Strike Sense

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2. Project Description

2.1 Project Background and Motivation

Martial arts, much like other disciplines of art, serve as a lens through which to interpret one's life. For those who dedicate enough of themselves to it, it even transforms into a way of life. One which starts as a warm embrace that gently guides you to increase confidence before turning into an inferno lit within your heart which pushes you towards self-actualization. It requires incredible amounts of **dedication, discipline, and repetition**. One of the ways that this takes form is in the thousands of intense heavy bag sessions. While doing this alone consistently may yield continued improvement, there is still space for efficiency in this improvement. This room is in **quantitative** and **qualitative** tracking of strikes. A fighter often relies on a pair of eyes to point out tendencies which they can then use to inform their training regimen. These eyes can come with their own set of biases and things they miss due to the limitations of human perception as time continues. We propose a **sensor based system with vision modularity** that can see past all these issues and towards a path of **calculated continuous improvement**.

While this may be an ambitious goal, we have worked to package it into a concise and deliverable Senior Design project. We considered the restrictions and purpose of a senior design project to do so. We understand a successful senior design project to be one where a problem is acutely identified then addressed then solved through well-defined methodologies and a success case that is quantifiable. We believe that this project fits that definition and by the end, we will hone current skills, acquire new ones, and solve our original problem.

2.2 Goals and Objectives

Our high-level goal is to provide a tool for martial artists to utilize to identify their natural striking dispositions as well as provide insightful advice into what direction to move towards for future training sessions. This tool will be composed of wearable sensors as well as central application components. We hope to accelerate a fighters' understanding of themselves as well as stimulate constant evolution.

Main Goals

- Real time counting of strikes thrown out of a defined set of strikes [Straight, Hook, Uppercut, Elbow, Body Shot]
    - Real Time heart rate monitoring
    - Post training session insight on strikes
    - Post Training information on heart rate in relation to strikes
- · Integration of computer vision in real time counting of strikes
- All data displayed in a clean UI on a local application

Main Objectives

- Create a system with a hardware component comprised of 2 IMU designs: one with 9 DoF, heart rate monitor, charging circuit, and MCU and the other with 9Dof, charging circuit, and MCU

    o Hardware component will be contained in housing and will be equipable with a strap on left and right wrist

    o Accelerometer, Gyroscope and Magnetometer output will be translated to quaternions

- ·Design deep neural network architecture which takes the input of quaternions from the IMU's and can identify strikes within that stream of data
    - This neural network architecture will have a strike identification percentage of >=80%

    o This architecture will be, at a high level, composed of a transformer and LSTM

- Create a quaternions dataset that is deep and broad enough to be used to train the neural network.
    - Neural network will run locally on machine where application is running
- · Deepen neural network architecture by adding the Alpha pose (CITE) pose estimation model + Transformer+LSTM+LLM to use spatiotemporal coordinates obtained through video to further support initial predictions provided by IMU data

Advanced Goals

- Post Training ‘pathway’ suggestions to move towards based on tendencies and specific strike occurrences observed

Advanced Objectives

- Add an LLM to the network architecture that can understand the strikes being identified as input and output coherent output which suggest 1-3 combos as well as general suggestions towards direction.

Stretch Goals

- Data displayed on an iPhone application
- · Add 2 more IMU’s to system to extract data on kicks as well
- ·Real time skeleton reflection on Unity (digital twin)
- · Add support for multiple users

Stretch Objectives

- Develop an iPhone application that runs locally on iPhones running IOS 16+. This app will not be on the app store.
- With addition to neural network architecture, machine learning components to be hosted on server to relieve tax on iPhone.
- Duplicate IMU design without heart rate monitor and use those to place on a right leg and left leg

2.2.1 Hardware

The sensor component’s primary function is to capture the absolute location of the appendage to which it is attached to. This is achieved by leveraging a 9 Degrees of Freedom (DoF) Inertial Measurement Unit (IMU), composed of an accelerometer, gyroscope, and magnetometer. Each of these sensors contributes uniquely to motion tracking: the accelerometer measures linear acceleration, the gyroscope measures angular velocity, and the magnetometer provides directional heading. When combined through sensor fusion algorithms such as the Madgwick or Kalman filter, these data streams yield highly accurate representations of orientation in the form of quaternions or Euler angles.

The importance of the 9 DoF configuration lies in its ability to correct weaknesses present in lower-DoF setups. For example, a 6 DoF IMU (accelerometer + gyroscope) can track movement and rotation but suffers from drift and alignment issues over time. The addition of the magnetometer in a 9 DoF IMU anchors orientation to an external reference, reducing drift and providing greater long-term stability. This is especially critical in martial arts strike detection, where precise and repeatable motion data ensures that the system can differentiate between subtle strike variations (straight, hook, uppercut) and deliver reliable metrics for both training feedback and machine learning analysis.

From a hardware perspective, incorporating 9 DoF sensors ensures that strike tracking is not only accurate in the short term but also robust across extended sessions. The IMUs will be housed in custom enclosures with straps to secure them to the athlete's wrists, ensuring consistent alignment during motion. In addition, the hardware design includes a heart rate sensor, charging circuit, and microcontroller unit (MCU) to manage data acquisition and wireless transmission. The integration of these hardware elements provides a comprehensive data capture platform capable of supporting the project's broader objectives of real-time analysis, post-training insights, and machine learning–driven recommendations.

2.2.2 Software

The software component of this project serves as the 'intelligence' layer that interprets raw sensor data into meaningful insights. The primary function is to take quaternion outputs from the 9 DoF IMUs and process them in real time to identify specific strike types. This is accomplished by integrating sensor fusion algorithms such as the Madgwick filter, which converts accelerometer, gyroscope, and magnetometer data into stable quaternion representations. Quaternions are advantageous because they capture 3D orientation without the gimbal lock issues inherent in Euler angles, and they also provide smoother data streams well-suited for downstream machine learning models.

On top of this foundation, the software will employ a deep neural network architecture designed to classify strikes (e.g., straight, hook, uppercut) from the quaternion streams. The architecture is envisioned to include a transformer-based sequence model to recognize temporal strike patterns and a large language model (LLM) component to generate legible training suggestions for users. These layers allow not only strike classification but also contextual recommendations, such as identifying common tendencies and proposing future strike combinations.

The software stack will also manage real-time strike counting, session logging, and heart rate monitoring integration. Data is displayed through a clean, user-friendly application interface, enabling athletes to view both real-time and post-session insights. Stretch objectives extend the software's capability to include computer vision modules like AlphaPose, which could add spatial-temporal coordinates from video to further support IMU predictions, and Unity-based visualization for a digital twin of the athlete.

Together, these software systems transform raw motion data into actionable feedback. By combining robust sensor fusion, advanced neural network models, and clear data visualization, the software ensures the project delivers reliable, interpretable, and performance-enhancing insights for martial artists.

3. Requirements and Specifications

Overall system requirements

Parameter	Specification
⭐**Strike Classification Accuracy**	**≥ 80% correct identification of strikes**
⭐**Heart Rate Monitoring**	**Continuous, ± 2 BPM accuracy**
Size	**≤ 50 mm × 40 mm × 15 mm (L × W × H)**
Session Runtime	**≥ 1 hour continuous operation**
⭐**Wireless Data Transmission**	**≥ 95% packet success rate**
Weight	**≤ 60 g per wrist unit (including strap)**
Total Cost	**≤ $800 BOM**

3 Demonstratables:

1. ⭐**Strike Classification Accuracy:** The machine learning model demonstrates the ability to classify strikes with an accuracy exceeding 80% during testing trials.

2. ⭐**Heart Rate Monitoring:** The system's heart rate measurements are comparable to a commercial standard monitor, with a deviation of no more than ±2 bpm.

3. ⭐**Wireless Data Transmission:** Wireless data transfer is validated with a packet success rate of 95%, ensuring reliable communication of sensor outputs.

To fully reconstruct a signal per the Nyquist-Shannon theorem one must sample at least twice the highest frequency component of said signal. This directly relates to the output data rate (ODR) of our sensors, meaning in order to fully reconstruct our signal the ODR of each sensor must be >= twice the highest frequency component. We can approximate this using the relationship between time and frequency, that being $f = 1/t$, where time in this scenario represents impact duration(the brief period when the fist makes contact with the target). We focus on impact duration specifically as this is the critical phase where peak accelerations and forces occur.

Deriving the sample rate:

The average impact duration across various types of strikes last between 15 - 25ms. The shortest being 15ms, we will use this value for the calculations.

Minimum sample frequency : $f = 1/t = 1/15ms \sim= 66.67$ Hz
Per Nyquist-Shannon Theorem the minimum ODR must be $2*66.67Hz \sim= 133.333$ data points per second

This aligns well with current IMU based performance tracking studies which recommend a sample rate between 200 - 400 Hz

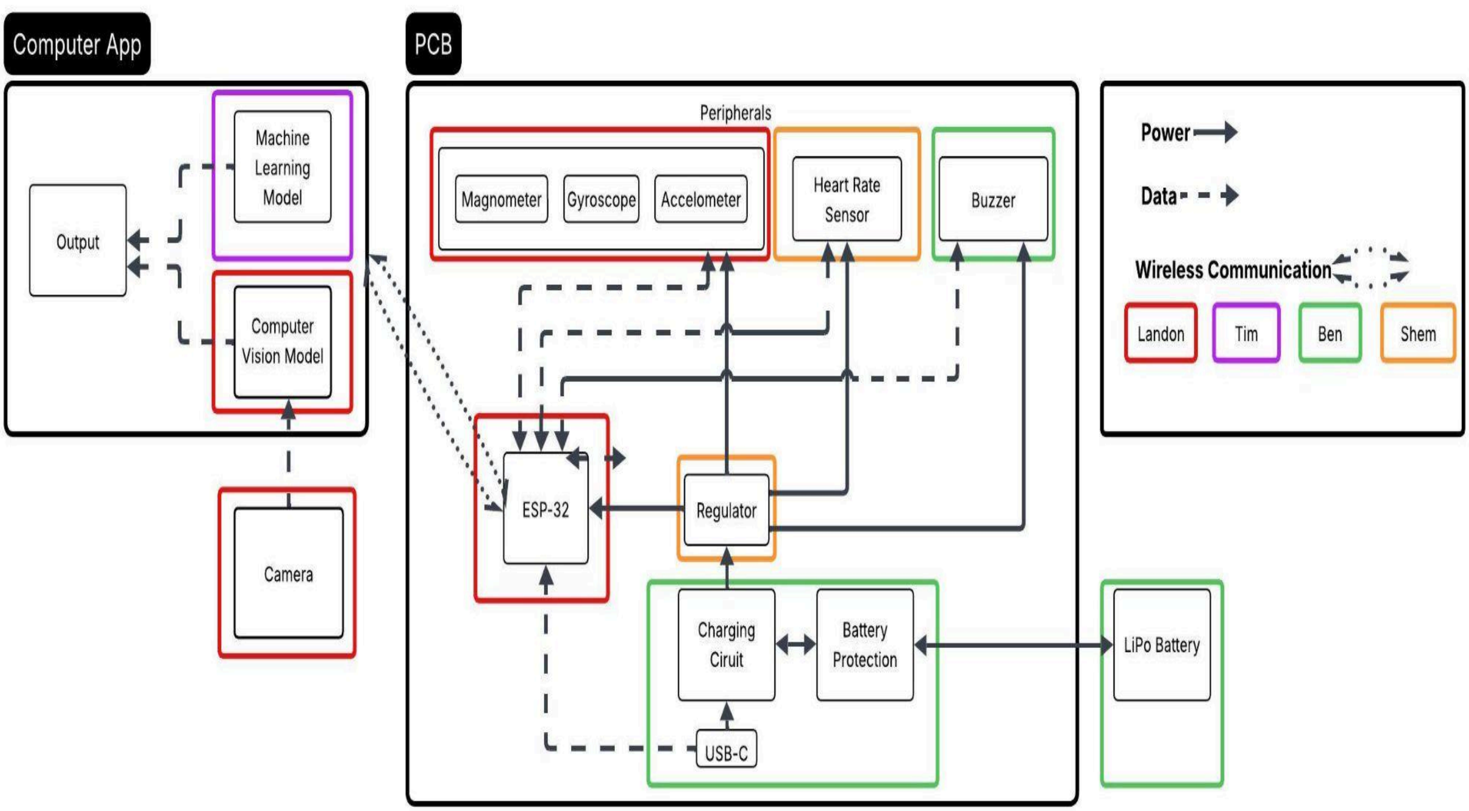
Practical Considerations:
In practice strike impacts can generate much higher frequency components than previously mentioned because of abrupt acceleration changes during impact, within the range of 500 to 1000Hz. Per Nyquist-Shannon theorem that would mean a ODR of 1000 - 2000 points per second however, the computational load would be too great resulting in lower battery life and increased memory use. Especially considering there are diminishing returns on the practical metrics we are interested in extrapolating in these higher frequency components.

Component-Level Specifications

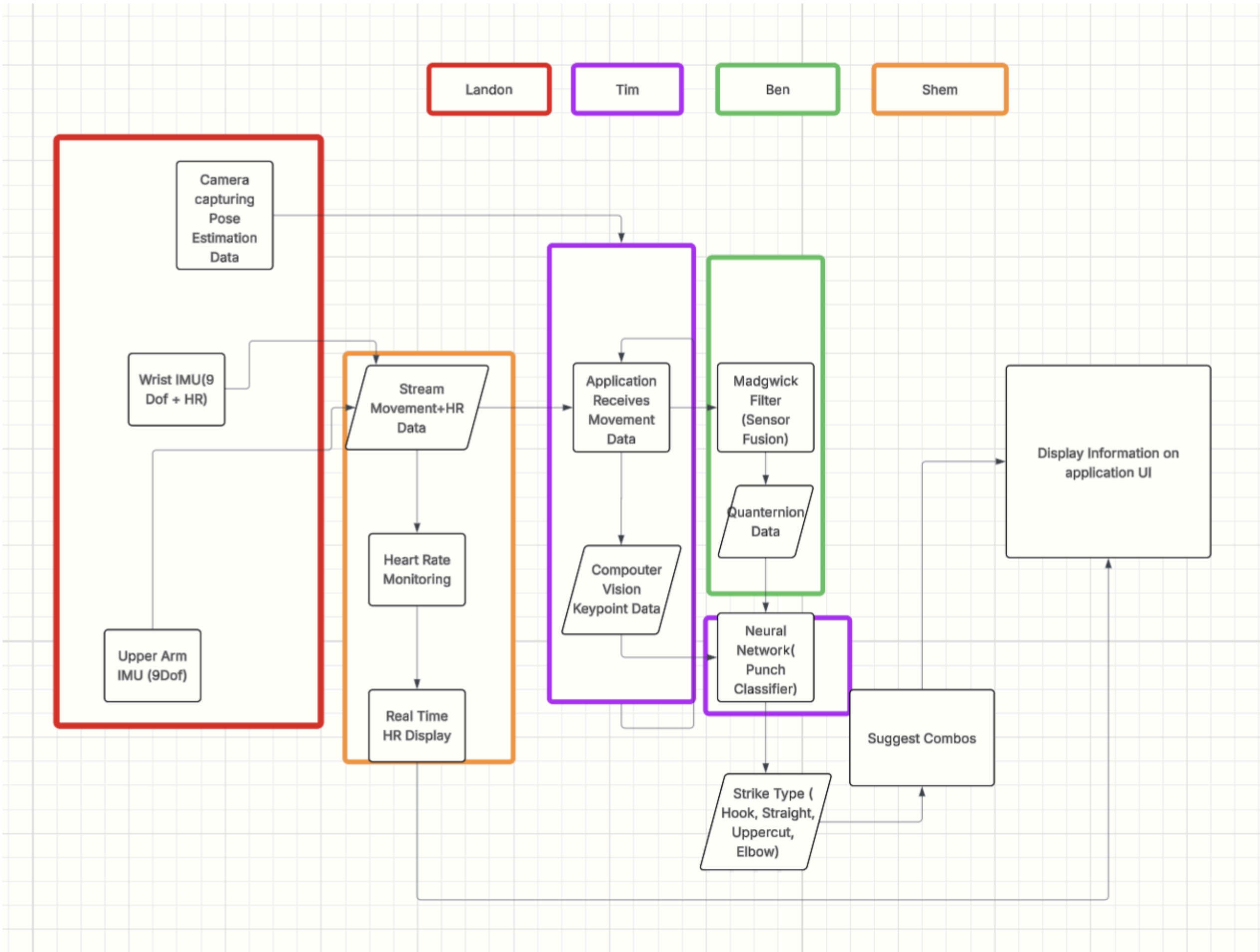
Component	Parameter	Specification
Accelerometer	**Full Scale Range**	**± 16 g**
Accelerometer	**Output Data Rate**	**≥ 200 Hz**
Gyroscope	**Full Scale Range**	**± 2000 °/s**
Gyroscope	**Bias Stability**	**≤ 10 °/h**
Magnetometer	**Range**	**± 65 µT**
Magnetometer	**Output Data Rate**	**≥ 100 Hz**
MCU	**Processing Latency**	**≤ 10 ms per packet**
MCU	**Wireless Protocol**	**Bluetooth Low Energy (BLE)**
Heart Rate Sensor	**Accuracy**	**± 2 BPM vs reference**
Heart Rate Sensor	**Sampling Rate**	**≥ 25 Hz**
Power System	**Battery Life**	**≥ 1 hour**
Power System	**Charging Time**	**≤ 2 hours**
Application (Software)	**Strike Count Accuracy**	**≥ 80%**
Application (Software)	**Suggestion Generation**	**Human-readable training advice**

4. System Design

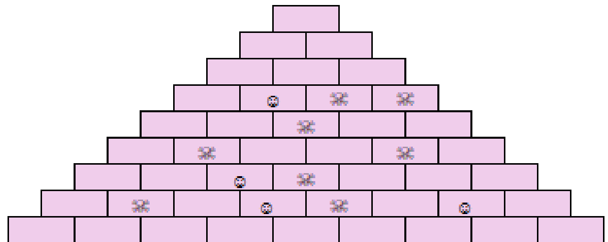
4.1 Hardware



4.2 Software


Landon
Tim
Ben
Shem
Camera capturing Pose Estimation Data
Wrist IMU(9 Dof + HR)
Upper Arm IMU (9Dof)
Stream Movement+HR Data
Heart Rate Monitoring
Real Time HR Display
Application Receives Movement Data
Compouter Vision Keypoint Data
Madgwick Filter (Sensor Fusion)
Quanternion Data
Neural Network(Punch Classifier)
Strike Type (Hook, Straight, Uppercut, Elbow)
Suggest Combos
Display Information on application UI

5. House of Quality



			1	2	3	4	5	6	7	8	9
	Design Requirements / Customer Requirements	Direction of Desirability	Strike Accuracy	HR Accuracy	Latency	Weight	Cost	Battery	UI Update	Wireless Data Transfer	Drop resistance
	Direction of Desirability		1	1	0	0	0	1	1	1	1
1	Accurate Strike Recognition	1	(+)		(+)				+	+	
2	Reliable heart rate monitoring	1		(+)	+						
3	Low system latency	1	(+)	+	(+)			-	(+)	+	
4	Comfortable to wear	1				(+)		-			+
5	Affordable device	1	+	+	+	+	(+)	-	+	+	+
6	Long battery life	1		+	-	-	-	(+)		-	
7	Easy-to-use app	1	+		+				(+)	+	
8	Reliable wireless connectivity	1	+	+	+			-	+	(+)	
9	Durable under use	1	+				+	+		+	(+)
10	Lightweight and stylish	1				(+)	+	-			+
	Product Targets		≥ 60% correct	± 2 BPM	≤ 10 ms per packet	≤ 60 g per unit	≤ $800 BOM	≥ 1 hour	≥ 10 Hz	≥ 95% packet success	≤ 4feet

Correlation:
Positive
Negative
Nocorrelation

Direction of desirability:
High
Low

Relationship:
Strongly Positive
Weakly Positive
No Relation
Weakly Negative
Strongly Negative

6. Budget and Financing

Below is a rough Bill of Materials.

#	Category	Part / Option	P/N (Pkg)	Qty	Est. Unit $	Notes
1	MCU / Wireless	ESP32-WROOM-32E	ESP32-WROOM-32E (SMD)	1	5	Wi-Fi/BT; 3.3 V I/O; FCC modular.
2	9-DoF IMU	ICM-20948	ICM-20948 (QFN-24, 3x3mm)	1	6.5	Accel+Gyro+Mag; VDDIO ~1.8 V
3	Level Shifter	TXS0108E	TXS0108EPWR (TSSOP-20)	1	1.5	Bidirectional 3.3 V <-> 1.8 V
4	Li-ion Charger IC	MCP73871	MCP73871 (QFN/MSOP)	1	2.5	USB charger + power-path
5	Battery Connector	JST B2B-PH	JST B2B-PH-SM4-TB	1	0.5	2-pin, vertical, 2.0 mm pitch
6	USB-C Receptacle	USB4110-G	USB4110-G	1	1	USB-C 2.0; add 5.1 kΩ CC resistors
7	3.3 V Regulator	TLV75533	TLV75533PDBVR	1	0.5	LDO 500 mA
8	1.8 V Regulator	TLV75718	TLV75718PDBVR	1	0.5	LDO 300 mA
9	Input Protection	Polyfuse	MF-R110	1	0.3	USB input protection fuse
10	Surge/ESD	TVS diode	ESD9B5.0ST5G	1	0.2	USB ESD protection

11	Pull-ups (I^2C)	Resistor	0603, 2.2–4.7kΩ	2	0.02	I^2C bus pull-ups
12	CC Resistors	Resistor	0402, 5.1kΩ	2	0.02	USB-C CC pulldowns
13	Bulk Capacitors	Capacitor	0603/0805, 10µF	6	0.03	Power filtering
14	Decoupling Capacitors	Capacitor	0402/0603, 0.1µF	12	0.01	One per power pin
15	Sense Divider	Resistors	0402/0603, 100kΩ+200kΩ	4	0.02	Battery sense divider
16	Status LEDs	LED + R	0603, Red/Green + 1kΩ	4	0.02	Charge/power status
17	Power Switch	SPDT Switch	JS102011SAQN	1	0.3	Battery disconnect

7. Milestones

To ensure a successful project, remaining organized is key. Creating a guideline for the project will enable a strong dynamic among members and contribute to overall success. The project was kicked off by group selection and project topic discussion. The schedule below presents our plan for Senior Design 1:

SD1 Project Schedule				
Task:	Start:	End:	Assigned Due Date:	Description:
Team formation	5/07/2025	6/07/2025	08/19/2025	Team: Landon Wright Benjamin Bolton, Shem Fils-Aime, Timothy Azinord
Brainstorming	6/07/2025	8/12/2025	8/12/2025	Researched multiple ideas for our project and elected a final one.

Initial Document	8/28/2025	9/04/2025	9/05/2025	Complete the Divide and Conquer Assignment to get a synopsis of our project.
Sponsor meeting	9/08/2025	9/08/2025	9/08/2025	Discuss ideas and get feedback on potential improvements.
30-page milestone	9/10/2025	9/30/205	9/30/205	Begin writing SD1 report
Component Selection	9/10/2025	10/20/2025	10/20/2025	Complete a BOM of all the necessary parts of the project
60-page milestone	9/10/2025	10/31/2025	10/31/2025	Hit the halfway point for our SD1 Report
First PCB Design/ Breakout Boards	9/10/2025	11/03/2025	11/03/2025	Design our first PCB for our sensor and create break out boards to begin testing
120-page milestone	9/10/2025	11/25/2025	11/25/2025	Produce the final Report for SD1

Considering planning for Senior Design 2 allows us to successfully carry out our design. At this stage of our project, we have a placeholder (TBD) allowing for flexibility till we get further down the line in Senior Design 1

SD2 Project Assembly				
Task:	Start:	End:	Assigned Due Date:	Description:
System Design	1/06/2025	1/20/2025	TBD	Complete system design and finish the overall schematic for the project

System Testing	1/20/2025	1/27/2025	TBD	Test each section of our project individually and check for compatibility.
Completed PCB Design	TBD	TBD	TBD	Finish the PCB and ensure robustness
PCB Test/Optimize	TBD	TBD	TBD	Continue testing for any more improvements.
Prototype Completion	TBD	TBD	TBD	Have a final working Prototype for SD2

8.References

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