2 documentation,” docs.python.org. https://docs.python.org/3/library/unittest.html
[83] “🔥Make GridSearch Faster for xgboost🔥 | Kaggle,” www.kaggle.com. https://www.kaggle.com/discussions/general/407135 (accessed Nov. 26, 2023).
[84] “Joblib: running Python functions as pipeline jobs — joblib 1.3.2 documentation,” joblib.readthedocs.io. https://joblib.readthedocs.io/en/stable/
[85] M. Marais and D. Brown, “Golf Swing Sequencing Using Computer Vision,” Lecture Notes in Computer Science, pp. 351–365, Jan. 2022, doi: https://doi.org/10.1007/978-3-031-04881-4_28.
[86] “Singular Value Decomposition.” Wikipedia, 30 Dec. 2020, en.wikipedia.org/wiki/Singular_value_decomposition.