

Smart Cricket Bat

Gavin Dahl, Jiakai Hu, Pablo Barron, Nolapat Pipitvitayakul

CONCEPT OF OPERATIONS

REVISION – 2
17 November 2022

CONCEPT OF OPERATIONS FOR Smart Cricket Bat

TEAM <22>

APPROVED BY:

Project Leader _____ **Date** _____

Prof. Kalafatis Date

T/A Date

Change Record

Rev.	Date	Originator	Approvals	Description
-	2/9/2022	Pablo Barron		Draft Release
1	2/23/2022	Pablo Barron		First Revision
2	11/17/2022	Gavin Dahl		Final Revision

Table of Contents

Table of Contents	3
List of Figures	4
1. Executive Summary	6
2. Introduction	7
2.1. Background	7
2.2. Overview	7
2.3. Referenced Documents and Standards	7
3. Operating Concept	8
3.1. Scope	8
3.2. Operational Description and Constraints	8
3.3. System Description	8
3.4. Modes of Operations	9
3.5. Users	9
3.6. Support	10
4. Scenario(s)	11
4.1. Indoor Cricket Batting Practice	11
4.2. Outdoor Cricket Batting Practice	11
5. Analysis	11
5.1. Summary of Proposed Improvements	11
5.2. Disadvantages and Limitations	11
5.3. Alternatives	11
5.4. Impact	12

List of Figures

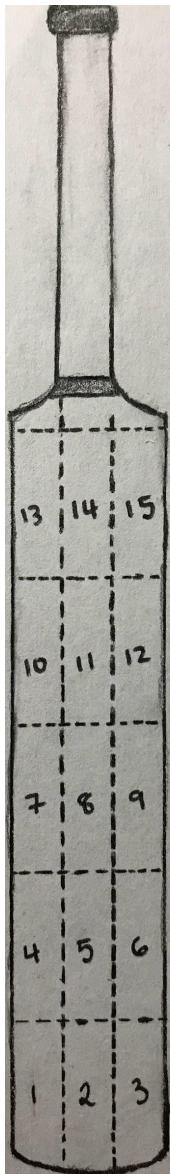


Fig. 1: Cricket Bat Region Subdivision



Fig. 2: StanceBeam Device

Charging Dock on the right. Main hardware housing is in yellow. The mounting to attach to the bat below the main hardware housing. Figure above the main housing is to lock the device in place

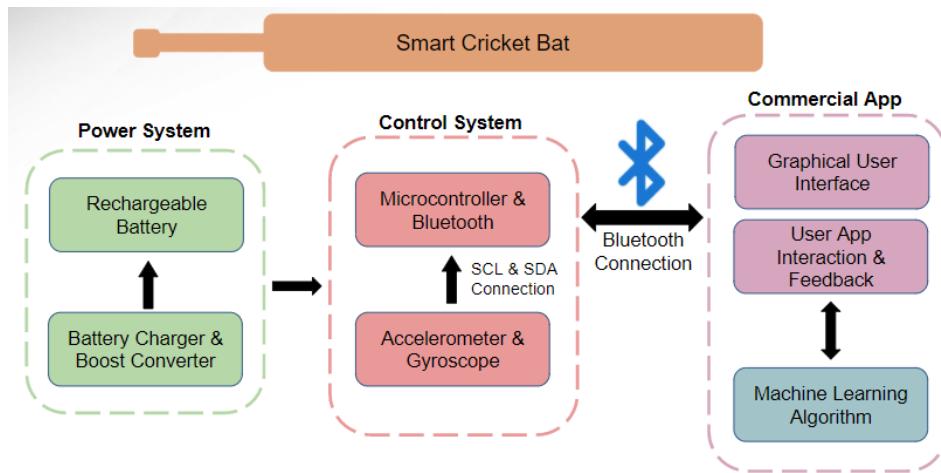


Fig.3: Subsystem Block Diagram

1. Executive Summary

While cricket has been around for much longer than its contemporary baseball, there is a stark difference in training equipment available for casual enjoyers, the smart cricket bat plans to fill that space. The smart cricket bat offers an easy at home alternative to coaching lessons in the form of an app and a device you put on your cricket bat of choice. The app will display measurements and calculations from the bat, such as the angle of the swing, the speed of the swing, the efficiency of the user's swing, and the approximate position of where the ball hit the bat. The last of which is found via a machine learning algorithm that takes the other measurements and triangulates the impact location. This will help improve both accuracy and precision when swinging for the bats sweet spot.

2. Introduction

Cricket is more of a niche sport than others, so it's no surprise that the community overall is lacking in training and feedback equipment. Most of the training equipment they do have are primarily rudimentary items, such as ball rebounders, batting tees, etc. And recently, one start up, StanceBeam, that is trying to provide easier at home training is a little on the expensive side. The smart cricket bat will fill this gap by providing a device that will attach to the user's cricket bat of choice and acquire various data points on each swing. This device will then connect to the player's phone via bluetooth, process the data acquired from the sensors on the bat, and give real time feedback to help the user.

2.1. Background

In cricket, the goal is to score runs, this is accomplished through completing runs, hitting boundaries, losing wickets, and free runs. Half of these, completing runs and hitting boundaries, involve hitting the ball into a desired area of the field, to accomplish these feats easier the cricket bat is designed to have a "sweet spot" where the bat is thicker than everywhere else, thus having more force behind it. The goal is to have a consistent enough swing to hit the sweet spot as often as possible. StanceBeam is a start-up out of India that is trying to help the average player with this. Their product is a sensor that connects to an app and displays measurements from the bat such as swing angle, swing speed, power generated from swing, and overall swing efficiency. The app also has drills and real-time coaching from real coaches to help improve aspects of their play. In contrast, the app will display where the ball impacted the bat via a histogram and give advice for improvement, as well as displaying swing angle, swing speed, and overall swing efficiency. Despite being limited in the ability to display drills or video analysis, the Smart Cricket Bat will be able to help the user improve swing consistency and ball placement, specifically for the bats sweet spot, through the use of small advice and a histogram from swing data.

2.2. Overview

The overall goal of the smart cricket bat is to deliver concise, analyzed data from the users swings to the app and give real-time feedback to the user to help improve their overall swing consistency and efficiency. This will be accomplished by a device that will mount to the end of the cricket bats handle and collect both speed and angle of the cricket bat during the user swing. It then sends that data to the smartphone app via bluetooth to process the data, through a machine learning algorithm, and output real time feedback to the user.

2.3. Referenced Documents and Standards

- Reference Device:
 - <https://www.stancebeam.com/>
- Standard for the Specification of IMU's:
 - <https://standards.ieee.org/ieee/1780/5700/>
- Cricket Bat Standard:

- <https://www.cricketequipmentusa.com/cricket-bats-specifications-recent-changes-to-the-law-52#:~:text=Length%20and%20width%20of%20the,than%2052%25%20of%20the%20bat>
- Determination of the “Sweet Spot” of a Cricket Bat using COMSOL Multiphysics
 - https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwjL-HEtt77AhUzmmoFHRNFBawQFnoECBMQAQ&url=https%3A%2F%2Fcn.comsol.com%2Fpaper%2Fdownload%2F362441%2Fmulchand_paper.pdf&usg=AOvVaw05RGQGwEzXQR0SqD7-Cp9

3. Operating Concept

3.1. Scope

The main functionality of the smart cricket bat will be to calculate where on the bat the ball hits based on data gathered from a gyroscope and an accelerometer. Based on data collected from the gyroscope and accelerometer, the speed of the swing and angle of the swing will be calculated by an offline machine learning algorithm. The data gathered from the IMU sensors will be sent via bluetooth to an app. From the gathered data and ML algorithm results, the app will display to the user with a histogram of where on the bat the ball collided. From the data on the histogram, how efficient the user is hitting the ball will be calculated. The app will also show details of every swing ie. speed of the swing and swing angle.

3.2. Operational Description and Constraints

The device will be attached on the bottom of the handle of the bat. Once the device is attached, it will need to be calibrated to accurately measure collision location and efficiency. The calibration of the device will be the main constraint, since failure to properly calibrate the device will lead to false data being produced. The calibration step will be a simple button press while the bat is resting in an upright position. Once calibrated, the user will be able to practice for about six hours on full battery. During the user’s practice session or after the session, the user can check the app to view the data gathered for each swing. Once the battery is drained or the user’s practice session is finished, the user will need to recharge the device via a micro-USB cable. Another constraint for the device is size and weight. The device must be small enough to attach to the bottom of the handle on the cricket bat and light enough to not affect the overall feel of the bat and performance of the user.

3.3. System Description

- Power: The device will be powered by a lithium battery with a battery life of about six hours. The device will be rechargeable via a micro-USB cable.
- Sensors and Microcontroller: The sensors (IMU) will encompass one 3-axis accelerometer and one 3-axis gyroscope. The device will gather the angular velocity and rate of change from the IMU and transfer data via bluetooth to be processed in a machine learning algorithm.

- App: The app will receive data from the MCU and send the data to an offline machine learning algorithm to calculate and predict the location of collision and the efficiency of the user's swing. Once the region of collision and efficiency is determined, the app will display a histogram of the different collisions that occurred during the user's training session. It will also display the swing speed, swing angle, and efficiency of the user.

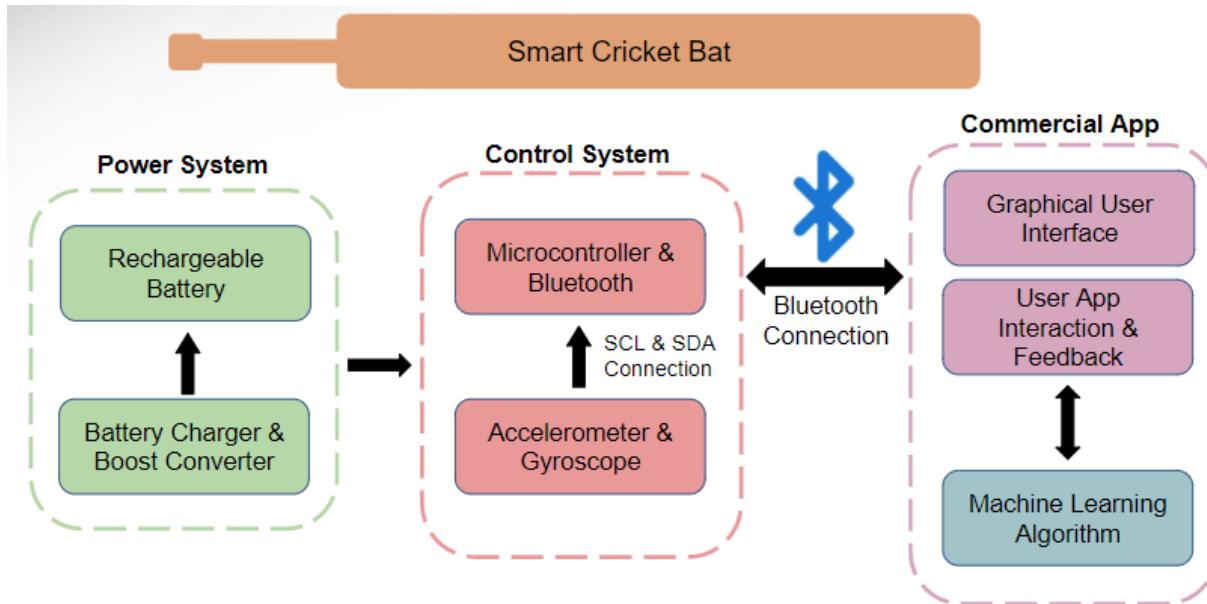


Figure 1: Subsystem block diagram

3.4. Modes of Operations

The device will have two modes of operation:

- Calibration Mode: Before the user can use the device, the device needs to be calibrated, doing so is as simple as pushing a button on the mobile application while the device is at rest in the upward position.
- Practice Mode: Once the device is calibrated, the user is now able to begin their training session. The device will have a six hour battery life. During the training session, the microprocessor will send data gathered from the IMU to the app to be sent to a server housing the machine learning algorithm to determine the location of collision and the efficiency of the user. The app will then display a histogram to show the collision location of each swing, the speed of the swing, swing angle, and user's efficiency.

3.5. Users

The main users will be cricket players trying to improve their swing. Their experience with cricket will range from grade-school level to professional players. The necessary skill level to operate the device is knowing how to use a phone app and read a histogram.

3.6. Support

The user will be provided with a user's manual to know how to properly use the device. The user's manual will encompass how to calibrate the device to be used in different sized cricket bats, the different functions of the app, ie. efficiency and swing speed, and how to charge the device. If any problems occur with the device, the user can send the device back to be fixed.

4. Scenario(s)

4.1. Indoor Cricket Batting Practice

The first scenario for the smart cricket bat is the user uses the device to practice their swing in an indoor training environment. In this scenario, the only potential damage that the device will encounter is the energy transfer of the ball and the bat colliding and potential sweat from the user. The device will have to be able to work efficiently under these conditions

4.2. Outdoor Cricket Batting Practice

The second scenario is if the user wants to use the device to practice their swing in an outdoor training environment. In this scenario, many potential damages can occur. The device will need to not only withstand the conditions of the indoor scenario, but also take into account dirt, water, and extreme temperatures, for both cold and heat.

5. Analysis

5.1. Summary of Proposed Improvements

The device will offer a user-friendly app and system to allow them to increase the efficiency of their swing by seeing real time data and details on each swing. This device will be able to work on any size of cricket due to the required calibration mode prior to beginning a practice session.

5.2. Disadvantages and Limitations

- There is a limitation to the size of the system because it should be small enough to fit on to the bottom of the cricket bat handle.
- Unable to record video for each swings and analyze the video
- The device cannot be too heavy to disrupt the feel of a natural cricket bat
- Every user hold the bat differently, which can cause inconsistencies in the data collection and calculations

5.3. Alternatives

- The sensors could be attached to the back of the cricket bat instead of on the handle if size is an issue. Although we opposed from using this design due to a high risk of damaging the sensors due to the energy transfer from the collision of the ball and the cricket bat
- Additional sensors can be added to improve the accuracy of the results.

5.4. Impact

- This project will help cricket players study and improve the user's batting performance.
- If the device becomes as popular as cricket, it can cause an increase in the need for lithium batteries. This higher demand will then cause the mining of lithium and other raw metals to increase.
- The device has the potential to reduce the need for cricket trainers.

Smart Cricket Bat

Gavin Dahl, Jiakai Hu, Pablo Barron, Nolapat Pipitvitayakul

INTERFACE CONTROL DOCUMENT

REVISION – 1
18 November 2022

INTERFACE CONTROL DOCUMENT

FOR

Smart Cricket Bat

PREPARED BY:

Author _____ **Date** _____

APPROVED BY:

Project Leader _____ **Date** _____

John Lusher II, P.E. Date

T/A Date

Change Record

Rev.	Date	Originator	Approvals	Description
-	2/23/2022	Gavin Dahl		Draft Release
1	11/18/2022	Gavin Dahl		Final Revision

Table of Contents

List of Figures	4
1. Overview	4
2. References and Definitions	5
2.1. References	5
2.2. Definitions	5
3. Physical Interface	6
3.1. Weight	6
3.2. Dimensions	6
3.2.1. Dimensions of Power System	6
3.2.2. Dimensions of Control System	6
3.3. Mounting Locations	6
4. Thermal Interface	7
5. Electrical Interface	8
5.1. Primary Input Power	8
5.2. Signal Interfaces	8
5.3. User Control Interface	8
6. Communications / Device Interface Protocols	9
6.1. Wireless Communications (Bluetooth & Internet)	9
6.2. G.U.I.	9
6.3. Device Peripheral Interface	9

List of Figures

Figure 1: Mounting Locations on Bat	7
Figure 2: Sample UI	10

1. Overview

In this ICD, the details for physical dimensions and weight will be provided in section 3. The sensing unit will be attached to the end of the bat, the details for attaching will also be provided. This unit does not have a cooling system. Temperature limits will be shown in section 4. This unit shall last for two hours of battery life after fully charged. The electrical details and thresholds for sensors and the whole system are listed in section 5. The details for communication between systems and the user control interface are provided in the last section.

2. References and Definitions

2.1. References

- Reference Device:
 - <https://www.stancebeam.com/>
- Standard for the Specification of IMU's:
 - <https://standards.ieee.org/ieee/1780/5700/>
- Cricket Bat Standard:
 - <https://www.cricketequipmentusa.com/cricket-bats-specifications-recent-changes-to-the-law-52#:~:text=Length%20and%20width%20of%20the,than%2052%25%20of%20the%20bat.>
- Determination of the “Sweet Spot” of a Cricket Bat using COMSOL Multiphysics
 - https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwjL_HEt77AhUzmmoFHRNFBawQFnoECBMQAQ&url=https%3A%2F%2Fcn.comsol.com%2Fpaper%2Fdownload%2F362441%2Fmulchand_paper.pdf&usg=AOvVaw05RGQGwEzXQR0SqdD7-Cp9

2.2. Definitions

m	Meter
mm	Millimeter
mA	Milliamp
mAh	Milliamp-hour
mW	Milliwatt
V	Volt
MCU	Microcontroller
IMU	Inertial Measurement Unit (Accelerometer & Gyroscope)
LiPo	Lithium Polymer Battery
BLE	Bluetooth Low Energy
SCL	Serial Clock Line
SDA	Serial Data Line

3. Physical Interface

3.1. Weight

The goal is to keep the weight as low as possible, to not interfere with the players swing. The exact weight of the housing unit that will hold the components is still unknown, but ideally will be around 50 grams. The internal components of the device approximately add up to 40 grams. Weighing the device as a whole, including both the housing unit and the device internals, it will be less than 100 grams.

3.2. Dimensions

The mounting device's interior restriction is limited by the internal components of the device, which will be around 30mm x 35mm x 30mm. The exact dimensions of the housing unit for the device is still unknown, but basing them off the known restrictions for internals of the device, it should be approximately 35mm x 40mm x 35mm, with the goal being to make it a cylindrical mounting device that will have a diameter of about 60mm and height of 35mm.

3.2.1. Dimension of the power system

The power system itself, being composed of 1 Li-Po battery and 1 boost converter/recharging station, makes up approximately 33mm x 20mm x 14mm

3.2.2. Dimension of the control system

The control system is made up of 1 Beetle BLE MCU and 1 6-axis IMU sensor (containing a 3-axis gyroscope and a 3-axis accelerometer), totaling up to approximately 30mm x 35mm x 8mm.

3.3. Mounting Locations

The mounting location will be at the end of the cricket bat's handle. It will use a kind of sleeve that is put over a little more handle and will securely lock together with the housing device for the control and power systems. If there are any complications with trying to mount the device in this location, the back up spot for mounting will be on the back of the bat at the other end of the handle.

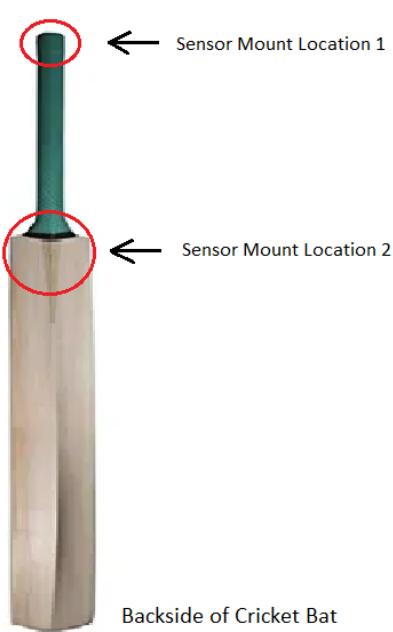


Figure 1: Mounting Locations on Bat

4. Thermal Interface

Since our device will be small enough to be attached to the bottom of a cricket bat, there will not be a need for fans or heat sinks for cooling. The only thermal interface our device will require is having vents or perforations on the main housing of the MCU and IMU's to allow airflow, as the MCU is the limiting factor and cannot run properly over 85°C (185°F). This will prevent overheating in case the user is using our device outdoors on a summer's day.

5. Electrical Interface

5.1. Primary Input Power

Power will be supplied by a rechargeable 3.7V lithium ion polymer battery with 500mAh capacity. The voltage will be regulated and the boost converter will convert the voltage to 5V, which is within the acceptable range of input voltage levels for the MCU and the sensors.

5.2. Signal Interfaces

The signal interfaces are the input to the MCU from the IMU sensor containing a 3-axis gyroscope and a 3-axis accelerometer. The IMU sensor module uses SCL/SDA for communicating with the microcontroller.

5.3. User Control Interface

The interface with the user will be an android app which will display the data collected by the IMU sensor as well as the data for the location of collision with the ball and the efficiency of the user's swing predicted by a machine learning algorithm.

6. Communications / Device Interface Protocols

6.1. Wireless Communications (*Bluetooth & Internet*)

Our device will communicate with our app via bluetooth, which will have a connectivity range of about 50m. The app itself will also connect to our machine learning algorithm, that's stored in the cloud, via an internet connection.

6.2. GUI

All user interactions with our device will be controlled by an android app. These interactions will include calibration of our device and data output. The user will be able to navigate through different pages of the app via designated buttons on the home screen. A screen show of the buttons on the dashboard is shown below.

Figure 2: Sample UI



6.3. Device Peripheral Interface

The MCU and IMU will communicate with each other via a SCL and SDA connection. This connection allows the SCL to be the synchronized clock signal between the MCU and IMU for data transfer over the IC2 bus, and SDA is the data line that holds the actual data.

Smart Cricket Bat

Gavin Dahl, Jiakai Hu, Pablo Barron, Nolapat Pipitvitayakul

FUNCTIONAL SYSTEM REQUIREMENTS

REVISION – 2
18 November 2022

FUNCTIONAL SYSTEM REQUIREMENTS FOR Smart Cricket Bat

PREPARED BY:

Author **Date**

APPROVED BY:

Project Leader _____ **Date** _____

John Lusher, P.E. Date

T/A Date

Change Record

Rev.	Date	Originator	Approvals	Description
-	2/23/2022	Gavin Dahl		Draft Release
1	4/22/2022	Gavin Dahl		First Revision
2	11/18/2022	Gavin Dahl		Final Revision

Table of Contents

List of Figures	4
1. Introduction	5
1.1. Purpose and Scope	5
1.2. Responsibility and Change Authority	5
2. Applicable and Reference Documents	6
2.1. Applicable Documents	6
2.2. Reference Documents	6
2.3. Order of Precedence	7
3. Requirements	8
3.1. System Definition	8
3.2. Characteristics	9
3.2.1. Functional / Performance Requirements	9
3.2.2. Physical Characteristics	10
3.2.3. Electrical Characteristics	11
3.2.4. Environmental Requirements	13
3.2.5. Failure Propagation	14
4. Support Requirements	15
Appendix A Acronyms and Abbreviations	16

List of Figures

Figure 1. The Smart Cricket Bat Conceptual Image	5
Figure 2. Block Diagram of System	8

1. Introduction

1.1. Purpose and Scope

Our purpose is to help users improve their cricket skill through a training session using our system. The sensing unit will be attached to the end of the bat. This unit shall last for six hours of battery life after fully charged. The sensors will receive data and transfer them via bluetooth to an android phone app. The ML algorithm shall calculate the necessary data to the ones that need to be shown on the phone app like the hit location, swing angle and speed. The users shall be able to access these data through the phone app. The users will be able to know whether their hit was on the “sweet spot” or not as well as how efficient their swing was.

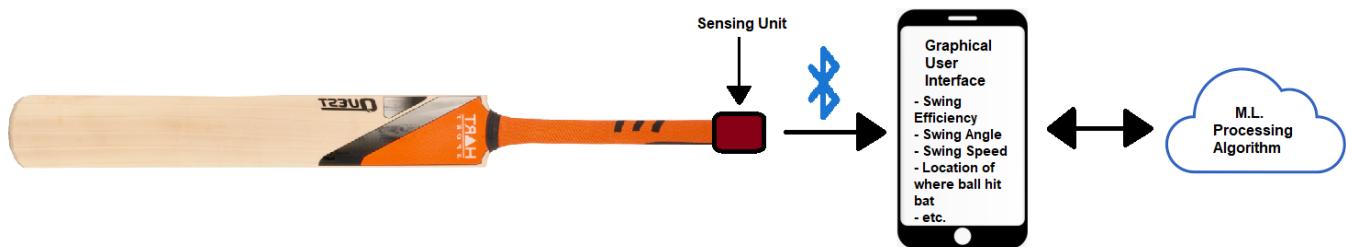


Figure 1. The Smart Cricket Bat Conceptual Image

1.2. Responsibility and Change Authority

Gavin Dahl has the responsibilities of making sure the team is sticking to the execution plan, completing milestones, and producing deliverables. He is also responsible for making the team confined to deadlines. The team's sponsor, Pranav Dhulipala, is the only one with the authority to make changes to the end goal requirements. If there is an unforeseen element that causes us to be unable to meet a requirement, Gavin and Pranav will discuss what will need to be done to change the requirement.

2. Applicable and Reference Documents

2.1. Applicable Documents

The following documents, of the exact issue and revision shown, form a part of this specification to the extent specified herein:

Document Number	Revision/Release Date	Document Title
IEEE 1780-2022	2022-02-09	Standard for the Specification of Inertial Measurement Units
10.1109/ICIAFS.2008.4783997	2009-02-13	Design and Implementation of a Bluetooth based General Purpose Controlling Module
IEEE 802.15.1	2005-02-14	Standard for Telecommunications and Information Exchange Between Systems
IEEE 802.15.4	2020-05-06	Standard for Low-Rate Wireless Networks

2.2. Reference Documents

The following documents are reference documents utilized in the development of this specification. These documents do not form a part of this specification and are not controlled by their reference herein.

Link	Document Title
https://www.cricketequipmentusa.com/cricket-bats-specifications-recent-changes-to-the-laws-52#:~:text=Length%20and%20width%20of%20the,than%2052%25%20of%20the%20bat	CRICKET BATS SPECIFICATIONS - RECENT CHANGES TO THE LAW
https://www.stancebeam.com/	Stance Beam
https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwjL-HEtt77AhUzmmoFHRNFBawQFnoECBMQAQ&url=https%3A%2F%2Fcn.comsol.com%2Fpaper%2Fdownload%2F362441%2Fmulchand_paper.pdf&usg=AOvVaw05RGQGwEzXQR0SqdD7-Cp9	Determination of the “Sweet Spot” of a Cricket Bat using COMSOL Multiphysics

2.3. Order of Precedence

In the event of a conflict between the text of this specification and an applicable document cited herein, the text of this specification takes precedence without any exceptions.

All specifications, standards, exhibits, drawings or other documents that are invoked as "applicable" in this specification are incorporated as cited. All documents that are referred to within an applicable report are considered to be for guidance and information only, except ICDs that have their relevant documents considered to be incorporated as cited.

3. Requirements

3.1. System Definition

In cricket, ball placement on the bat is very crucial to maximize the points you receive. To better improve a player's ball placement, we will design a device that can be attached to any cricket bat and predict the location of the collision between the bat and the ball. The device will be powered by a rechargeable lithium battery with a battery life of six hours. Data will then be gathered via a 3-axis accelerometer and gyroscope. A MCU will then send the data via bluetooth to an Android app to send to a server-based machine learning algorithm to predict the location of the collision. All results will then be displayed on the app.

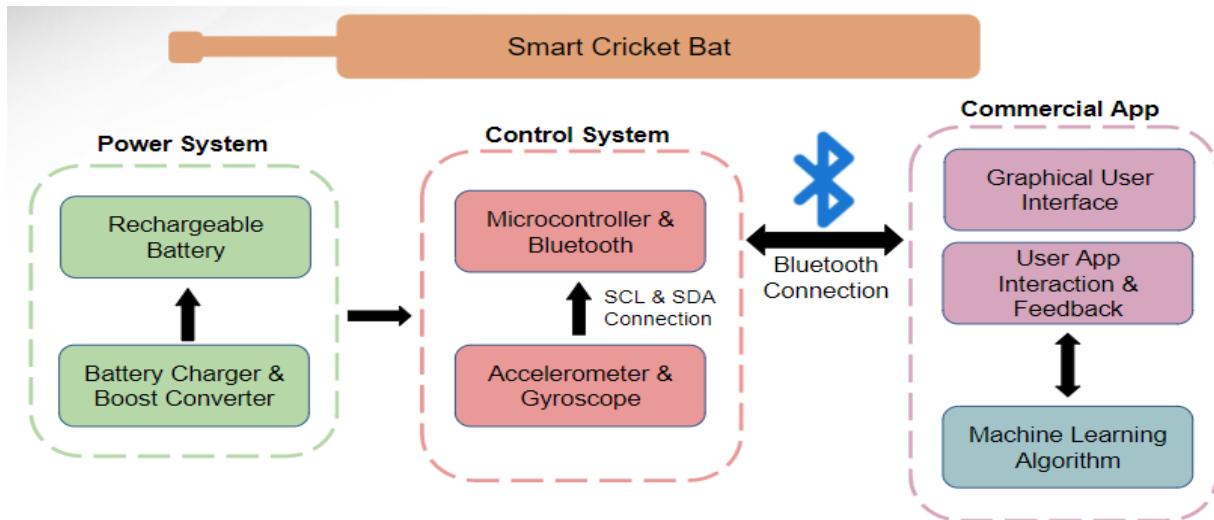


Figure 2. Block Diagram of System

The block diagram above shows the individual subsystems of the device. The subsystems include: Power System, Control System, and Commercial App. The device will be powered by a lithium battery connected to a boost converter to deliver the necessary power requirement for the control system. This battery will be connected to the control system through a PCB, that will also hold the charging circuit for the battery that will require a microUSB to charge. The control system encompasses a 3-axis accelerometer, a 3-axis gyroscope and a ATmega328p microprocessor. The angular momentum and rate of change data we measured with the gyroscope and accelerometer will then connect and be sent via bluetooth to the commercial app. The commercial app will then send the data to a machine learning algorithm via an internet connection to calculate collision location and efficiency. The results of the device will then be displayed on the easy to use app. Each output variable will have its own designated page to be viewed.

3.2. Characteristics

3.2.1. Functional / Performance Requirements

3.2.1.1. Calibration

The device must be able to be calibrated to properly calculate results. The process of calibration will entail leaving the device at rest in an upright position, and pushing the calibration button on the corresponding mobile app.

Rationale: The IMU sensor used in the device needs to be calibrated after start-up to deliver accurate and clean data to the machine learning algorithm. Calibrating the device before usage will result in a higher certainty percentage.

3.2.1.2. Collision Location Determination

The main function of the device will be able to determine the location of the collision between the cricket bat and the ball based on the magnitude of the force felt by the bat and the torque produced by the ball on the bat, which is obtained from the data measured by the IMU sensor. The certainty must be at least 90%. This will require a machine learning (ML) algorithm.

Rationale: Cricket players will use the device to improve their swing efficiency. The location of the collision will dictate how far and in which direction the ball will go. Depending on where the ball lands on the field is how many turns (points) a player can achieve. Therefore, knowing where the ball collides with the bat is crucial for the player to know.

3.2.1.3. Efficiency Calculation

The device will be able to calculate how efficient the user is swinging the bat based on gathered data from previous swings. Efficiency is determined by how close the collision was to the “sweet spot” of the bat. The sweet spot of a cricket bat is located on the thickest section of the bat and is different for each cricket bat.

Rationale: Based on the efficiency the user will be able to tell how far off from the sweet spot their swing is.

3.2.1.4. Bluetooth Range

The device will be able to communicate with the app within a range of 50m.

Rationale: The user should be able to do their practice swings with their phone clear from any danger of being hit while in the batting box.

3.2.1.5. Easy to Use App/GUI

The app will be easy navigable and easy to read the outputs

Rationale: The user might not have programming or data analysis skills so having an app that anyone can use and read is crucial for the device to be successful in the cricket market.

3.2.1.6. Battery Life

The device will be powered by a lithium battery that must have a battery life of 2 hours and must be rechargeable.

Rationale: Battery life and rechargeability were requirements set by the customer.

3.2.2. Physical Characteristics

3.2.2.1. Mass

The mass of the sensing unit that mounts to the handle of the cricket bat should be no more than 100g.

Rationale: This is a requirement specified by the sponsor due to wanting the device to be as unobtrusive to the users swing as possible.

3.2.2.2. Volume Envelope

The volume envelope of the smart cricket bat's sensor unit shall be less than or equal to 40mm in height, 70mm in outer diameter.

Rationale: This is a requirement specified by the sponsor due to wanting the device to be as unobtrusive to the users swing as possible.

3.2.2.3. Mounting

The mounting device will attach to the bottom of the cricket bat's handle and will have a locking mechanism with the sensor unit to give it a secure fit.

Rationale: The vibrations that occur from the impact of a swing can be quite intense. The requirement is to have the device stay on the bat at all times during the user's use, through any kind of outside interference.

3.2.3. Electrical Characteristics

3.2.3.1. Inputs

- a. The presence or absence of any combination of the input signals in accordance with ICD specifications applied in any sequence shall not damage the smart cricket bat, reduce its life expectancy, or cause any malfunction, either when the unit is powered or when it is not.
- b. No sequence of command shall damage the smart cricket bat, reduce its life expectancy, or cause any malfunction.

Rationale: By design, should limit the chance of damage or malfunction by user/technician error.

3.2.3.1.1 Power Consumption

The maximum peak power of the system shall not exceed 300 mW.

Rationale: This requirement is to ensure that enough power is being supplied to each of the components for at least 2 hours when the battery is fully charged.

3.2.3.1.2 Input Voltage Level

The input voltage level for the MCU and the IMU shall be +5 V.

Rationale: The microcontroller's operating voltage is 5V and the IMU input voltage can be between 3.3V to 5V.

3.2.3.1.3 External Commands

The smart cricket bat shall document all external commands in the appropriate ICD.

Rationale: The ICD will capture all interface details from the low level electrical to the high-level packet format.

3.2.3.2. Outputs

3.2.3.2.1 Data Output via App

The app will be able to output data gathered from the accelerometer and gyroscope and the calculated results from the ML algorithm. The outputs will include: swing speed, swing angle, collision location, and efficiency. Each output will have its own page the user can navigate to via buttons on the home screen.

Rationale: By having an app that can constantly be gathering and outputting data in an easy to read manner, it eliminates the need for the user to have tech. and data analysis skills. Without the app, users will have to download the data onto their computer to view their results.

3.2.3.3. Connectors

The smart cricket bat will use a microUSB to charge the sensor unit, and will also be able to get the sensor data via a microUSB in the case of bluetooth not working.

Rationale: Most efficient way to make the device is to make it rechargeable, so that it can be as small and light as possible.

3.2.3.4. Wiring

The smart cricket bat will use a PCB to connect all the internal components (MCU, IMU, Li-Po Battery, Boost Convertor/Charger) of the sensor unit.

Rationale: Normal wiring will most likely not be secure or robust enough for the amount of shock that the device will encounter.

3.2.4. Environmental Requirements

The device will be adequate for indoor and outdoor use.

Rationale: Although the device will not be used during a cricket match, a user might be holding their practice session indoors or outdoors.

3.2.4.1. Pressure (Altitude)

The device will be designed to operate in 1 atm pressure.

3.2.4.2. Temperature

The device will be able to operate between temperature ranges of 0°C to 85°C.

Rationale: Since the device can be used outdoors, temperatures during the summer in Texas are between 97°F - 105°F.

3.2.4.3. External Contamination

The device will be housed in a casing to protect the components from any dirt or foreign objects.

Rationale: Since the device can be used outdoors, it must be protected from any materials that can cause damage to the components.

3.2.4.4. Rain

The device will not be able to be used during the rain, but it should be waterproof enough to protect the components from the sweat of the user. The device will operate as intended within the humidity range of 0 to 80%, and should have the possibility of correct operation through 90 to 100%.

3.2.5. Failure Propagation

The smart cricket bat shall not allow propagation of faults beyond the app's interface.

3.2.5.1. Failure Detection, Isolation, and Recovery (FDIR)

3.2.5.1.1 Communication Test

The Smart Cricket Bat System shall provide users a notification if the user is using the system out of range or the internet/bluetooth connection is unstable at this moment.

3.2.5.1.1.1 BIT Critical Fault Detection

The BIT shall be able to detect a critical fault in the smart cricket bat's sensing unit, machine learning algorithm, or consumer app, 95 percent of the time.

Rationale: This is to provide the best user experience we can, letting the user know that we know there is an error and the system is working to fix it.

3.2.5.1.1.2 BIT False Alarms

The BIT shall have a false alarm rate of less than 5 percent.

Rationale: Due to some of the possible erroneous uses of the cricket bat, it might interpret an action of the user as an error, when in reality it is not.

3.2.5.1.1.3 BIT Log

The BIT shall save the results of each test to a log that shall be stored in the machine learning system for retrieval and will be used to improve common errors and overall quality of life of the user experience.

Rationale: The device is very user focused, so providing the best user experience is of high priority.

3.2.5.1.2 Isolation and Recovery

The smart cricket bat should provide for fault isolation and recovery by enabling subsystems to be disabled based upon the result of the BIT.

Rationale: If there are any errors, we want to turn the device off and let the user know to stop using it so they aren't wasting energy on swings that will not be analyzed.

4. Support Requirements

The user will be provided with a user's manual to know how to properly use the device. The user's manual will encompass how to calibrate the device to be used in different sized cricket bats, the different functions of the app, ie. efficiency and swing speed, and how to charge the device. If any problems occur with the device, the user can send the device back to be fixed.

Appendix A: Acronyms and Abbreviations

m	Meter
mm	Millimeter
mA	Milliamp
mAh	Milliamp-hour
mW	Milliwatt
V	Volt
MCU	Microcontroller
IMU	Inertial Measurement Unit (Accelerometer & Gyroscope)
PCB	Printed Circuit Board
LiPo	Lithium Polymer Battery
BLE	Bluetooth Low Energy
GUI	Graphical User Interface
BIT	Built-in-test

Smart Cricket Bat

Gavin Dahl, Jiakai Hu, Pablo Barron, Nolapat Pipitvitayakul

EXECUTION PLAN

Execution Plan for the Smart Cricket Bat

	9/2/2022	9/9/2022	9/16/2022	9/23/2022	9/30/2022	10/7/2022	10/14/2022	10/21/2022	10/28/2022	11/4/2022	11/11/2022	11/18/2022	11/25/2022	12/2/2022
Status Update 1														
Control System PCB														
Control System and App Communication														
Power System PCB Design														
App/Control System Iteration via Bluetooth														
Connection and Data sending Validation														
Status Update 2														
PCB Fabrication and Assembly														
ML and App Intergration														
Improve App User Interface														
ML Data Collection														
Data Training with New Data														
Status Update 3														
PCB Testing and Validation														
Sensing Unit Housing Design														
Sensing Unit Handle Mount Design														
Validate ML with Real Time Swings														
Status Update 4														
Final PCB Manufacturing														
Sensing Unit Housing Manufacturing														
Sensing Unit Handle Mount Manufacturing														
Status Update 5														
Complete System Integration														
Final PCB Validation														
System Validation														
Final Design Presentation														
Final Demo														
Final Report														

Legend

	Not Started		Jiakai Hu
	In Progress		Nolapat Pipitvitayakul
	Completed		Pablo Barron
	Behind Schedule		Gavin Dahl
			Everyone

Smart Cricket Bat

Gavin Dahl, Jiakai Hu, Pablo Barron, Nolapat Pipitvitayakul

VALIDATION PLAN

Validation Plan for the Smart Cricket Bat

Paragraph	Test Name	Success Criteria	Methodology	Status	Responsible Engineer(s)
3.2.1.2	Sending Data via Android device	The app should be able to send data (input for ML Algorithm)	Upload the app to a simulated android phone and test by outputting data to a localized device to test data sending	TESTED: App is able to send real time data to a device via an input stream	Pablo Barron
3.2.1.2	ML Algorithm Precision	The ML algorithm provides precise results of output data within acceptable error range.	Use all data gathered to test the training and testing accuracy.	TESTED: Training accuracy around 98% and Testing accuracy around 23%	Jiakai Hu
3.2.1.3	Communication Range	Communication between the sensing unit and app stays active for a distance of up to 100ft.	Test normal functionality of the smart cricket bat's operations at 10ft intervals ranging from 0ft to 100ft, or until bluetooth cuts off.	TESTED: Bluetooth module and mock phone had strong connection until 230 ft, where the connection would cut off.	Gavin Dahl Pablo Barron
3.2.1.2	System Latency	User swing analysis deliver to user via the app in no greater than 10s after the user's bat has struck the ball.	Take 20 practice swings with the bat, timing the time from the ball's impact on the cricket bat till the analyzed swing data is available to the user on app.	FAILED: As of current ML and App integration the process from hit to data available on app takes approximately 10 minutes	Full Team
3.2.1.4	Wireless Connection Stability	Connection between sensing unit and smartphone app does not drop.	Sensing unit connected to smartphone app via bluetooth, set to default mode, and left to run for 1 hour. Connection is monitored via smartphone app.	TESTED: Device Bluetooth connection stayed strong and was able to send data for 5 hours 21 minutes and 6 seconds.	Gavin Dahl Pablo Barron
3.2.1.4	Full Range of Motion	Sensing unit can measure the angle of the bat at a full 360°.	Sensing unit is attached to the pivoting arm on a protractor, the angle is tracked on both a	TESTED: Sensing unit tracks accurate	Gavin Dahl

			piece of paper and in a text file, and then compared.	degree of turn for all 3 axes	
3.2.1.5	Easy to Use GUI	The app is easily navigable to allow any person, regardless of technical skills, to use our device	Upload the app to a simulated android phone to view the clarity of the app	TESTED: App is able to run on physical device and does not crash	Pablo Barron
3.2.1.5	Operation Time	System operates continuously on battery power for a minimum of 2 hours.	Sensing unit is turned on, set to default mode, and left to run for 2 hours. Power is monitored via a digital multimeter.	TESTED: Fully charged 500 mAh lipo battery can run for about 6 hours	Nolapat Pipitvitayakul
3.2.1.6	Detection Range	Sensing unit can detect vibrations from at least 38in away when mounted on a bat.	Mount sensing unit on end of the cricket bat handle and hit the top of the bat 10 times to ensure full range.	TESTED: Hit from anywhere on bat registers movement in IMU.	Gavin Dahl
3.2.1.7	Detection Accuracy	Sensing unit is able to detect a collision between ball and bat on any area of the cricket bat.	Mount sensing unit on cricket bat, measure data from hits in a variety of areas on the bat (at least 15) until it is confirmed there are no dead areas.	TESTED: IMU sensor leaves no dead zone on bat	Gavin Dahl
3.2.1.8	Detection Sensitivity	Sensors are able to detect degrees of motion within 1 deg of change and is able to give changes in speed to 1 decimal places.	Mount sensing unit to cricket bat, connect to PC via microUSB, and watch real time data output of angle of bat and speed and compare to movements made in real life.	TESTED: IMU can detect the change in angle within 1 degree of sensitivity	Gavin Dahl
3.2.1.9	Ease of Use	System is easily attached to the end of the handle of the cricket bat, is easily connected to the app via bluetooth, and is easy to calibrate during first time startup calibrations. Whole process should take no more than 5 minutes.	Use a stopwatch to measure how long it takes the user to mount the device, pair to phone, and do the calibration setup.	TESTED: Device takes 3 minutes and 28 seconds to set up, 2 minutes of which is calibration time.	Full Team
3.2.2.1	Mass	Mass of the combined control system (MCU and IMU sensors), power system (Li-Po Battery and boost converter), and our housing unit, will weigh no more than 100g.	Use a digital scale to measure the weight of the combined unit.	TESTED: Took average of 10 weigh-ins of sensing unit in its entirety, averaged out to 85.89 ± 0.01 g.	Nolapat Pipitvitayakul Gavin Dahl

3.2.2.2	Volume Envelope	The housing unit for the sensing device should be cylindrical shape, be no more than 70mm in diameter, and have a height of 35mm.	Measure inner and outer diameters and height of the created housing unit for sensors.	TESTED: Outer diameter is 68mm and the height of the device is 36mm	Nolapat Pipitvitayakul Gavin Dahl
3.2.2.3	Mounting	The sensing unit is able to be mounted to the handle of any cricket bat and can lock securely into place.	Use the developed mounting device to mount the sensing unit onto the end of the handle of the bat, and do various shack and shock tests to confirm secure fit.	TESTED: Device does not detach from bat handle via outside forces.	Nolapat Pipitvitayakul Gavin Dahl
3.2.3.1.1	Input Voltage (MCU)	The input voltage for our Beetle BLE board shall be between 5V - 8V.	Use a multimeter to validate input voltage level.	TESTED: Boost Converter Output is 5V +- 0.1	Nolapat Pipitvitayakul
3.2.3.1.3	Battery Charging Voltage and Current	The sensing unit has a 3.7V 150mAh Li-Po battery as its power supply. These can be charged through a microUSB cable that can supply a maximum 150mA of charge current with a 4.2V charge voltage.	Use a multimeter to validate voltage levels and charge current levels.	TESTED: Charge voltage is 4.2 V and maximum charge current is 150 mA	Nolapat Pipitvitayakul
3.2.3.2.1	App Data Gathering via Bluetooth	The Android device should be able to receive data from our MCU via bluetooth	Upload the app to a simulated android phone and input different "dummy" data to see if the android device received the data	TESTED: Data is able to send without interruptions or skipping over lines	Pablo Barron
3.2.4.1	Thermal Resistance	The system should be able to operate in environments with temperatures ranging from 0°C to 85°C.	Use a heating mechanism to raise temperature to 85°C and test systems functionality. Place system in cooling mechanism to lower temperature to 0°C and test systems.	TESTED: Device works in Texas summer of approx. 110°F and in winter at about 32°F.	Gavin Dahl
3.2.4.2	Shock Tolerance	The IMU should be able to handle g shocks up to a max of 10,000g.	Test dropping IMU at differing heights and then use systems normal functionality to try to validate that IMU will still function after taking shocks more than 10,000	TESTED: IMU and PCB can withstand shocks up to 200 g's (an approx 30 ft fall) and strongest expected hit is about 100 g's	Gavin Dahl

Performance on Execution Plan

The execution plan was executed completely. Some tasks had to be completed out of their original order as there were many complications regarding the consumer application. There were two main problems, integration through bluetooth and integration with the machine learning. The bluetooth integration was a simple fix once the problem was finally discovered, however the machine learning integration took much longer than expected and by the end was only barely integrated and was missing a few of the key components desired by the sponsor, such as the process being fully automatic. Besides that hiccup, however, the rest of the execution plan was completed, the project was mostly completed on time, besides said machine learning and application compromise.

Performance on Validation Plan

The validation plan was completed in full. The validation of all components gave expected results, such as IMU, bluetooth, and power system, however there was one validation requirement set by the sponsor that failed to be completed. The sponsor wanted the time it took to process the hit to be a minute at most, however after all the issues with the machine learning and app integration, that process takes about 9 minutes. The key cause of this is that the database used to house the machine learning to process the data is not automatic and takes about 8 minutes to simply export the data delivered from the phone, and once completed then takes about 1 minutes to process and give the desired data from the data set given.

Smart Cricket Bat

Gavin Dahl, Jiakai Hu, Pablo Barron, Nolapat Pipitvitayakul

SUBSYSTEM REPORTS

REVISION – 1
20 November 2022

SUBSYSTEMS REPORT

FOR

Smart Cricket Bat

PREPARED BY:

Author Date

APPROVED BY:

Project Leader Date

John Lusher II, P.E. Date

T/A Date

Change Record

Rev.	Date	Originator	Approvals	Description
-	4/20/2022	Gavin Dahl		Draft Release
1	11/20/2022	Gavin Dahl		Final Revision

Table of Contents

Table of Contents	3
List of Tables	5
List of Figures	6
1. Introduction	7
2. Power Subsystem Report	8
2.1. Subsystem Introduction	8
2.2. Subsystem Details	8
2.3. Subsystem Validation	10
2.4. Subsystem Conclusion	17
3. Control Subsystem Report	19
3.1. Subsystem Introduction	19
3.2. Microcontroller and Bluetooth	19
3.2.1. Overview	19
3.2.2. Operation	19
3.2.3. MCU Validation	20
3.2.4. Bluetooth Validation	21
3.3. Gyroscope	22
3.3.1. Operation	22
3.3.2. Validation	23
3.4. Accelerometer	29
3.4.1. Operation	29
3.4.2. Validation	29
3.5. Housing Unit	31
3.6. Subsystem Conclusion	33
4. App Subsystem Report	34
4.1. Subsystem Introduction	34
4.2. Subsystem Details	34
4.2.1. Bluetooth Communication	34
4.2.2. Sending Gathered Data to Cloud	35
4.2.3. User Interaction / Dashboard	36
4.3. Subsystem Validation	37
4.3.1. Validation From 403	37
4.3.2. Validation From 404	38
4.3.2.1. Bluetooth Validation	38
4.3.2.2. Data Sending to S3 bucket Validation	40
4.4. Subsystem Conclusion	40

5. Machine Learning Subsystem Report	41
5.1. Machine Learning Introduction	41
5.2. Machine Learning Details	41
5.2.1. Bat Region Dividing	41
5.2.2. Data Gathering, Inputting, and Plotting	42
5.2.3. Finding the Impact	43
5.2.4. FFT and PSD	44
5.2.5. Peak Detection	45
5.2.6. Making Feature and Label	45
5.2.7. Training and Testing Sets	46
5.2.8. Training the model	46
5.2.9. Feature Importance	47
5.2.10. Correlation, association, and relationships	50
5.2.11. ML integration	52
5.3. Machine Learning Validation	52
5.3.1. Validation for actual hit on the bat	52
5.3.2. ML integration on EC2 Validation	53
5.4. Subsystem Conclusion	53

List of Tables

Table 1: Load Regulation with Input Voltage Vin =3V	11
Table 2: Load Regulation with Input Voltage Vin =3.7V	12
Table 3: Load Regulation with Input Voltage Vin =4.2V	13
Table 4: Battery Voltage and Charge Current	16
Table 5: Accelerometer Measured Vs Calculated Acceleration	31

List of Figures

Figure 1: Schematic of Boost Converter Circuit	8
Figure 2: Schematic of Battery Charging Circuit	9
Figure 3: PCB Layout for Boost Converter Circuit	10
Figure 4: Load Regulation of Boost Converter Circuit with Vin =3V	12
Figure 5: Load Regulation of Boost Converter Circuit with Vin =3.7V	13
Figure 6: Load Regulation of Boost Converter Circuit with Vin =4.2V	14
Figure 7: Complete Charge Cycle (500 mAh Lipo Battery)	17
Figure 8: Flow Diagram of Microcontroller Logic	20
Figure 9: Bluetooth Distance Validation	21
Figure 10: Bluetooth Data Transfer Validation	22
Figure 11: X-Axis Gyroscope Validation	24
Figure 12: Y-Axis Gyroscope Validation	26
Figure 13: Z-Axis Gyroscope Validation	27
Figure 14: Falls from Various Heights Accelerometer Validation	30
Figure 15: Picture of Housing Unit On and Off Bat	32
Figure 16: Dashboard and Paired Devices list	35
Figure 17: Data sending to AWS cloud page	36
Figure 18: User Feedback/Results	37
Figure 19: HC-05 Bluetooth Module Circuit	37
Figure 20: Bluetooth Validation Data and Arduino Code	38
Figure 21: Bluetooth Validation with Temporary Page	39
Figure 22: Android Studio Console Displaying Proper Data	39
Figure 23: AWS Amplify Page Showing Data Received	40
Figure 24: Bat Division	41
Figure 25: Data Plotting	42
Figure 26: Impact Window	43
Figure 27: FFT & PSD	44
Figure 28: Peak Detection on FFT over X-axis Gyroscope of Region 8	45
Figure 29: Feature and Label	45
Figure 30: Training Results	46
Figure 31: Confusion Matrix	47
Figure 32: Feature Importance 1	47
Figure 33: Feature Importance 2	48
Figure 34: Feature Importance from	49
Figure 35: Feature Importance to	49
Figure 36: Heat Map	50
Figure 37: Seaborn Pairplot	51
Figure 38: Upload ML to EC2 instance	52
Figure 39: Example output on EC2 instance	52
Figure 40: Hit location on the bat and ML output on EC2 console	53
Figure 41: Same ML output on EC2 and Colab	53

1. Introduction

The smart cricket bat will acquire data during the user's swing and give feedback to the user on how to further improve their swing. The system gathers data through the inertial measurement unit mounted at the handle of the bat, where it is transmitted to the consumer app via a microcontroller with a Bluetooth module. The data transferred to the app is then uploaded to the machine learning algorithm to be processed and then returns to the user the characteristics of the swing and what can be done to improve. The system is broken down into the power, control, app, and machine learning subsystems, each of which was designed and rigorously tested. Since each subsystem was validated to be working correctly and fulfilling all requirements, there is a clear path to integration for these subsystems into the full system specified in the Conops, FSR, and ICD.

2. Power Subsystem Report

2.1. Subsystem Introduction

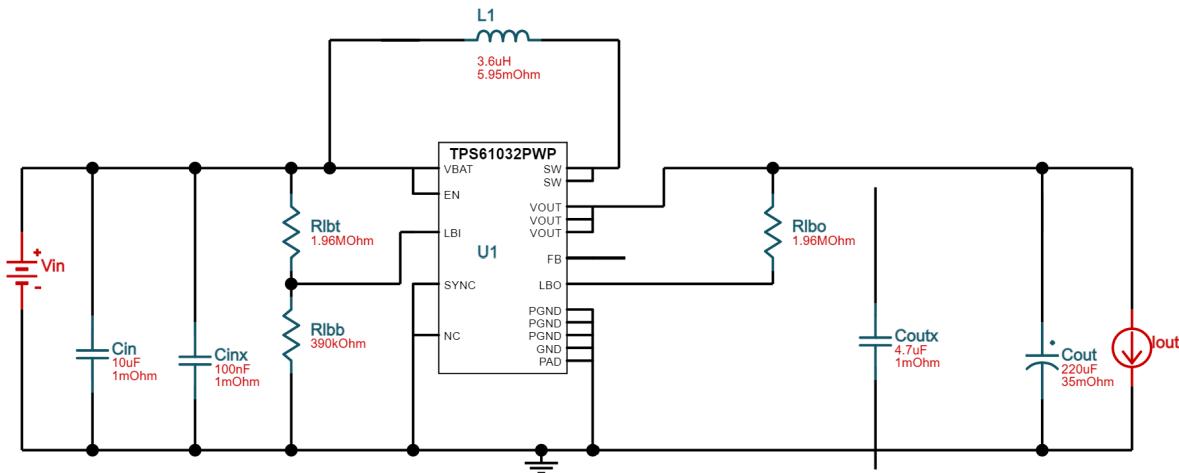
The power subsystem of the smart cricket bat consists of a lithium-ion polymer battery (LiPo), a DC-DC boost converter circuit, and a battery charger. A LiPo battery is rechargeable and can be charged with a battery charger circuit. A boost converter is used to raise the voltage from the LiPo battery in order to supply the power to the microcontroller, IMU, and bluetooth module which are part of the control subsystem. The boost converter and the battery charging circuit were tested to confirm its stability and to validate that it performed correctly according to the design.

2.2. Subsystem Details

The source of power for the smart cricket bat is a 3.7V LiPo battery that has a capacity of 500 mAh. The reason for choosing LiPo battery as a power source is because it is rechargeable, small, and lightweight. These features are important due to the size and weight requirements of the smart cricket bat. The battery output ranges from 3.0V to 4.2V with a nominal voltage of 3.7V. When fully charged, the battery outputs 4.2V, and it will be completely cut out when the voltage goes below 3.0V.

A 5V DC-DC boost converter circuit was designed to raise the voltage levels of the battery that ranges from 3.0V to 4.2V to a 5V voltage level in order to power the microcontroller, IMU, and bluetooth module in the control subsystem. A boost converter circuit was designed based on the requirements using TI WEBENCH Power Designer. The chip used for the boost converter was TPS61032 from Texas Instruments. The MCP73831 chip was used for the battery charging circuit that employs a constant-current/constant-voltage charge algorithm for the battery. Figure 1 shows the schematic of a 5V DC-DC boost converter circuit.

Figure 1: Schematic of Boost Converter Circuit



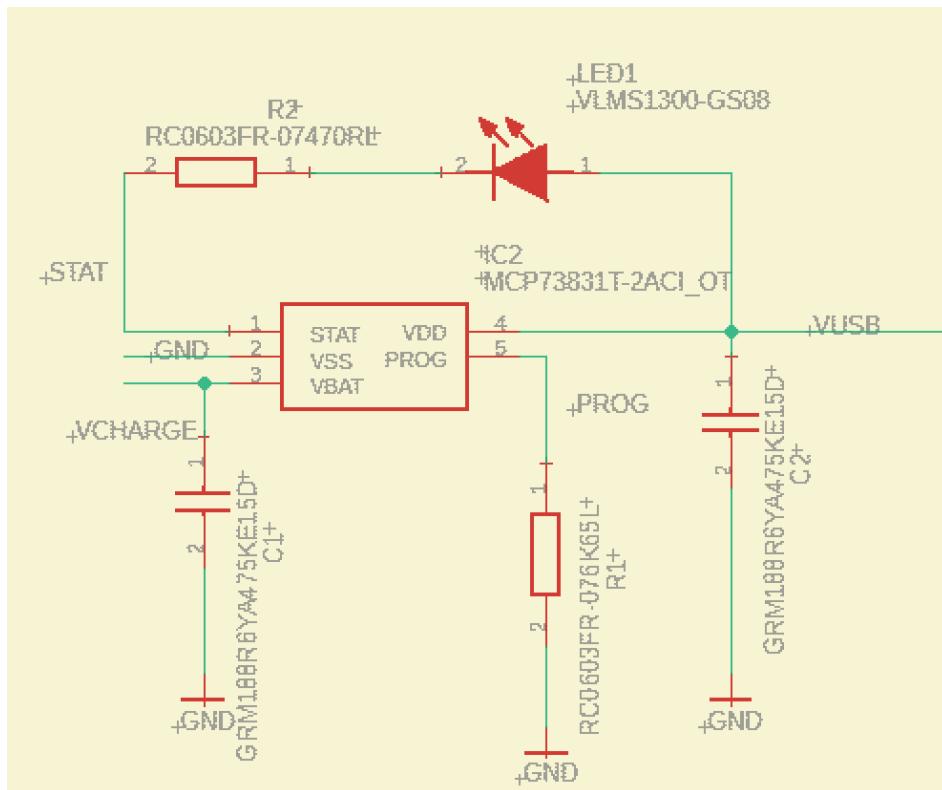
A boost converter circuit was first built on a breadboard by connecting all the components according to the schematic and the output voltage was tested to confirm that it performed according to the design. The circuit was then moved from breadboard to a perfboard for a more robust and stable design, and then finally on a PCB. The circuit was then tested to validate the load and line regulation of the boost converter circuit.

For the battery charging circuit, the MCP73831 charge controller IC was used which employs a constant-current/constant-voltage charging method. The constant voltage regulation is at 4.2 V. The circuit was designed to provide a maximum charging current of 150 mA. So, a program resistor $R_{PROG} = 6.67 \text{ k}\Omega$ to limit the charging current to 150 mA. The formula for the program resistor and charging current is found from the MCP73831 datasheet and are calculated using the following equation:

$$R_{PROG} (\text{k}\Omega) = 1000 \text{ V} / I_{REG} (\text{mA})$$

So in order to limit the charging current of the battery to 150 mA, a program resistor should be 6.67 kΩ. The red LED on the board turns on when the battery is charging and will turn off when the battery is fully charged. A schematic for the charging circuit is shown below in Figure 2.

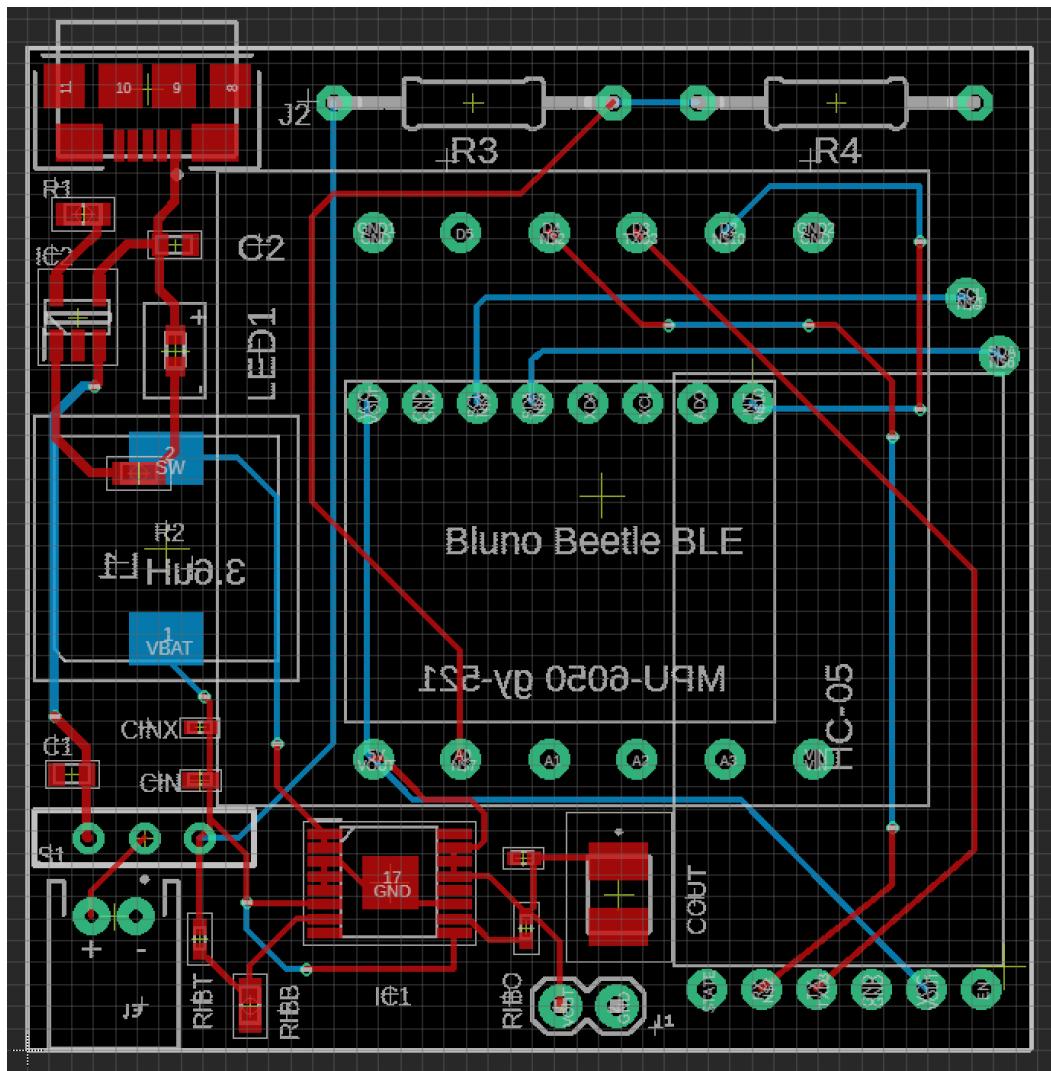
Figure 2: Schematic of Battery Charging Circuit



Smart Cricket Bat

A PCB was designed to provide connections between the power and control subsystems. The entire smart cricket bat device is on a single PCB. For the power subsystem, the boost converter and battery charging circuits were designed using surface mount components. There is a microUSB port on a PCB which can be used to recharge the LiPo battery. A PCB layout was designed using EAGLE and is shown in Figure 3.

Figure 3: PCB Layout



2.3. Subsystem Validation

The 5V DC-DC boost converter was tested for line regulation and load regulation. Line regulation is the ability of the power supply to maintain its specified output voltage over changes in input voltage. Load regulation is the ability of the power supply to maintain its specified output voltage over changes in the load. In this case, the output voltage of the boost converter should be able to maintain around 5V. Since a LiPo battery voltage ranges from 3V to 4.2V with a nominal voltage of 3.7V, the load and line regulation were tested for

input voltages of 3V which is the minimum, 3.7V the nominal voltage, and 4.2V the maximum voltage of the battery. The load current was varied from 0 to 300 mA using the electronics load equipment and the output voltages were measured. Table 1 to Table 3 shown below are the data collected from the test, and each table has a corresponding plot.

Table 1: Load Regulation with Input Voltage Vin =3V

Vin (V)	Vout (V)	Iout (A)
3	4.956	0
3	4.963	0.037
3	4.973	0.057
3	4.99	0.077
3	4.961	0.1
3	4.948	0.12
3	4.934	0.14
3	4.924	0.16
3	4.914	0.18
3	4.907	0.2
3	4.895	0.22
3	4.887	0.24
3	4.877	0.26
3	4.868	0.28
3	4.855	0.3

Figure 4: Load Regulation of Boost Converter Circuit with Vin =3V

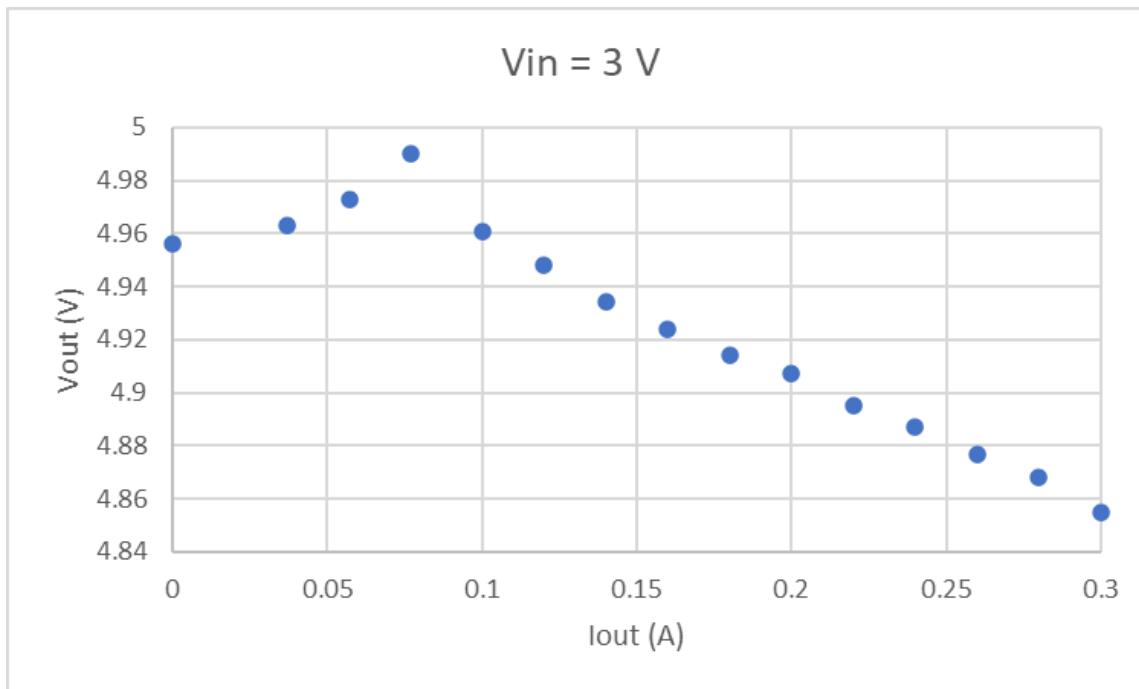


Table 2: Load Regulation with Input Voltage Vin =3.7V

Vin (V)	Vout (V)	Iout (A)
3.7	4.956	0
3.7	4.958	0.037
3.7	4.963	0.057
3.7	4.987	0.077
3.7	4.983	0.1
3.7	4.968	0.12
3.7	4.956	0.14
3.7	4.948	0.16
3.7	4.941	0.18
3.7	4.931	0.2

3.7	4.926	0.22
3.7	4.921	0.24
3.7	4.912	0.26
3.7	4.907	0.28
3.7	4.899	0.3

Figure 5: Load Regulation of Boost Converter Circuit with Vin =3.7V

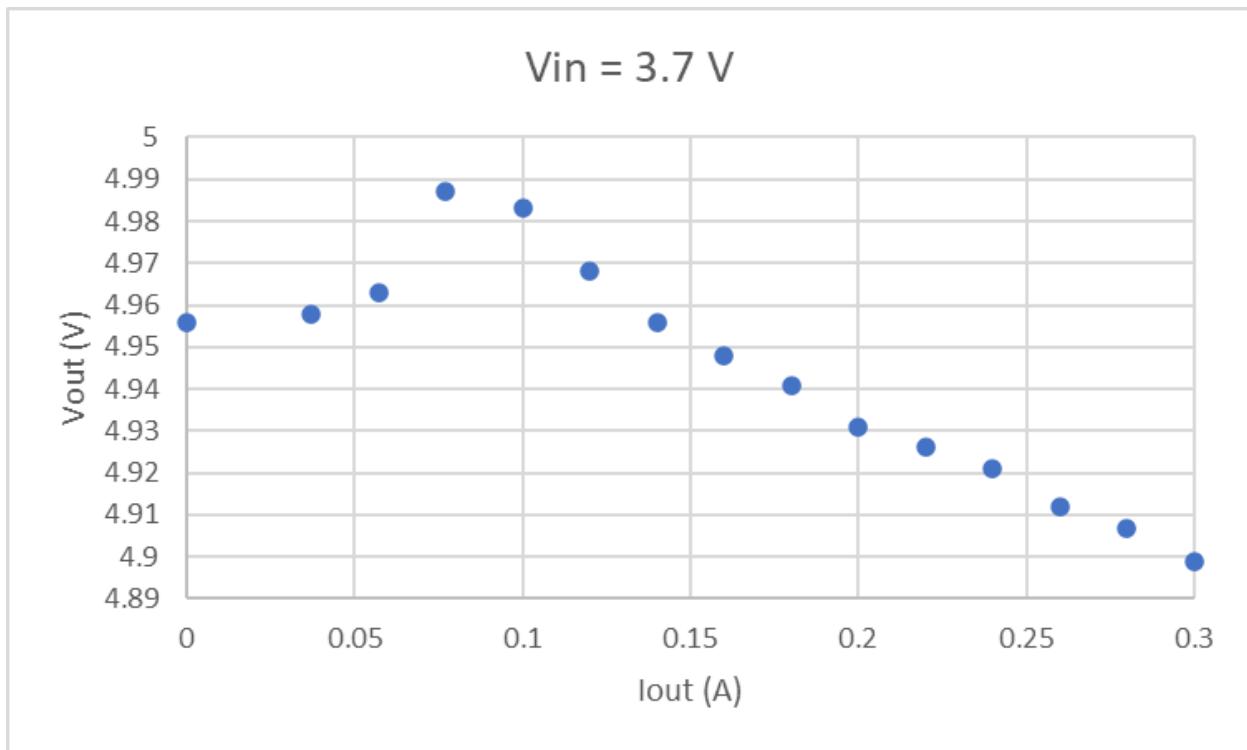
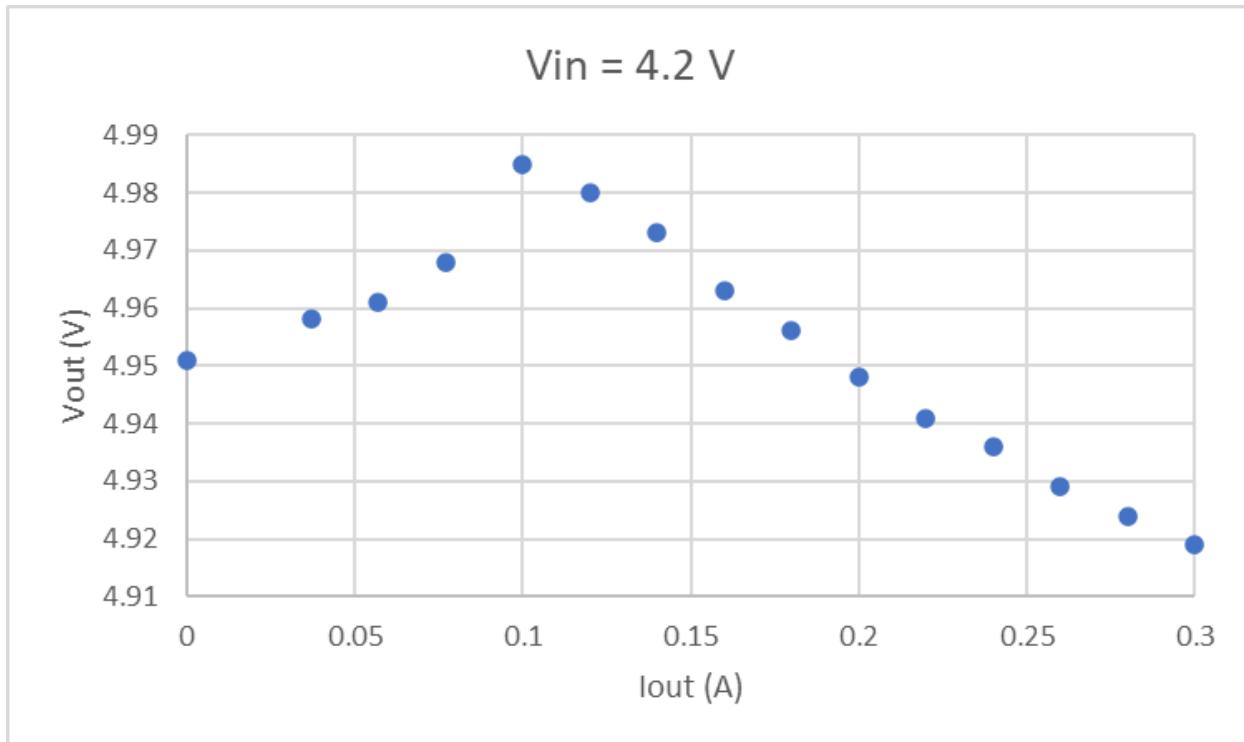


Table 3: Load Regulation with Input Voltage Vin =4.2V

Vin (V)	Vout (V)	Iout (A)
4.2	4.951	0
4.2	4.958	0.037
4.2	4.961	0.057
4.2	4.968	0.077

4.2	4.985	0.1
4.2	4.98	0.12
4.2	4.973	0.14
4.2	4.963	0.16
4.2	4.956	0.18
4.2	4.948	0.2
4.2	4.941	0.22
4.2	4.936	0.24
4.2	4.929	0.26
4.2	4.924	0.28
4.2	4.919	0.3

Figure 6: Load Regulation of Boost Converter Circuit with $V_{in} = 4.2V$



As can be seen from the tables and figures above, the output voltages are very close to 5V even when the input voltages are varied from 3V to 4.2V and the load currents are varied from 0 to 300 mA. The lowest output voltage is 4.855V when Vin = 3 V and load current is at the maximum 300mA, which is still close to 5V. From the data collected, the load and line regulation were calculated. The load regulation is calculated using the following formula:

$$Load\ regulation = \frac{V_{(no-load)} - V_{(full-load)}}{V_{(full-load)}} \times 100$$

The line regulation is calculated using the following formula:

$$Line\ regulation = \frac{\Delta V_{out}}{\Delta V_{in}} \times 100$$

Using the above formula and the data above, the load and line regulation are

$$Load\ regulation = \frac{V_{(no-load)} - V_{(full-load)}}{V_{(full-load)}} \times 100 = \frac{4.956 - 4.899}{4.899} \times 100 = 1.1635\%$$

$$Line\ regulation = \frac{\Delta V_{out}}{\Delta V_{in}} \times 100 = \frac{4.963 - 4.961}{4.2 - 3} \times 100 = 0.167\%$$

The values obtained from the load and line regulation calculations are small which means that the boost converter is well regulated. Thus, the ability for the boost converter to power the entire system containing MCU, IMU and bluetooth module was confirmed by the data collected and the calculations above, regardless of changes in the input voltage from 3V to 4.2V and load current from 0 to 300 mA.

The battery charging circuit was tested by measuring the battery voltage and charge current going into the battery. The circuit is designed to limit the maximum charge current at 150 mAh and the voltage at 4.2 V. When the voltage is supplied to the charging circuit, the charge current is at about 150 mAh as designed. When a certain voltage is reached, the voltage is regulated until current goes to zero. When this happens, the battery is fully charged and the red LED turned off. Table 4 shows the battery voltage and charge current. Figure 6 shows the plot corresponding to the data shown in Table 4.

Table 4: Battery Voltage and Charge Current

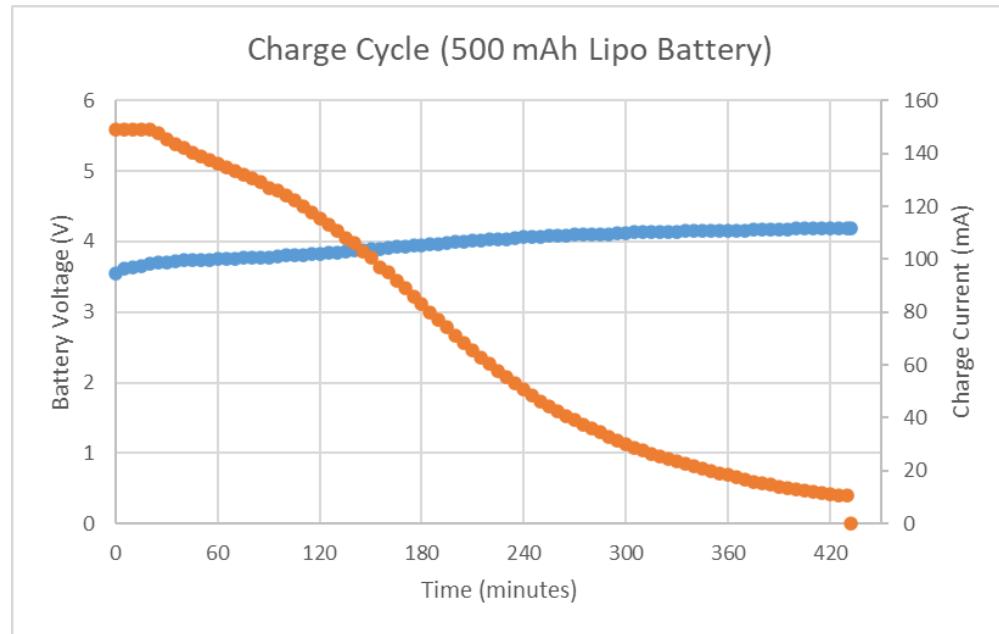
t (minute)	v (V)	I (mA)			
0	3.55	149.1	105	3.8	122.3
5	3.61	149.1	110	3.81	120
10	3.64	149.1	115	3.82	117.6
15	3.66	149.1	120	3.83	115.4
20	3.68	149.1	125	3.84	113.1
25	3.7	147.6	130	3.85	110.7
30	3.71	145.3	135	3.86	108.1
35	3.72	143.5	140	3.87	106
40	3.73	141.9	145	3.88	103.1
45	3.73	140.3	150	3.89	100.5
50	3.74	138.8	155	3.9	97
55	3.74	137.5	160	3.91	95.1
60	3.75	136	165	3.92	92
65	3.75	134.6	170	3.93	88.9
70	3.76	133.3	175	3.94	85.9
75	3.77	132	180	3.95	83
80	3.77	130.5	185	3.96	80
85	3.78	129	190	3.97	77
90	3.78	127.1	195	3.98	74.1
95	3.79	125.9	200	3.99	71.2
100	3.8	124.2	205	4	68.4
			210	4.01	65.7
			215	4.02	63
			220	4.03	60.4
			225	4.03	57.9
			230	4.04	55.4
			235	4.05	53
			240	4.06	50.7
			245	4.06	48.5
			250	4.07	46.4
			255	4.08	44.4
			260	4.08	42.6
			265	4.09	40.8
			270	4.1	39.1
			275	4.1	37.6
			280	4.1	36
			285	4.11	34.5
			290	4.11	33
			295	4.12	31.5
			300	4.12	30.2
			305	4.13	28.9
			310	4.13	27.7
			315	4.13	26.6
			320	4.14	25.5
			325	4.14	24.4
			330	4.14	23.5

335	4.15	22.6
340	4.15	21.7
345	4.15	20.8
350	4.16	19.9
355	4.16	19.2
360	4.16	18.4
365	4.16	17.4
370	4.16	16.8

375	4.17	16
380	4.17	15.4
385	4.17	14.7
390	4.17	14.1
395	4.17	13.6
400	4.18	13
405	4.18	12.6
410	4.18	12

415	4.18	11.6
420	4.18	11.2
425	4.18	10.8
430	4.18	10.5
432	4.18	0

Figure 7: Complete Charge Cycle (500 mAh Lipo Battery)



On the plot above, the blue color shows the battery voltage and the orange color shows charge current going into the LiPo battery. As can be seen from the table and the plot above, the LiPo battery can be recharged with the charging circuit. The charging circuit is confirmed to work according to the design.

2.4. Subsystem Conclusion

The DC-DC boost converter works as designed and was able to raise the voltage signal from a LiPo battery to about 5V at the output of the converter to power the entire device. A

Smart Cricket Bat

battery is able to last for approximately 6 hours when the device is on and can be recharged with a microUSB via the charging circuit.

3. Control Subsystem Report

3.1. Subsystem Introduction

Since the purpose of the sensing unit is to relay swing data to the machine learning for accurate analysis, it is critical to confirm that the inertial measurement unit, bluetooth module, and the control subsystem as a whole, operates correctly. To accomplish this, the microcontroller was programmed and wired to establish a connection to both the IMU and Bluetooth module. Once the two were interfacing with the microcontroller, each of the two axes of the IMU, the 3-axis gyroscope and 3-axis accelerometer, and the Bluetooth module were tested to validate that it performed as the manufacturer described.

3.2. Microcontroller and Bluetooth

3.2.1. Overview

The hardware of the control system supports interfacing between the IMU sensor and the commercial user application via a HC-05 Bluetooth module. And as the bridge between the two, is essential in the data collection process, so it must run continuously to support the entire system.

3.2.2. Operation

A Bluno Beetle BLE microcontroller is currently used as the control system to deliver data from the IMU sensor to the app. The Bluno Beetle has a sufficient number of pins and supply voltages to meet the requirements of the Smart Cricket Bat. The Bluno Beetle does have a Low-energy Bluetooth 4.0 module as well, however for the sake of ease and time, an HC-05 Bluetooth 3.0 Module was used instead.

The Bluno Beetle BLE has 4 Digital I/O pins, 4 Analog Input pins, and a pair of Serial Clock Line and Serial Data Line pins. It is also able to provide a 5V output supply to power the IMU and HC-05. This is more than enough to interface with all required modules, the single IMU sensor needs power, a pair of SDA and SCL pins, and a single digital pin for the interrupt. And the HC-05 module only requires power and a pair of RX and TX pins (however due to the design and placement of the RX and TX pins on the Bluno, 2 digital pins were used as replacement utilizing the SoftwareSerial library in Arduino IDE). The Bluno Beetle can be powered on a range of 5 to 8 V, which will be supplied by the power subsystems boost converter.

The key feature of the microcontroller is to function as the bridge between the sensor data and the phone application that connects to the cloud which holds the machine learning algorithm, it must be able to maintain this connection for the duration of a training session. Utilizing the HC-05 Bluetooth module, communication between the MCU and the user app

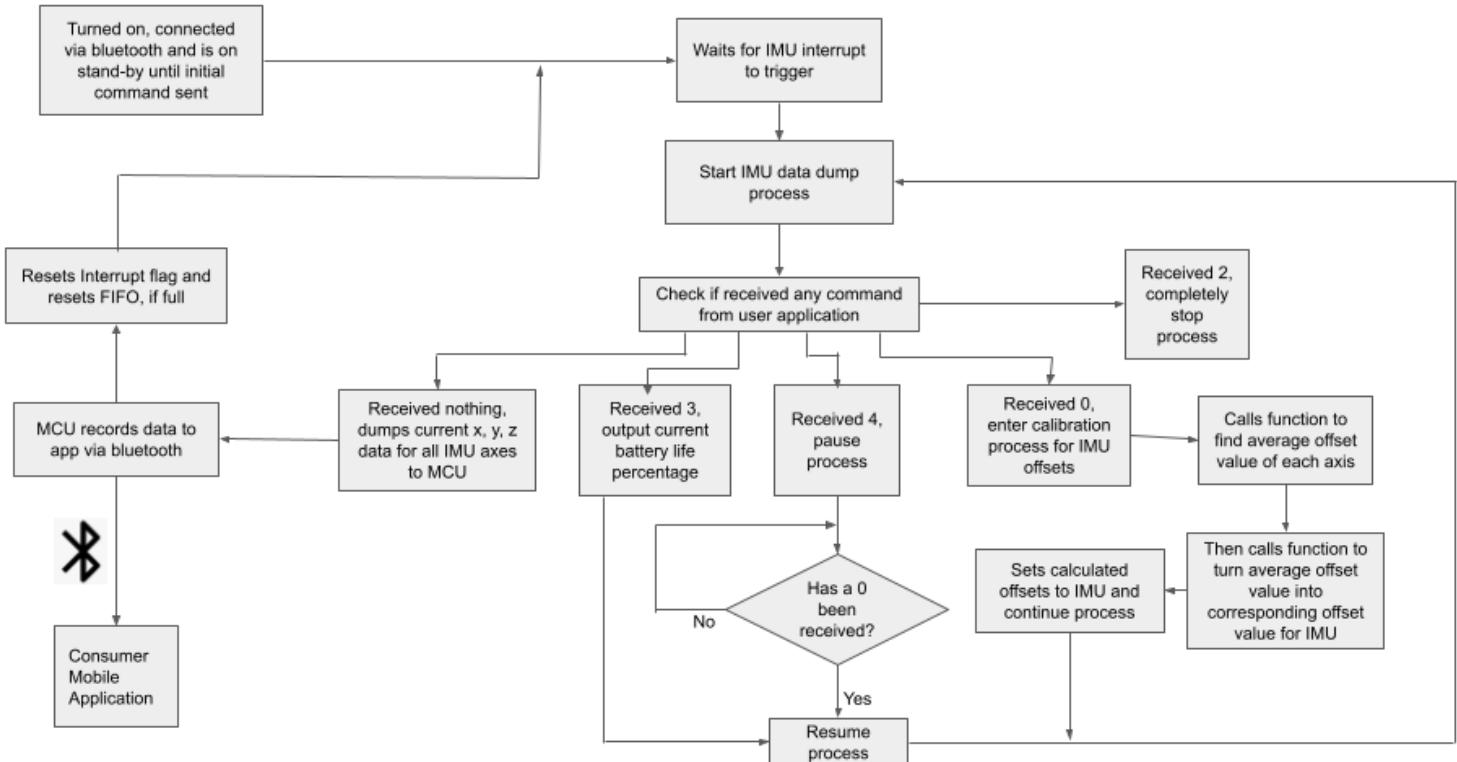
is stable and is able to reach a maximum distance of 240 feet (or approximately 74 meters). A PCB connects all control parts into a secure, robust design which is able to withstand the force of hits up to 200 gs. This is an important aspect of the Bluetooth design, as any physical connection issues on the board can affect the data transfer of any of the 3 main components, MCU, IMU, or the Bluetooth module. Specifically any connection issues on the RX/TX pins will cause discrepancies in the data sent from IMU to the application, leading to issues when trying to be processed by the machine learning algorithm. The PCB itself has dimensions of 45.7mm by 45.7mm, with only 2 layers, top and bottom.

3.2.3. MCU Validation

The control system was validated to meet all requirements. Since its primary function is to communicate with the application subsystem, it was validated by first linking and pairing with a laptop to confirm the HC-05 bluetooth module was operating as intended. Then to confirm the code written for the MCU to receive and send data works as intended with standard bluetooth, a dummy sketch was written to send dummy values when requested by phone via bluetooth.

The flowchart in figure 8 shows the logical operation of how the microcontroller goes about gathering the IMU data, interpreting user input, and delivering the data to the consumer application.

Figure 8: Flow Diagram of Microcontroller Logic



Smart Cricket Bat

Something not shown in the flowchart is the fact that for the IMU, the interrupt is constantly triggered after the first trigger, so within the code is a buffer step that checks for more data dumps from the IMU before the MCU checks the interrupt again allowing for quicker revolving of data. However, this on paper functions the exact same way as checking the interrupt each time, so it can be thought of the same way to avoid unnecessary confusion.

This logic was successfully executed on the Bluno Beetle with the validated IMU sensor results in turn validating the microcontroller.

3.2.4. Bluetooth Validation

The HC-05 Bluetooth module's connection distance was validated by writing a dummy sketch that simply connects the device to a laptop, and when prompted by a user input sends the current distance between the device and the laptop. This is done in intervals of 10 ft and was corroborated by walking with a measuring tape to insure exact distance that the bluetooth loses connection which was at approximately 220 ft to 240 ft, this test was done multiple times hence the range of give or take 20 ft. The received messages from the device at each 10 ft interval can be seen in figure 9, the figure also acts as the evidence to show the effect of a connection issue on the RX and TX pins of the Bluetooth module. One can notice the gaps in the strings caused by insufficient connections being unable to fully send the expected data.

Figure 9: Bluetooth Distance Validation

```

COM6
14:45:28.211 -> BT connection at: 10 ft
14:45:59.332 -> BT connection at: 20 ft
14:46:32.348 -> BT connection at: 30 ft
14:48:49.184 -> BT connect ft
14:49:28.085 -> Btion at: 50 ft
14:50:18.726 -> BT connection at: 60 ft
14:52:31.356 -> BT connection at: 70 ft
14:53:30.461 -> BT connection at: 80 ft
14:54:43.617 -> BT connection at: 90 ft
14:56:12.299 -> Bion at: 100 ft
14:58:25.228 -> BT connection at: 110 ft
14:59:28.717 -> BT connection at: 120 ft
15:01:02.842 -> BT connection at: 130 ft
15:02:11.232 -> BT connection at: 140 ft
15:03:25.615 -> BT connection at: 150 ft
15:05:20.859 -> BT connection at: 160 ft
15:07:03.971 -> BT connection at: 170 ft
15:08:31.987 -> BT connection at: 180 ft
15:10:15.585 -> B90 ft
15:12:56.856 -> BT connection at: 200 ft
15:14:36.078 -> BT connection at: 210 ft
15:15:46.228 -> BT connection at: 220 f

```

Autoscroll Show timestamp Newline 9600 baud Clear output

Figure 10: Bluetooth Data Transfer Validation

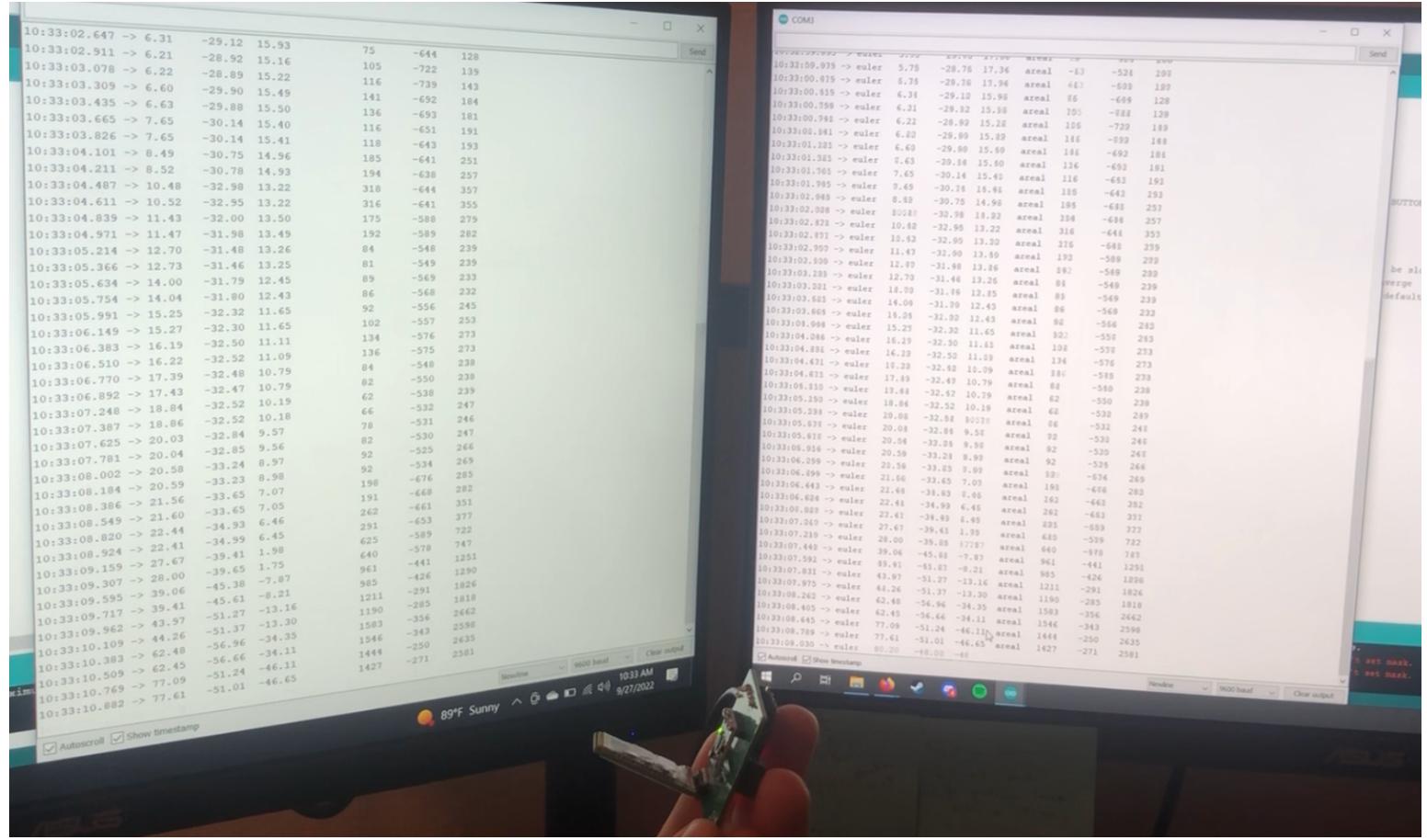


Figure 10 shows the data being sent via bluetooth to a laptop and the right shows the data being received through a mircoUSB via the serial interface. These two communication windows are receiving the same information with the left being at a delay of approximately 2 micro seconds. This shows the data sent via bluetooth has no discrepancies in data and is being received as expected.

3.3. Gyroscope

3.2.1. Operation

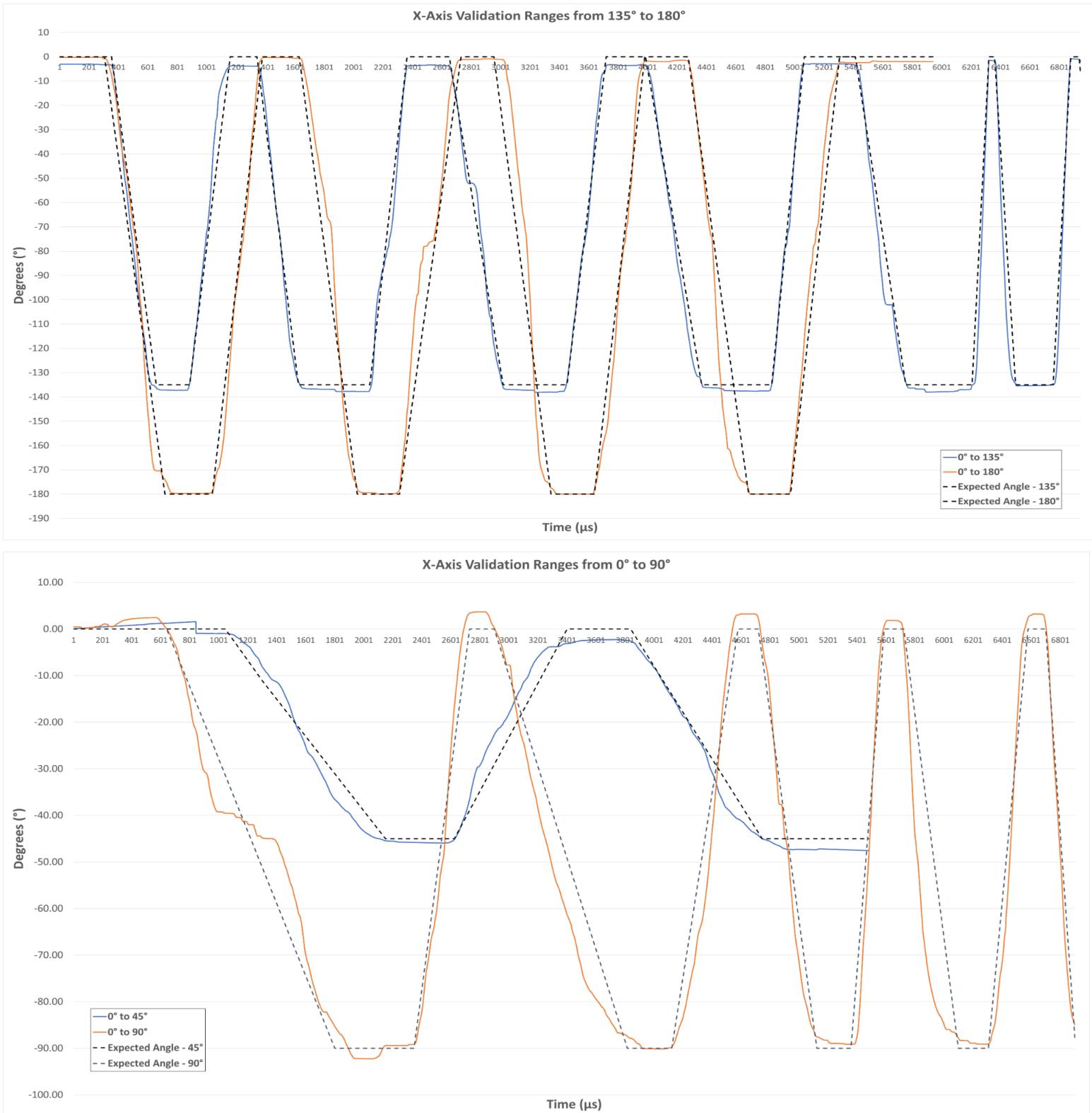
The inertial measurement unit used is a gy-521 board that uses an MPU-6050. The MPU-6050 has both a gyroscope and accelerometer inside, this was chosen for two option, one was to save on space as the design must stay small and unobtrusive, and two, its best if the gyro and accelerometer axes are lined up and this is are to do with two separate devices. For the gyroscope, it has 4 full scale ranges, ± 250 , ± 500 , ± 1000 , ± 2000 $^{\circ}/sec$ with the sensitivity being 131, 65.5, 32.8, 16.4 LSB/ $^{\circ}/sec$, respectively. For the purposes of the Smart Cricket Bat, the range will stay at the default range of ± 250 $^{\circ}/sec$, which has a noise rate of 0.005 mdps/rHz.

The gyroscope uses an I2C interface, which allows the microcontroller to take the measurements in via the serial clock and serial data lines. This is the standard way I2C devices communicate, by transmitting data that are 9 bits long along these 2 lines.

3.2.2. Validation

The gyroscope's angle accuracy was validated by attaching the gyroscope to the center of a protractor and rotating the protractor to the desired degree and comparing that to and confirming that the gyroscope's readings were accurate. This was done for each axis of the gyroscope, the x and z-axes from angle ranges of 0-45°, 0-90°, 0-135°, 0-180°, 0-215°, 0-270°, 0-305°, 0-360°, while the y-axis was done in the same method but only to 180° as that is the limit of that axis before the angle wraps back around. Below are all the plots of the validation, in color is the actual rotation received from the IMU and the black dashed line is the expected angle estimated from the protractor used during the process.

Figure 11: X-Axis Gyroscope Validation



Subsystem Report

Smart Cricket Bat

Revision - 1

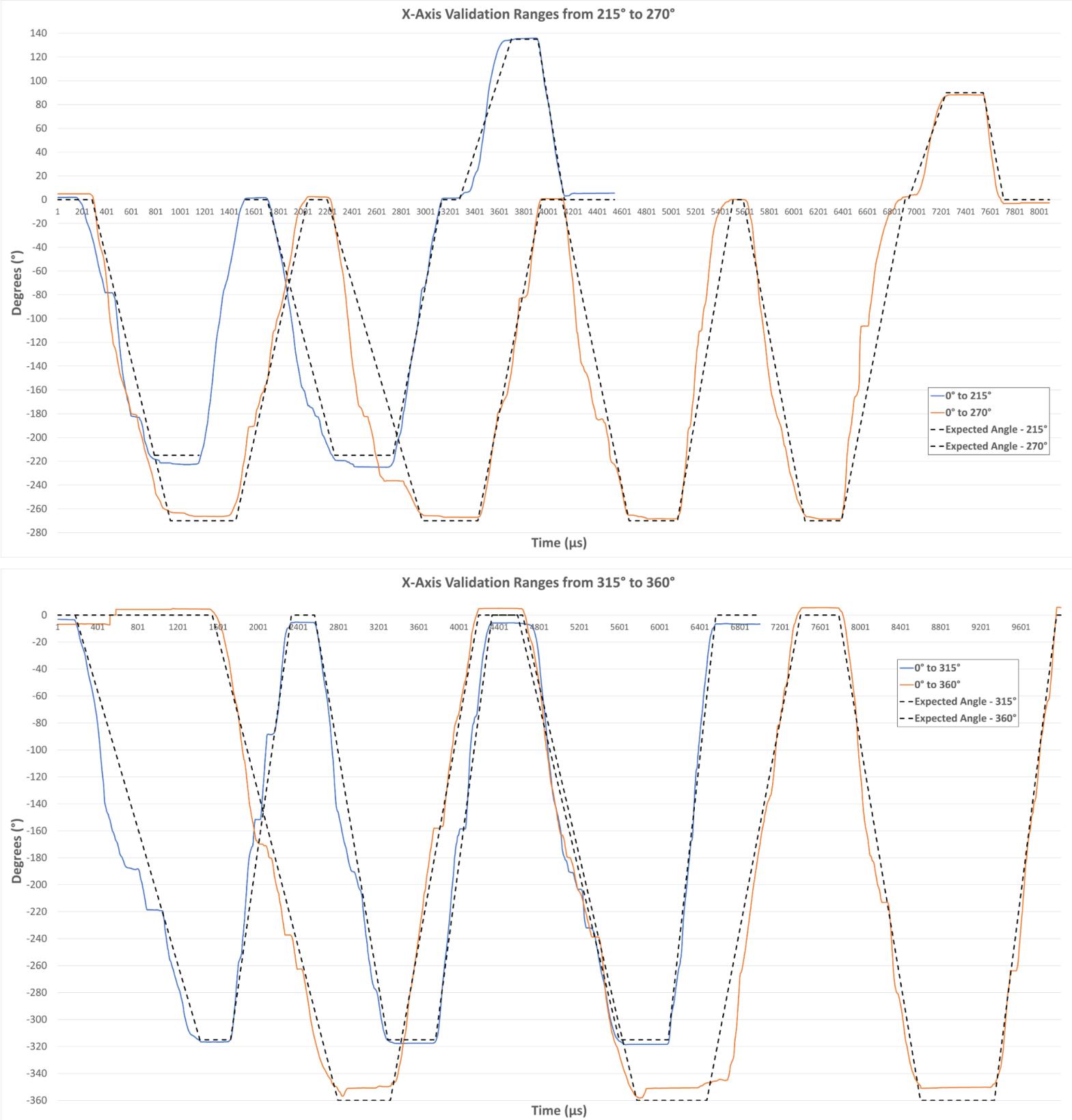


Figure 12: Y-Axis Gyroscope Validation

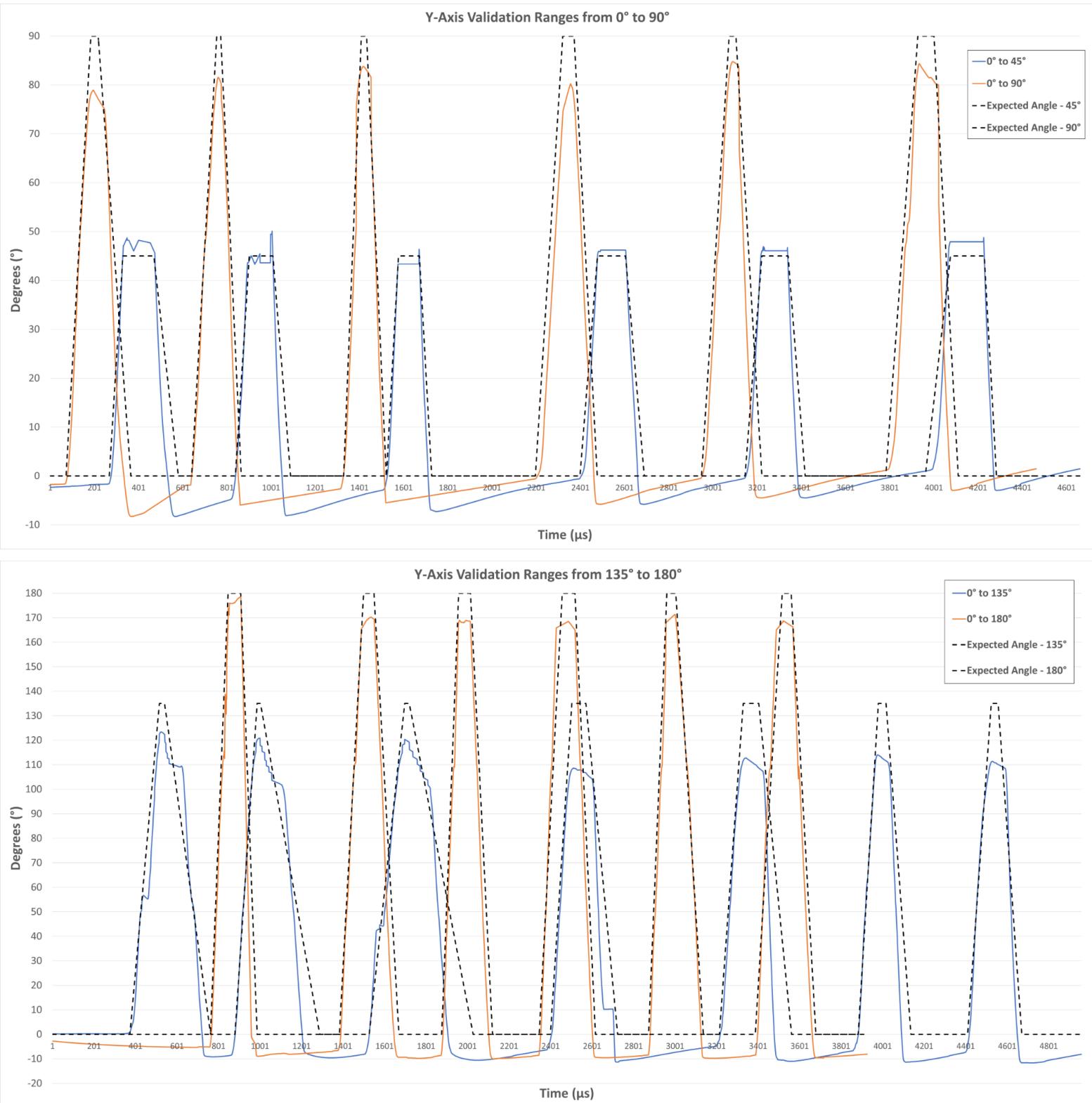
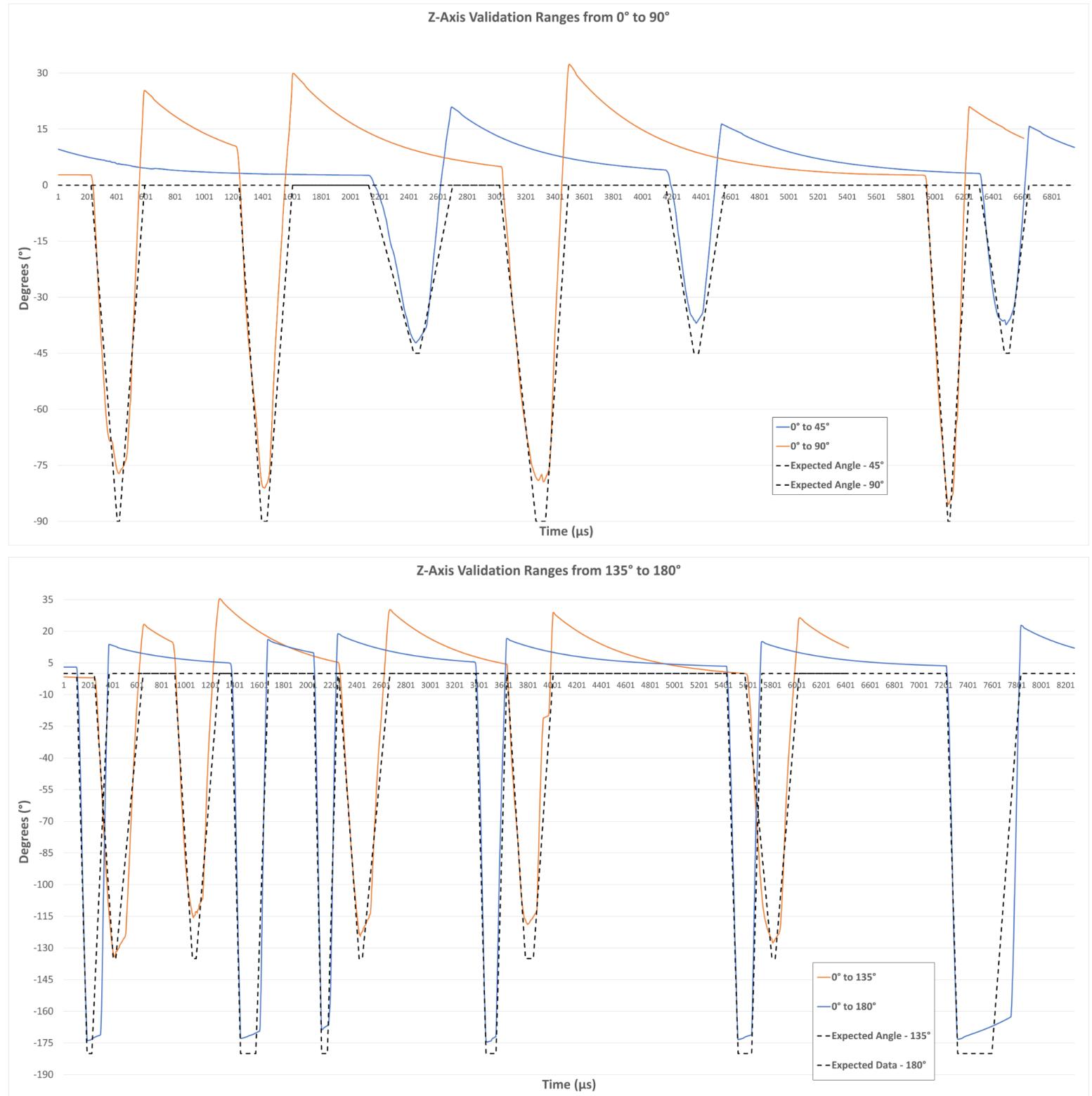


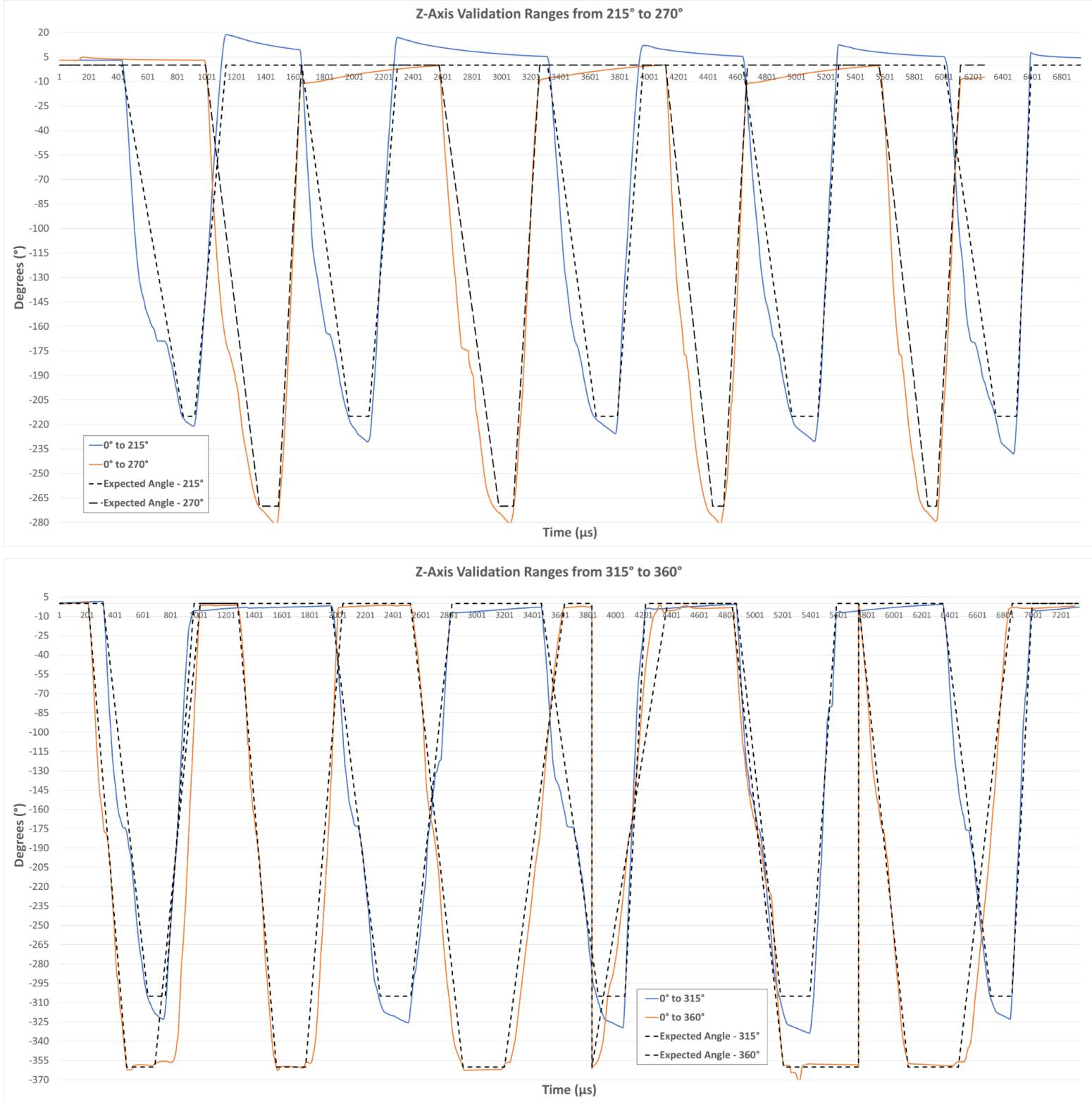
Figure 13: Z-Axis Gyroscope Validation



Subsystem Report

Smart Cricket Bat

Revision - 1



Notice, the graphs for the y and z axes drift a bit more when compared to expected angle, which causes them to lose track of where they started, being 5° to 10° off on return most of the time, with the outlier of an offset of nearly 35° for the z-axis during its 90° test. However,

Smart Cricket Bat

this won't be much of an issue as most swings won't start at 0° anyway and most swings will be moving fast enough that the drift will not have time to start taking effect. And the machine learning algorithm will already be subtracting the starting degree from the finished degree to get the true angle of the bat instead of what's given. The angle is also only important for giving the simple tilt of the bat on impact and to calculate the torque seen by the bat.

Through extensive validation, the gyroscope within the IMU is confirmed to be working as intended and gives the accurate degrees of change, within a given margin, for the system.

3.4. Accelerometer

3.4.1. Operation

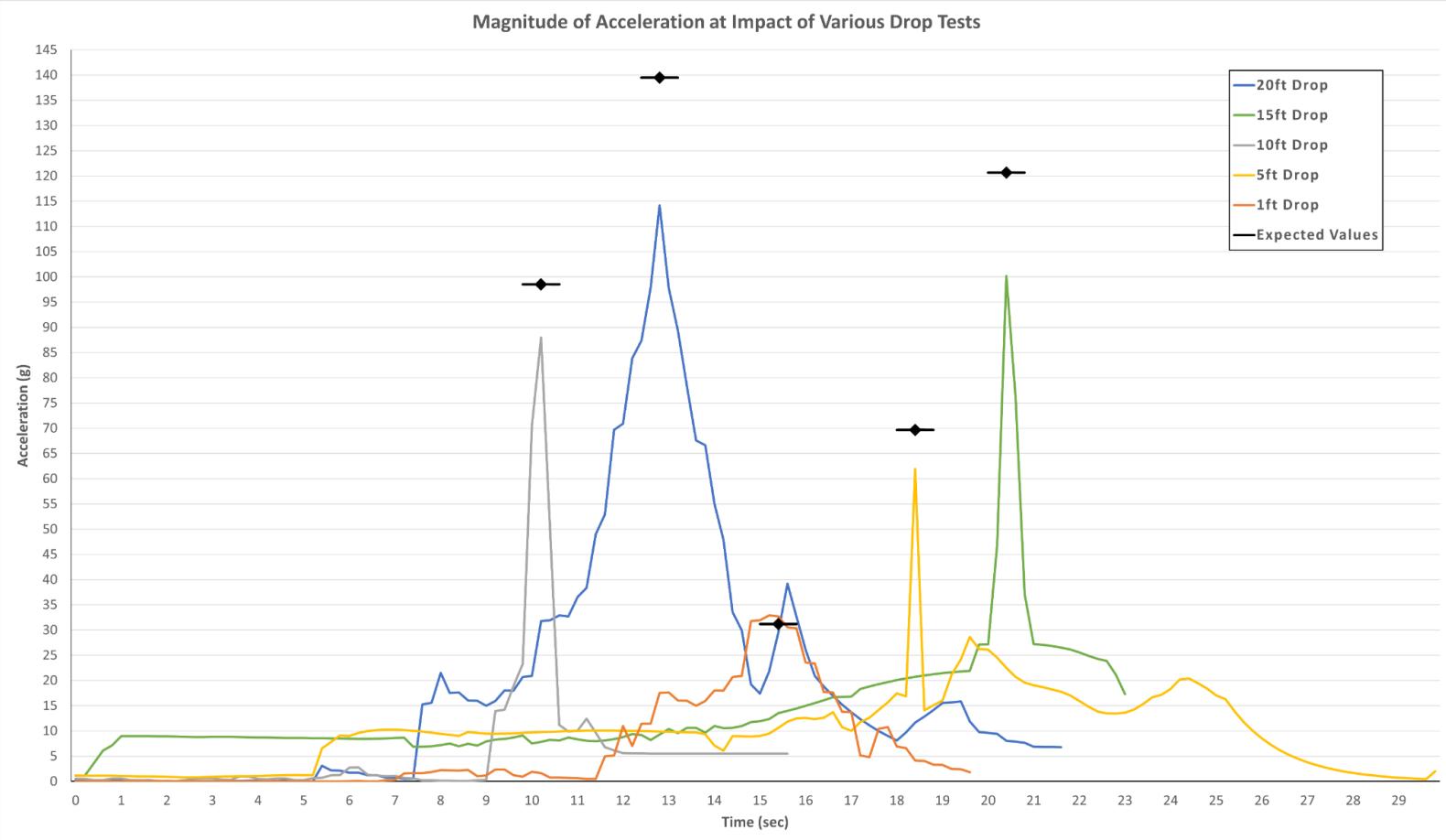
The inertial measurement unit used is a gy-521 board that uses an MPU-6050. For the accelerometer, it has 4 full scale ranges, ± 2 , ± 4 , ± 8 , ± 16 g with the sensitivity being 16384, 8192, 4096, 2048 LSB/g, respectively. The raw data received from the accelerometer is in terms of least significant bit per g (LSB/g) and must be divided by the sensitivity to get the data in terms of g's. For the purposes of the Smart Cricket Bat, the range will be the range of ± 8 g, which has a noise rate of 0.005 mdps/rtHz. This range and sensitivity was decided to give the best accuracy for our machine learning algorithm after testing all individually.

The accelerometer uses an I2C interface, which allows the microcontroller to take the measurements in via the serial clock and serial data lines. This is the standard way I2C devices communicate, by transmitting data that are 9 bits long along these 2 lines.

3.4.2. Validation

To validate the accelerometer, the device was dropped from 5 different heights ranging from 1 to 20 feet, in intervals of 5ft. The device was put into a padded box and dropped from each height respectively while sending the IMU data during the fall to the laptop to record said data. With this in mind, the following graph was produced from the magnitude of the acceleration of the x, y, and z axes when falling and hitting concrete from heights at 1, 5, 10, 15, and 20 feet. The collared plots are of the actual data gathered from the IMU during its fall and the black line is the expected value of each drop found through calculations.

Figure 14: Falls from Various Heights Accelerometer Validation



Compare these values to what the expected acceleration during the collision should be, based on calculations done using an estimated collision time of 10ms and the assumption that the device loses about 75% of its acceleration after the collision. When performing the validation previously there was a problem with the acquired values being a magnitude of 10 smaller than the expected values, this problem was rectified by redoing the conversion calculations from the IMUs LSB/g unit to meters per second and finding that a step involving multiplying by gravity was missing. With the corrected data one can notice that the measured results get further and further from the expected results the impact force increases, likely due to the sudden change that causes said impact becoming too quick for our IMU to accurately measure. Even still, the acquired data is much closer and within an acceptable range of the calculated expected value to claim it gives accurate enough reading for our purposes.

Method Used to Calculate gs

Use Kinetic Energy to find velocity right before collision:

$$KE = \frac{1}{2}mv^2 \rightarrow v_1 = \sqrt{2gh} = \sqrt{2 * 9.81 * h}$$

Use velocity to find acceleration during collision, assume $t = 10\text{ ms}$ & $v_2 = \frac{v_1}{4}$:

$$a = \frac{v_2 - v_1}{t} = \frac{\frac{\sqrt{2*9.81*h}}{4} + \sqrt{2*9.81*h}}{0.01}$$

Finally, convert acceleration from m/s^2 to gs :

$= a/9.81 \rightarrow$ gives acceleration during collision in terms of g

Table 5: Accelerometer Measured Vs Calculated Acceleration

Dropped Height	Calculated Acceleration	Measured Acceleration
1 ft	31.191 g	32.88 g
5 ft	69.673 g	61.95 g
10 ft	98.534 g	87.94 g
15 ft	120.681 g	100.19 g
20 ft	139.494 g	114.19 g

After comparing the two data sets it can be inferred that the accelerometer gives consistent data that is representative of the overall changes in acceleration, within a margin of error. This is more than passable for the purposes of the Smart Cricket Bat, as it only needs the relative gs enacted on the bat by the ball in a given section, relative to the other sections.

3.5. Housing Unit

The housing unit consists of 2 elements, the mounting mechanism and the housing unit for the power system and control system. The housing unit is 3-D printed using PLA material and is 50mm in height (plus 30mm as the height of the mounting unit, which will attach to part of the bat handle) with a radius of 34mm. The housing unit holds the PCB, which includes the MCU, IMU, HC-05 Bluetooth Module and the battery boost/charging circuit, has a small slit for access to the microUSB to charge said battery, and is attached to the handle via a connector with 2 prongs to firmly connect the two pieces. Through the process of collecting data, validation, and various drop/shock tests, the housing unit has proven to be robust enough to withstand the average hits and shocks that are to be expected from a cricket bat while in use. The housing unit is moderately unobtrusive, however depending on the hand placement of the user and swing follow-through, the device might be considered in the way. This is mostly a consequence of switching to the HC-05 module as it has a height

Smart Cricket Bat

of 38mm which inflates the overall height of the housing unit by 30mm, as without it the PCB only has a height of approximately 8mm. The device as a whole weighs approximately 85.91 ± 0.01 grams, which is within range specified for unobtrusive weight, which was no more than 100 grams.

The housing unit also has a few features for the user's convenience. The most important is that the unit has an alignment divot used to properly attach the device to the bat, the divot should align with the backside line of the bat to ensure machine learning can accurately calculate the position of the hit. The device also has an easy to use switch with two settings, on and charging. The unit's charging port is to the left of the alignment divot and above it is a window to be able to confirm the device is either on or charging. The housing unit is a closed box that the user will not have easy access to, however for image purposes the lid is taped to the unit to show a top down perspective.

Figure 15: Picture of Housing Unit On and Off Bat



3.6. Subsystem Conclusion

The Bluno Beetle BLE microcontroller works as designed and is able to utilize a classic bluetooth module, the HC-05, to link and pair with a mobile device. Each of the sensors on the MPU-6050 operate as designed. Despite some small discrepancies in the behavior of the IMU, the sensors function well within the scope of what the Smart Cricket Bat will need them to. The housing unit is robust and as unobtrusive as possible within the current limitations of the PCB. The microcontroller and sensors are a critical part of the overall system, and their ability to integrate with the consumer application ensures that they will be able to continuously collect data for processing.

4. App Subsystem Report

4.1. Subsystem Introduction

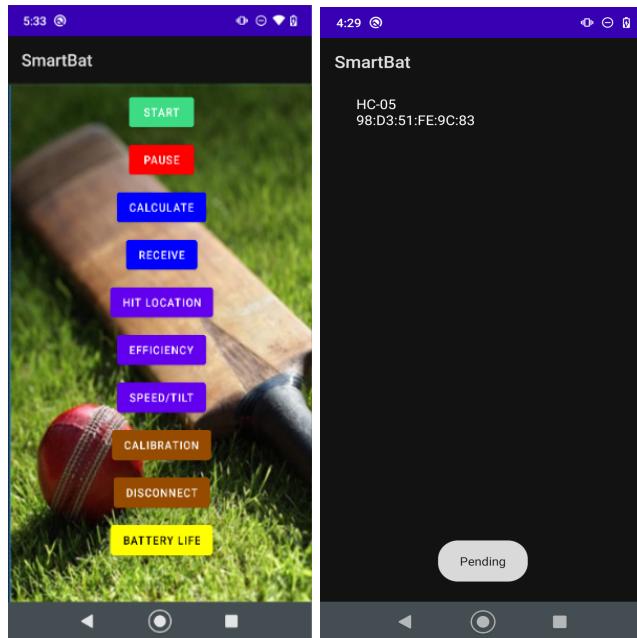
The android app has two main functions: communication between the control subsystem and the ML algorithm and handling user interaction. The app will receive the swing data gathered by the MCU via a bluetooth connection which will then be sent to the ML algorithm, that will run on a AWS ec2 instance, to be processed. Once processed and results have been received, the user can navigate through different pages of the app by clicking various buttons on the dashboard to view their results. Each page will consist of a certain data output i.e. hit location, efficiency, or swing speed. The app is user friendly and requires minimal technical skill to use our product.

4.2. Subsystem Details

4.2.1. Bluetooth Communication

As previously mentioned, the android app will handle the communication between the ML algorithm that will run on AWS cloud computer(EC2) and the control subsystem. To establish a bluetooth connection between the MCU, we will be using an HC-05 Bluetooth module. As soon as the user opens up the app, a list of their paired devices will appear on their screen to allow the user to connect to our device. The device list will show the device name as well as its MAC address. Once connected the paired device list will collapse to display the dashboard. To begin data collection, Before each swing, the user will press the designated “start” button on the dashboard that will then send a signal to trigger the MCU to send the swing data. Once the user has completed their swing, they press the “Stop” button to conclude their data collection. Apart from receiving data from the MCU, that app will also send trigger signals via bluetooth to the MCU to begin system calibration and determine the battery life of the device. Every time the device is first powered on the device must be calibrated by pressing the “Calibration” button on the dashboard. The app will then prompt the user with the calibration status and when the calibration is complete. To view the battery life percentage of the device, the user must press the “Battery Life” button on the dashboard. An image of the dashboard and bluetooth page is shown below. An image of the dashboard and paired devices list is shown in Figure 16.

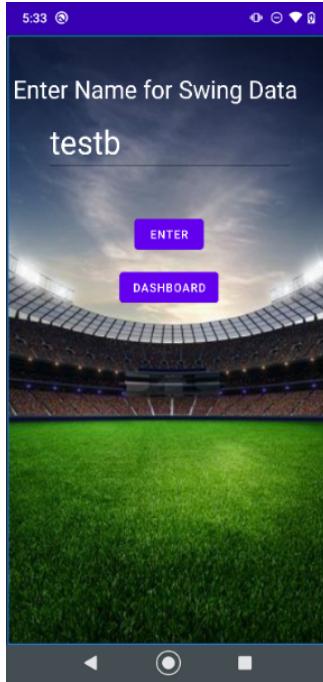
Figure 16: Dashboard and Paired Devices list



4.2.2. Sending Gathered Data to Cloud

Once the user has concluded their data collecting for the swing, they can press the calculate button to open up a window to allow them to enter a name they would like to give the data. The user has been given control of what name they would like to name their swing data to be able to know which data they are viewing the AWS cloud database. The Data sending page along with an example of a name is shown in Figure 17. Once they have entered a name, the user can press the “Enter” button and they will be prompted that data was sent to the AWS cloud database. The user can now press the dashboard button to return to the dashboard.

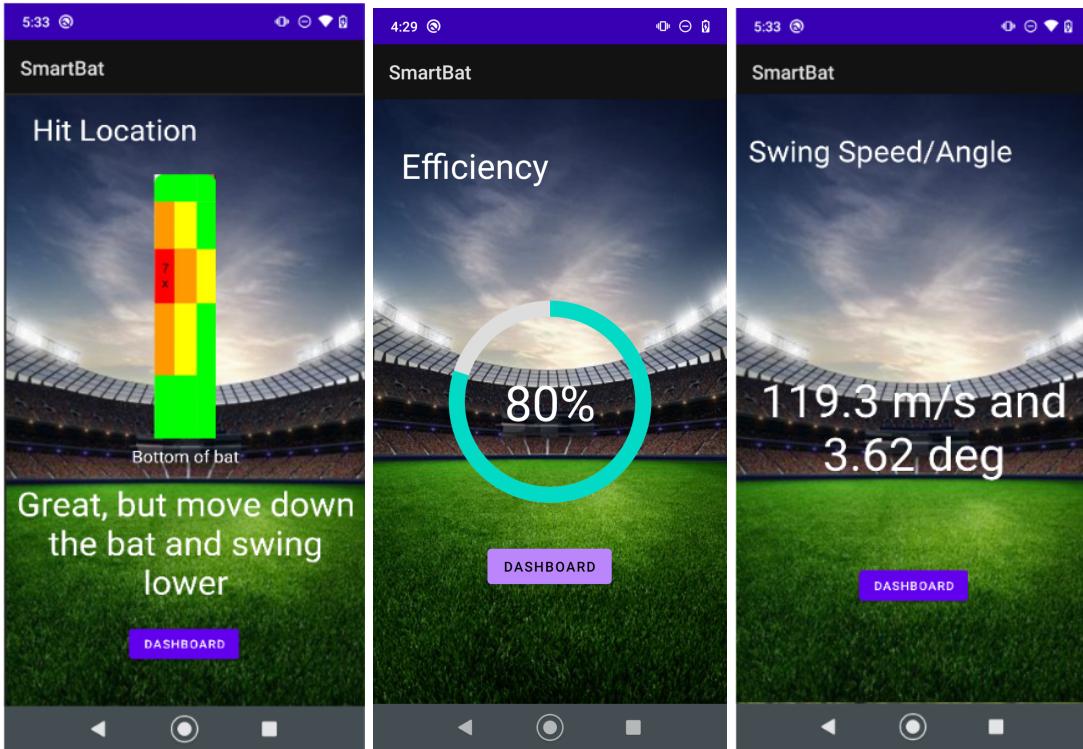
Figure 17: Data sending to AWS cloud page



4.2.3. User Interaction / Dashboard

The user interaction is controlled by the dashboard seen in Figure 16. Each button is named corresponding to the result type it will output. The dashboard was designed to gather all the results calculated by the ML algorithm and send them to the individual pages once the user presses the “Receive” button. The user can now view their results by pressing the designated buttons. The result types are as follows: Hit Location, Efficiency, Swing Speed and Tilt. The most important page is the hit location. In this page the user will be given the region where the collision with the ball occurred in the form of a heat map where the most probable hit location is shown in red. The regions are numbers 1 through 15, where 1 is near the tip of the bat and 15 is closer to the handle of the bat. These regions will be marked on the bat. Depending on which region the ball hit, the user will be given advice as to how to get closer to the “sweet spot” of the bat. An example of the swing results being displayed in their corresponding page is shown in Figure 18. In this example the user struck region 7 with a speed of 119.3 m/s and tilt of 3.62 degrees. This region is near the “sweet spot” of the bat on the lower edge, therefore the advice in the hit location page states “Great, but move down the bat and swing lower”. The location was near the sweet spot but on the lower edge, so the player needed to swing lower to get closer to the center of the bat. Since the collision was close to the “sweet spot” of the bat (region 8), but a bit off, its corresponding efficiency is 80%. The user can then navigate back to the dashboard by clicking on the dashboard button displayed on each page.

Figure 18: User Feedback/Results

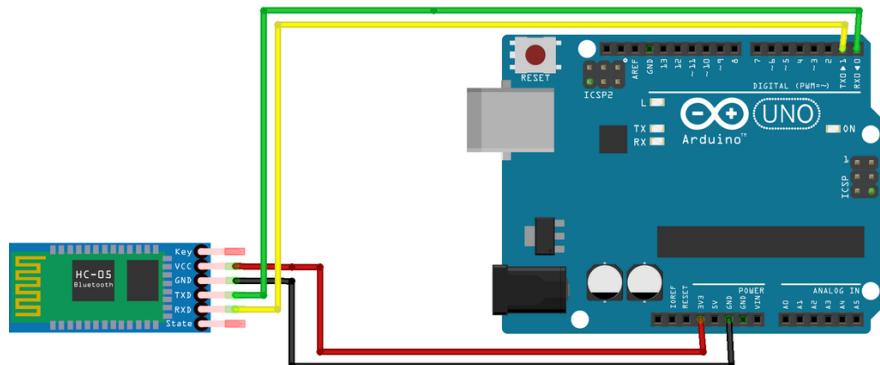


4.3. Subsystem Validation

4.3.1. Validation From 403

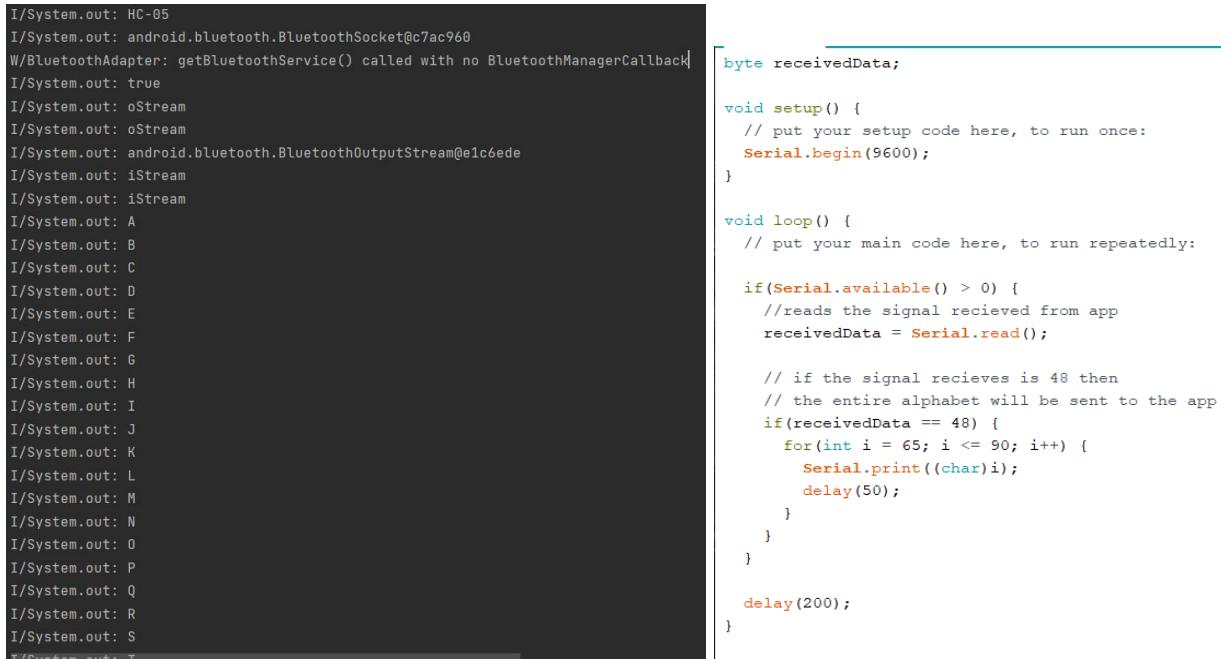
Since the MCU, the Bluno Beetle, uses the Arduino IDE and schematic, I separated the HC-05 bluetooth module and connected it to an Arduino Uno to be able to validate without needing the control subsystem. The circuit that will be used to connect the HC-05 module with the Arduino and Bluno Beetle is shown in Figure 19.

Figure 19: HC-05 Bluetooth Module Circuit



To validate the bluetooth connectivity and data sending between the MCU and the android app, the MCU was programmed to send the entire alphabet once the app sent an input of 48 signifying the ASCII code for the character ‘0’. An image of the console output showing data being received by the android app is shown in Fig. 20. The console also shows which device the app is connected to and whether we are connected to the bluetooth socket created. An image of the simple arduino code is also shown in Fig. 20.

Figure 20: Bluetooth Validation Data and Arduino Code



```
I/System.out: HC-05
I/System.out: android.bluetooth.BluetoothSocket@c7ac960
W/BluetoothAdapter: getBluetoothService() called with no BluetoothManagerCallback
I/System.out: true
I/System.out: oStream
I/System.out: oStream
I/System.out: android.bluetooth.BluetoothOutputStream@e1c6ede
I/System.out: iStream
I/System.out: iStream
I/System.out: A
I/System.out: B
I/System.out: C
I/System.out: D
I/System.out: E
I/System.out: F
I/System.out: G
I/System.out: H
I/System.out: I
I/System.out: J
I/System.out: K
I/System.out: L
I/System.out: M
I/System.out: N
I/System.out: O
I/System.out: P
I/System.out: Q
I/System.out: R
I/System.out: S

byte receivedData;

void setup() {
    // put your setup code here, to run once:
    Serial.begin(9600);
}

void loop() {
    // put your main code here, to run repeatedly:

    if(Serial.available() > 0) {
        //reads the signal received from app
        receivedData = Serial.read();

        // if the signal receives is 48 then
        // the entire alphabet will be sent to the app
        if(receivedData == 48) {
            for(int i = 65; i <= 90; i++) {
                Serial.print((char)i);
                delay(50);
            }
        }
        delay(200);
    }
}
```

4.3.2. Validation From 404

4.3.2.1. Bluetooth Validation

To validate the bluetooth connectivity and data sending between the MCU and the android app, a temporary page was added to the app to view the data that is being sent via bluetooth once the “Send” button is pressed on the temporary page. An image of the device next to the app displaying the data being sent via bluetooth in the temporary page is shown in Figure 19. The app was also programmed to display the data received to the Android Studio console as another form of validation. The data received should be composed of seven columns. First column is the time in milliseconds. The next three columns are the XYZ data of the Gyroscope, and the last three columns are XYZ data of the Accelerometer. A screenshot of the Android Studio console displaying the proper seven data columns is shown in Figure 20.

Figure 21: Bluetooth Validation with Temporary Page

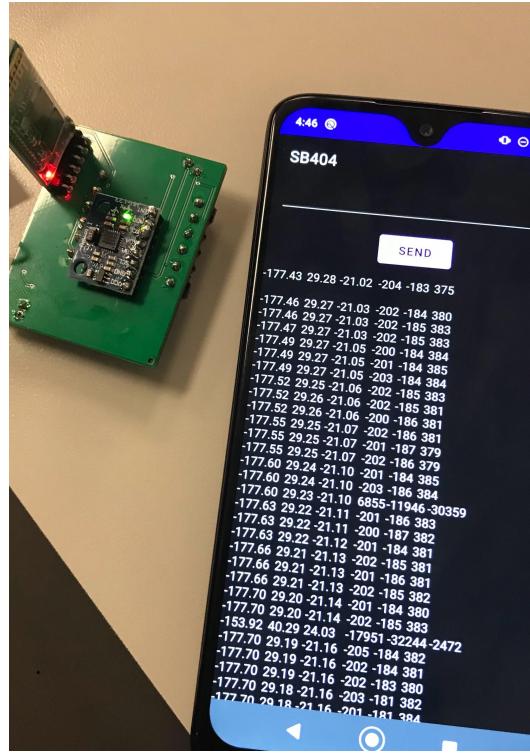


Figure 22: Android Studio Console Displaying Proper Data

Time	Gyro: XYZ	Acce: XYZ
I/System.out 100414	0.00 -0.24 -0.20	1135 -2052 -5713
I/System.out 100414	0.00 -0.24 -0.20	1135 -2052 -5713
I/System.out 100770	-0.88 -9.51 12.95	2307 -4828 819
I/System.out 100414	0.00 -0.24 -0.20	1135 -2052 -5713
I/System.out 100770	-0.88 -9.51 12.95	2307 -4828 819
I/System.out 100924	-0.91 -9.69 13.21	2282 -4792 830
I/System.out 100414	0.00 -0.24 -0.20	1135 -2052 -5713
I/System.out 100770	-0.88 -9.51 12.95	2307 -4828 819
I/System.out 100924	-0.91 -9.69 13.21	2282 -4792 830
I/System.out 101178	-2.09 -15.34 21.53	1530 -3710 1341
I/System.out 100414	0.00 -0.24 -0.20	1135 -2052 -5713
I/System.out 100770	-0.88 -9.51 12.95	2307 -4828 819
I/System.out 100924	-0.91 -9.69 13.21	2282 -4792 830
I/System.out 101178	-2.09 -15.34 21.53	1530 -3710 1341
I/System.out 101434	-2.70 -18.05 25.50	1203 -3226 1660
I/System.out 100414	0.00 -0.24 -0.20	1135 -2052 -5713
I/System.out 100770	-0.88 -9.51 12.95	2307 -4828 819
I/System.out 100924	-0.91 -9.69 13.21	2282 -4792 830
I/System.out 101178	-2.09 -15.34 21.53	1530 -3710 1341
I/System.out 101434	-2.70 -18.05 25.50	1203 -3226 1660
I/System.out 101691	-3.09 -20.16 28.49	969 -2872 1932

4.3.2.2. Data Sending to S3 bucket Validation

To validate and ensure proper data sending to AWS Amplify API that stores our data in the cloud, the user was given control of what they would like to name the data they collected after each swing. This will allow them to match the name they entered to the name of data shown in AWS Amplify API. A screenshot of the data sending to AWS Amplify API app page with a name of “testb” for the data is shown in Figure 15. Once the user presses the “Enter” button, the App will then send the collected data via bluetooth to AWS Amplify API which can then be exported to our EC2 instance for our ML model to calculate the results. A screenshot of the AWS Amplify page showing our data from MCU and the name of “testb” the user entered is shown in Figure 21 signifying successful data sending to AWS Amplify API.

Figure 23: AWS Amplify Page Showing Data Received

Attributes		Add new attribute ▾																												
Attribute name	Value	Type																												
id - Partition key	2cff652e-fa9e-4b14-a3f2-aa890df3218d	New String																												
createdAt	2022-12-01T20:27:48.395Z	String Remove																												
inputData	<table border="1"> <tr><td>104480</td><td>-90.90</td><td>27.39</td><td>110.95</td><td>4122</td><td>-4510</td><td>17520</td></tr> <tr><td>164744</td><td>-112.64</td><td>-0.97</td><td>11.20</td><td>1200</td><td>1905</td><td>1373</td></tr> <tr><td>164898</td><td>-112.53</td><td>0.81</td><td>12.49</td><td>1514</td><td>2065</td><td>1610</td></tr> <tr><td>165153</td><td>-82.45</td><td>48.76</td><td>73.54</td><td>6959</td><td>3770</td><td>10505</td></tr> </table>	104480	-90.90	27.39	110.95	4122	-4510	17520	164744	-112.64	-0.97	11.20	1200	1905	1373	164898	-112.53	0.81	12.49	1514	2065	1610	165153	-82.45	48.76	73.54	6959	3770	10505	String Remove
104480	-90.90	27.39	110.95	4122	-4510	17520																								
164744	-112.64	-0.97	11.20	1200	1905	1373																								
164898	-112.53	0.81	12.49	1514	2065	1610																								
165153	-82.45	48.76	73.54	6959	3770	10505																								
name	testb	String Remove																												
updatedAt	2022-12-01T20:27:48.395Z	String Remove																												
__typename	DataIMU	String Remove																												

4.4. Subsystem Conclusion

The android app is easy to use with minor technical skills needed. The main skill the user will need to know is how to pair their phone to a bluetooth device in their device’s settings menu. Once paired, everything will be available to the user with a simple click of a button. The android app is able to communicate and receive data from the MCU via a bluetooth connection and send the data to the AWS cloud to be processed by our ML model. A link to the github repository containing the app source code is given below.

https://github.com/pablobarron7/SmartBat_Capstone_2022_Team22

5. Machine Learning Subsystem Report

5.1. Machine Learning Introduction

The Machine Learning subsystem for this project is returning the region that the ball and bat impact to the user with the input of swing data. The method we are using is to divide the bat into different regions and do test swings on each region. Then ML will take the data from IMU and process them to give feedback of which region the impact happened. Then the users can look at the regions of their hit so that they can improve with their training and try to hit their “Sweet Spot” that they are looking for.

5.2. Machine Learning Details

The Machine Learning subsystem is done on python jupyter with tensor and scikit-learn environments then it is implemented to a python file called sv.py and put on the AWS server.

5.2.1. Bat Region Dividing

Based on the research “Determination of the “Sweet Spot” of a Cricket Bat using COMSOL Multiphysics” by The University of West Indies, different regions of the bat provide different jerks when impact, which results in different eigenfrequency for us to determine. Based on that, we divided the bat into 15 regions like the image showing below. The thickest portion of the bat was marked as “perfect”, the area which encompasses the “Sweet Spot” that batters usually refer to. For the rest of the regions, they were named Bad-, OK-, OK+, and Bad+. Bad- is the tip of the bat which is where batter usually avoids while Bad+ is also a region that should be avoided by batter since it is close to the handle. The OK regions are closer to the sweet spot. They are better spots to hit, but they are not optimal. We also mark + and - to divide the region where + means impact region is closer to the handle and - means impact region is closer to the tip. Then we also marked all the regions as region 1-15 for processing in ML.

Figure 24: Bat Division



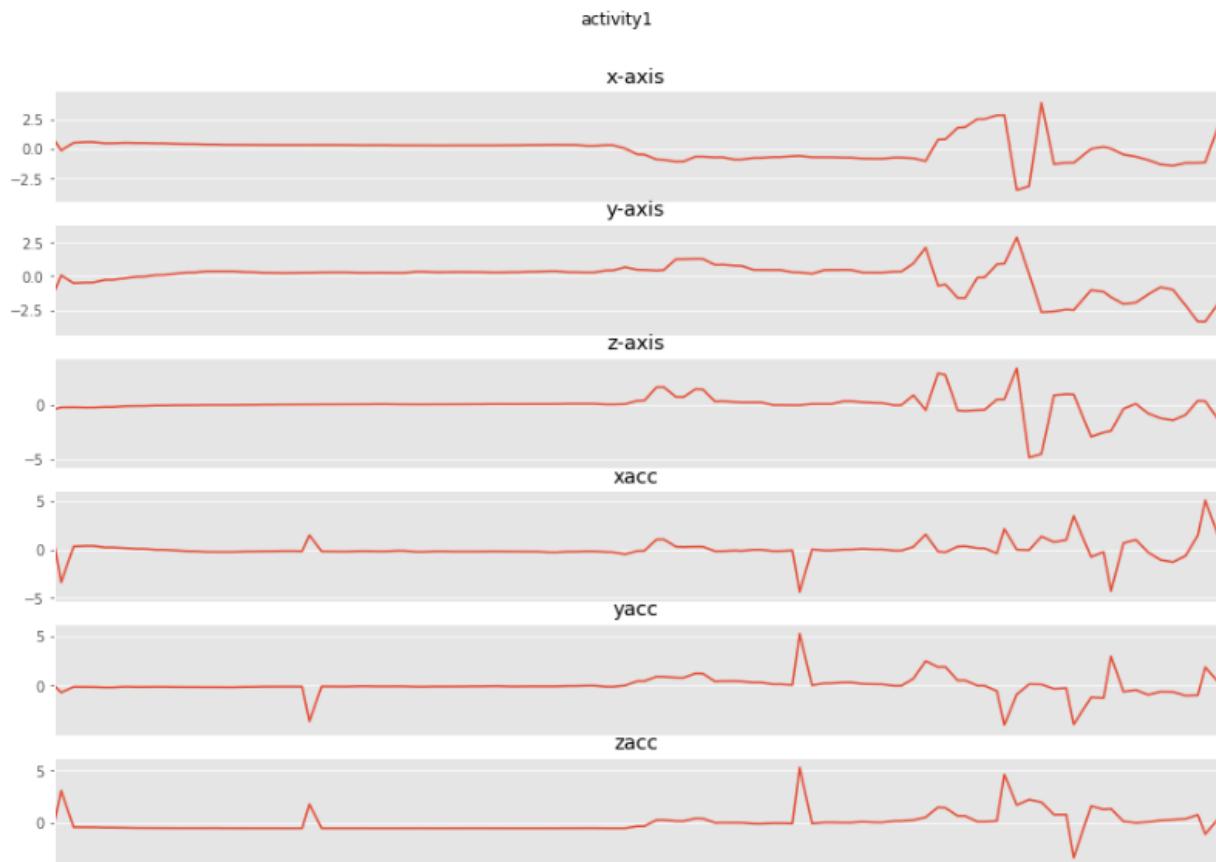
5.2.2. Data Gathering, Inputting, and Plotting

Our sponsor Pranav helped us do around 200 professional swings after we found a way to keep the orientation, but most hits are located in region 5 and 8. The ML takes the data gathered as input, then it does normalization on the data and plotting data over the entire duration out. The example figure shown below and all the examples later are from a set of data that corresponds to an impact on region “prefect 8”.

Figure 25: Data Plotting

```
C:\Users\hjk0811\Downloads\data3\8\8-3.txt
  timestamp  x-axis  y-axis  z-axis  xacc  yacc  zacc
0       620680  34.01 -30.90 -20.30  5239   724  1768
1       620833  -7.43 -2.88 -13.45 -15682 -3540 19920
2       621093  21.12 -15.29 -13.11  2510  -235  705
3       621347  23.60 -14.27 -13.86  2800  -273  657
4       621502  23.53 -14.21 -13.90  2808  -301  657
...
111     644038 -64.01 -25.80 -56.24 -5416 -3159  4636
112     644297 -53.59 -50.40 -38.78 -2295 -5411  5055
113     644556 -53.14 -76.45  8.02  8047 -5189  7189
114     644712 -51.20 -76.73  6.94  25956 11383 -2965
115     644970  74.95 -49.15 -50.71  8735  3068  4690

[116 rows x 7 columns]
```

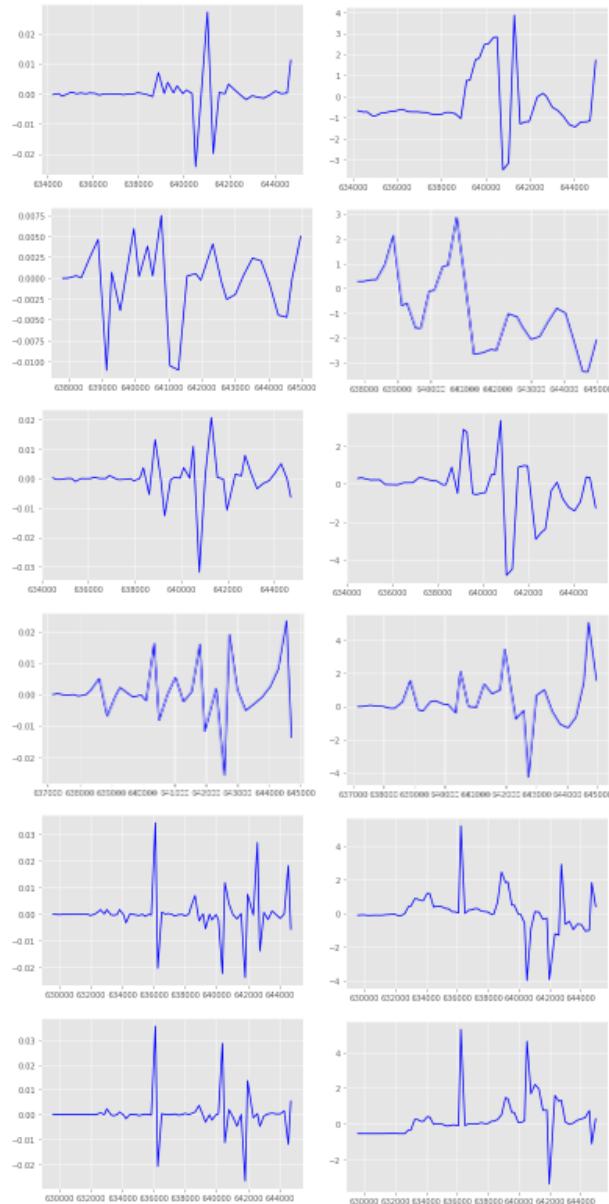


In the image, “x-axis”, “y-axis”, and “z-axis” are corresponding to the gyroscope and “xacc”, “yacc”, and “zacc” are corresponding to the accelerometer.

5.2.3. Finding the Impact

The ML took a derivative over the data and found the max point on the derivative to find out where the impact actually happens. From the max point on the derivative, 32 values taken before and 128 values after the max to define the time window as impact times. Then it finds the same place on the original data to find the impact window. In the figure below, the left graphs are the original, and the right is its derivative.

Figure 26: Impact Window

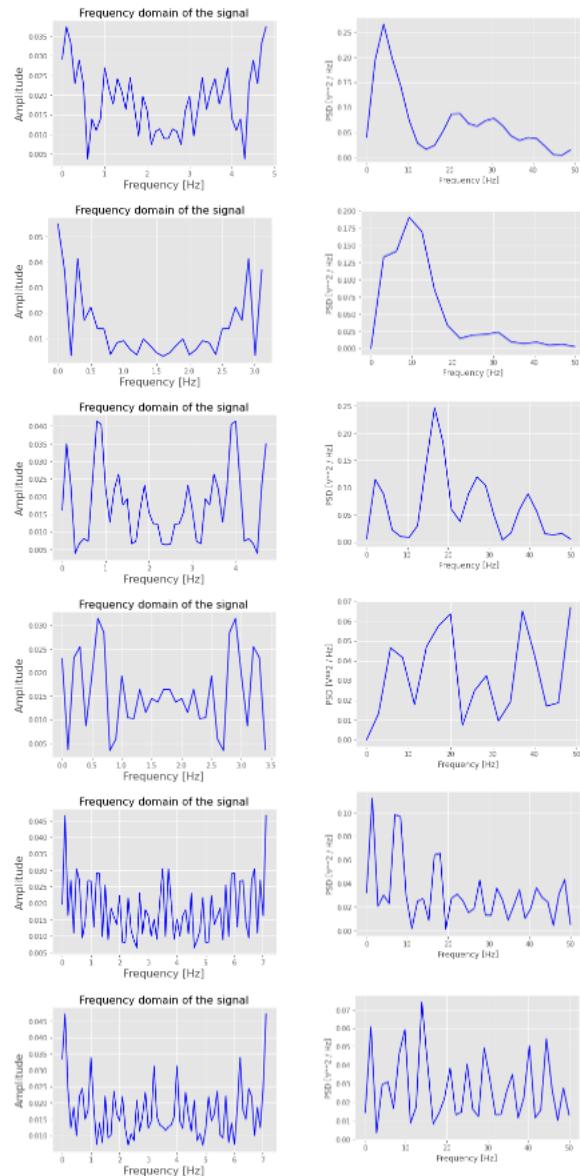


Timestamp used to be transferred here from hour, minute, sec, microsec format to total microseconds. Now, it's directly taking microseconds as input and saves a version in seconds format for other calculations.

5.2.4. FFT and PSD

Over the window that just got sectioned out, FFT and PSD are done over these data in order to observe differences between data to get started on identifying the data. From all the FFT we got, we also calculate the total energy to be later used as a feature. In figure 25, left group of graphs is the FFT and the right is the PSD.

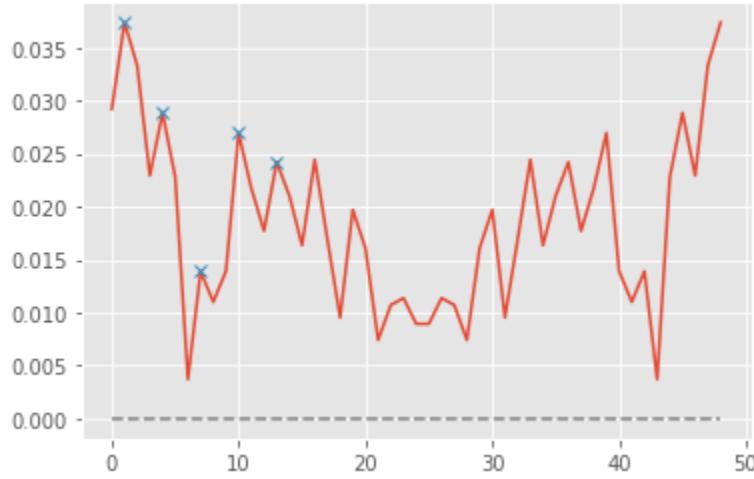
Figure 27: FFT & PSD



5.2.5. Peak Detection

The ML will try to find the first five peaks over each of the FFT and PSD that has been done and get x and y values for each of the peaks. This is our peak energy detection that forms our first 120 feature which are 5 peaks * 2 coordinates for each peak (X and Y) * 2 graphs for each axis (FFT and PSD) * 6 axis from IMU.

Figure 28: Peak Detection on FFT over X-axis Gyroscope of Region 8



5.2.6. Making Feature and Label

The ML combines all the first five peaks' X and Y values of both FFT and PSD for all axes on both gyroscope and accelerometer together and labels them as the region of impact just like the first 120 features and the labels in the image shown below. Total energy for all 6 axes from IMU and total impulse for all x,y, and z axis for the bat, were also added to total up to 129 features.

Figure 29: Feature and Label

```
[1, 0.03735847897165938, 3, 0.04141884322596024, 1, 0.03496258046753683, 3, 0.025450269479166454, 1, 0.04651838322108504, 1, 0.04716110252071357, 2, 0.2658381077829819, 3, 0.1907914720392945, 1, 0.11478825800110669, 2, 0.04657249226847999, 1, 0.11213897977967563, 1, 0.0607882974112672, 4, 0.028845927924546152, 5, 0.022262168046083466, 5, 0.008009100562404958, 6, 0.03145026668201492, 3, 0.026909104805321087, 4, 0.01859886415411125, 11, 0.08692972605561729, 10, 0.02355781111805536, 8, 0.2460503126932096, 7, 0.06375506511569687, 3, 0.029905584783063755, 4, 0.03081831506092497, 7, 0.013899779957530566, 10, 0.009051546553487694, 8, 0.04134043173520799, 10, 0.01924892827331978, 5, 0.030398169548108228, 7, 0.024351506839236696, 15, 0.07742929773665966, 13, 0.009094472410564613, 13, 0.11958060573633612, 10, 0.03248336217151577, 5, 0.09819986386691953, 7, 0.05931398066210309, 10, 0.026944467860569567, 13, 0.009786821695673964, 13, 0.026333704214750852, 13, 0.01637910969661312, 9, 0.026840280882389813, 10, 0.033871003403002566, 19, 0.03897402383016928, 15, 0.0060331461461047495, 19, 0.08813048914783374, 13, 0.0651924530369745, 10, 0.02689192930973262, 10, 0.07413198806403157, 13, 0.0241993010989335, 19, 0.009786821695673964, 15, 0.01935020891102702, 15, 0.01446116426258974, 12, 0.02899764474889994, 13, 0.013792303844802262, 19, 0.03897402383016928, 15, 0.0060331461047495, 23, 0.015499770760184646, 13, 0.0651924530369745, 13, 0.0653978502231611, 15, 0.03849105984173307, 0.020275511784260104, 0.012301219864403698, 0.020087663971489648, 0.010805404898733266, 0.029236123085759264, 0.026547743916735915, 14426753.09724816, 8861387.32354223, 23015076.64287367]
```

The same process is done for all sets of data that was acquired and combines them as features that contain all X and Y values and Labels that contain the impact regions.

5.2.7. Training and Testing Sets

The data are divided into 70% for training and 30% for testing through trial and error.

5.2.8. Training the model

The data will be trained over Random Forest Classifier. We have done more than 6 models and over 20 combinations like different portions of Train Test Split, or random shuffle with Random Forest, Decision Tree, Logistic Regression, svm with kernel, rbf, linear or ploy and many more. From the results and the pattern of the accuracy increasing and decreasing, the solution was to simply get more training data. Because for most regions, there were only 5 to 10, or even fewer, swings while some regions like 5 and 8 have the most amount of data, at around 30 swings. As a result, this result with Random Forest Classifier with 70% training and 30% testing is the best split available with our amount of data, and it can predict region 5 and 8 very well thanks to the amount of data available. In the image shown below the top is the accuracy on training and test set, in the middle is the specific precision and details for prediction over each region. In the bottom part is the predicted results and the actual result.

Figure 30: Training Results

Accuracy on training set is : 0.6428571428571429

Accuracy on test set is : 0.24074074074074073

	precision	recall	f1-score	support
1	0.00	0.00	0.00	2
2	1.00	0.25	0.40	8
3	0.00	0.00	0.00	2
4	0.22	0.33	0.27	6
5	0.30	0.60	0.40	10
7	1.00	0.20	0.33	5
8	0.09	0.50	0.15	4
9	0.00	0.00	0.00	1
11	0.00	0.00	0.00	5
12	0.00	0.00	0.00	1
13	0.00	0.00	0.00	2
14	0.00	0.00	0.00	6
15	0.00	0.00	0.00	2
accuracy			0.24	54
macro avg	0.20	0.14	0.12	54
weighted avg	0.33	0.24	0.21	54

```
[8 5 8 8 4 5 8 4 5 4 5 4 5 8 8 8 5 5 4 5 8 5 4 8 8 8 8 5 8 5 8 8 5 4 2 8 5
5 5 5 8 2 8 8 5 7 8 8 8 4 4 5 5 5]
[ 5 4 8 4 11 5 2 2 14 5 3 8 2 2 4 13 14 14 4 5 5 8 4 12
11 14 2 5 15 11 7 4 2 9 2 5 5 11 5 3 13 2 8 1 14 7 7 14
1 7 7 5 15 11]
```

A confusion matrix was then generated to spot whether they could predict the results correctly.

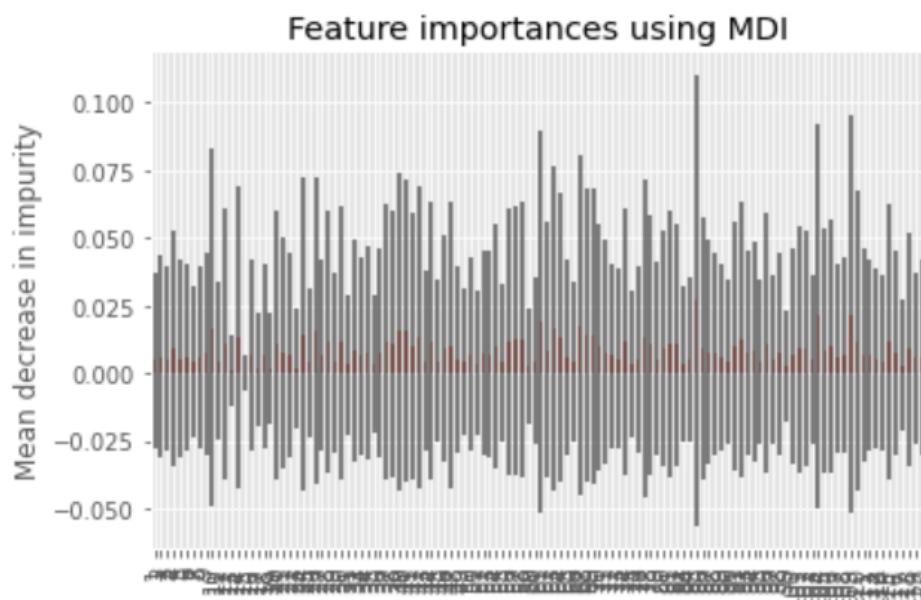
Figure 31: Confusion Matrix

```
[[0 0 0 0 0 2 0 0 0 0 0 0 0]
 [0 0 5 2 0 2 0 0 0 0 0 1 0]
 [0 0 3 0 0 1 0 0 0 0 0 0 0]
 [0 0 0 3 0 4 0 0 0 0 0 2 0]
 [0 0 0 0 2 2 0 0 0 0 0 0 0]
 [0 0 1 0 0 3 0 0 0 0 0 1 0]
 [0 0 0 1 0 0 0 0 0 0 0 1 0]
 [0 0 0 1 0 3 0 0 0 0 0 0 0]
 [0 0 2 2 0 2 0 0 0 0 0 0 0]
 [0 0 1 0 0 1 0 0 0 0 0 1 0]
 [0 0 0 0 0 1 0 0 0 0 0 0 0]
 [0 0 1 1 0 0 0 0 0 0 0 1 0]
 [0 0 0 0 0 0 0 0 0 0 0 1 0]]
```

5.2.9. Feature Importance

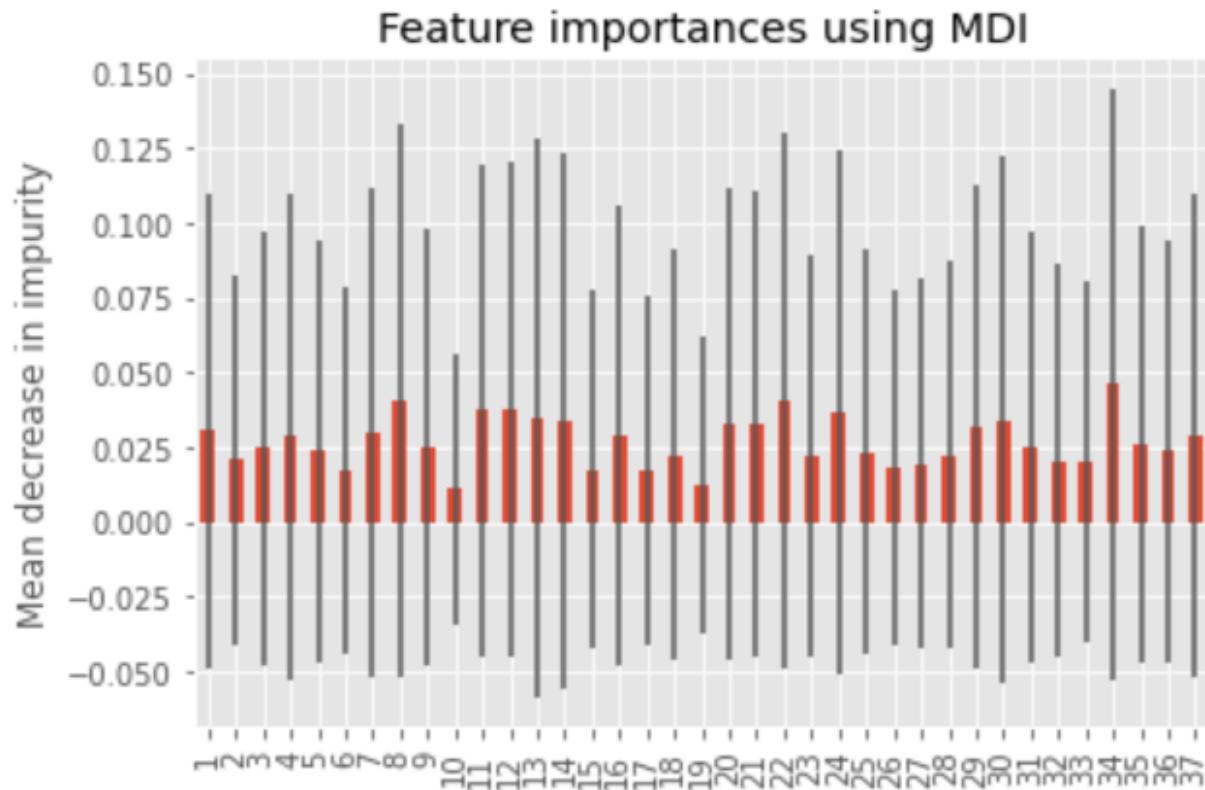
Then the ML will use feature importance to find out all the important features to increase accuracy.

Figure 32: Feature Importance 1



The first time, a very low limit was set to take out the least important features. The training was done again and this time it is more clear to see the more important features.

Figure 33: Feature Importance 2



This process is done again so we have the most important features going over the Random Forest Classifier.

Figure 34: Feature Importance from

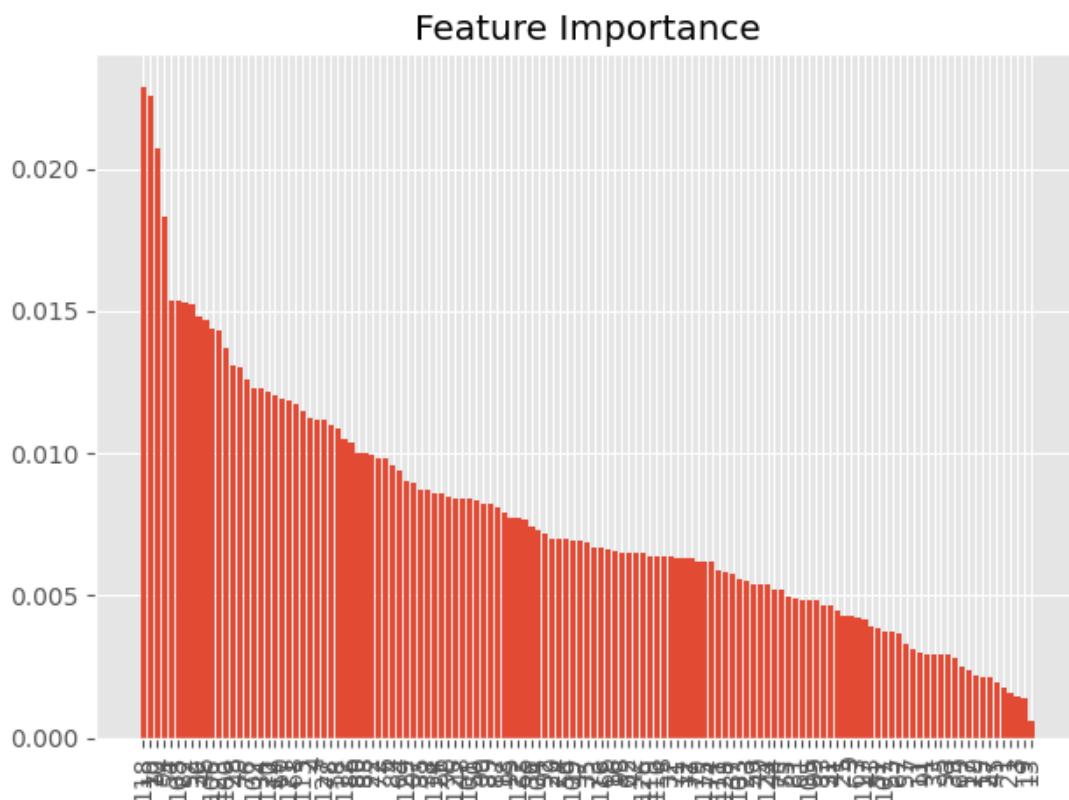
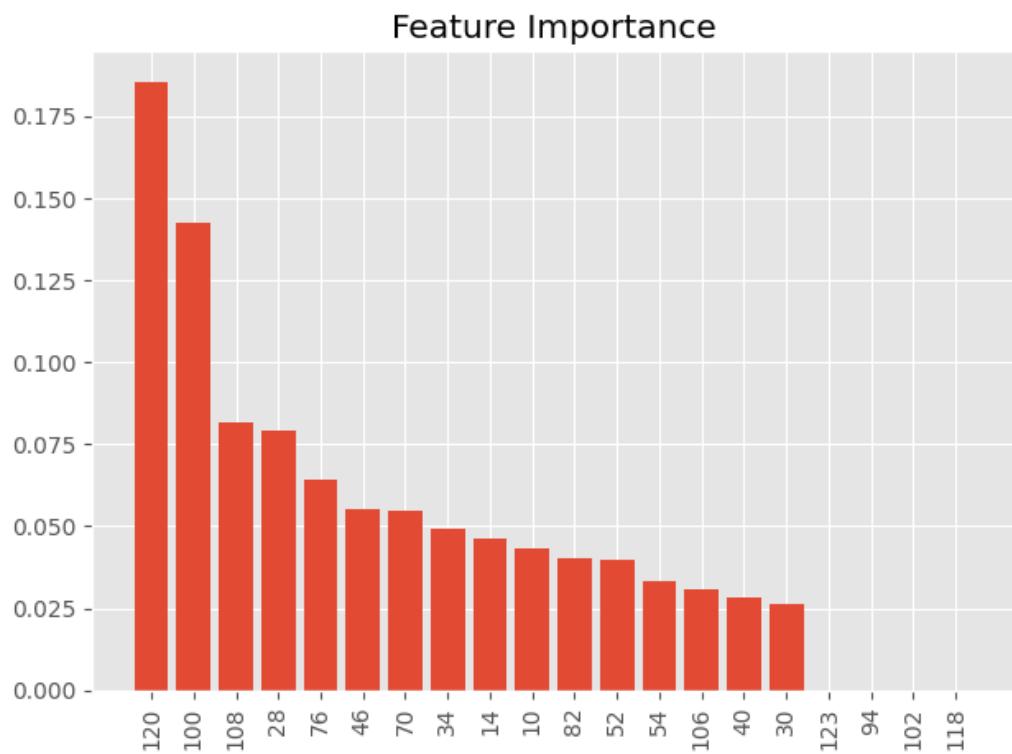


Figure 35: Feature Importance to



Smart Cricket Bat

Feature importance was used to get the top 20 important features, which were then analyzed to see whether keeping some important features over others could improve accuracy.

5.2.10. Correlation, association, and relationships

Figure 36: Heat Map

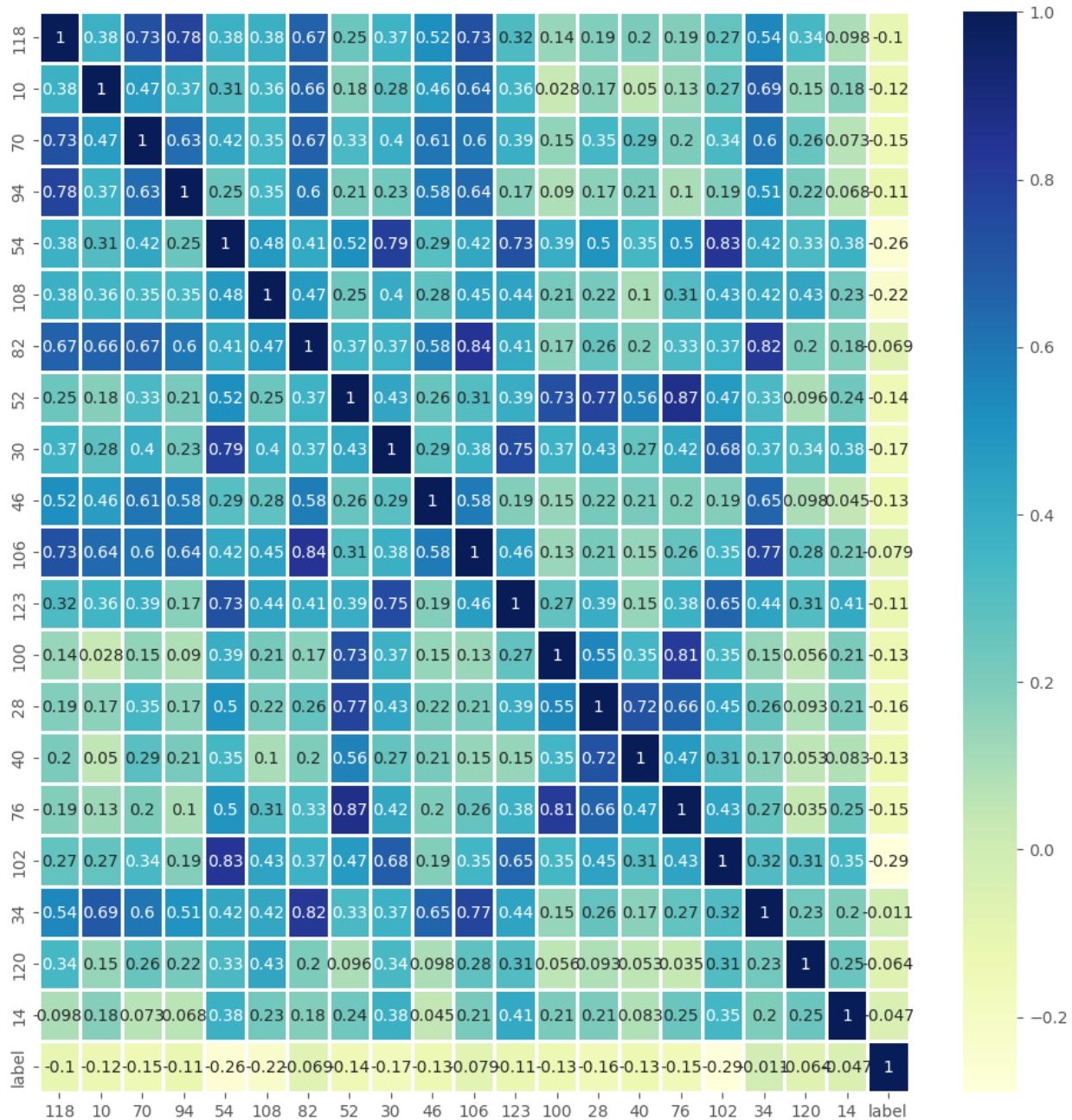
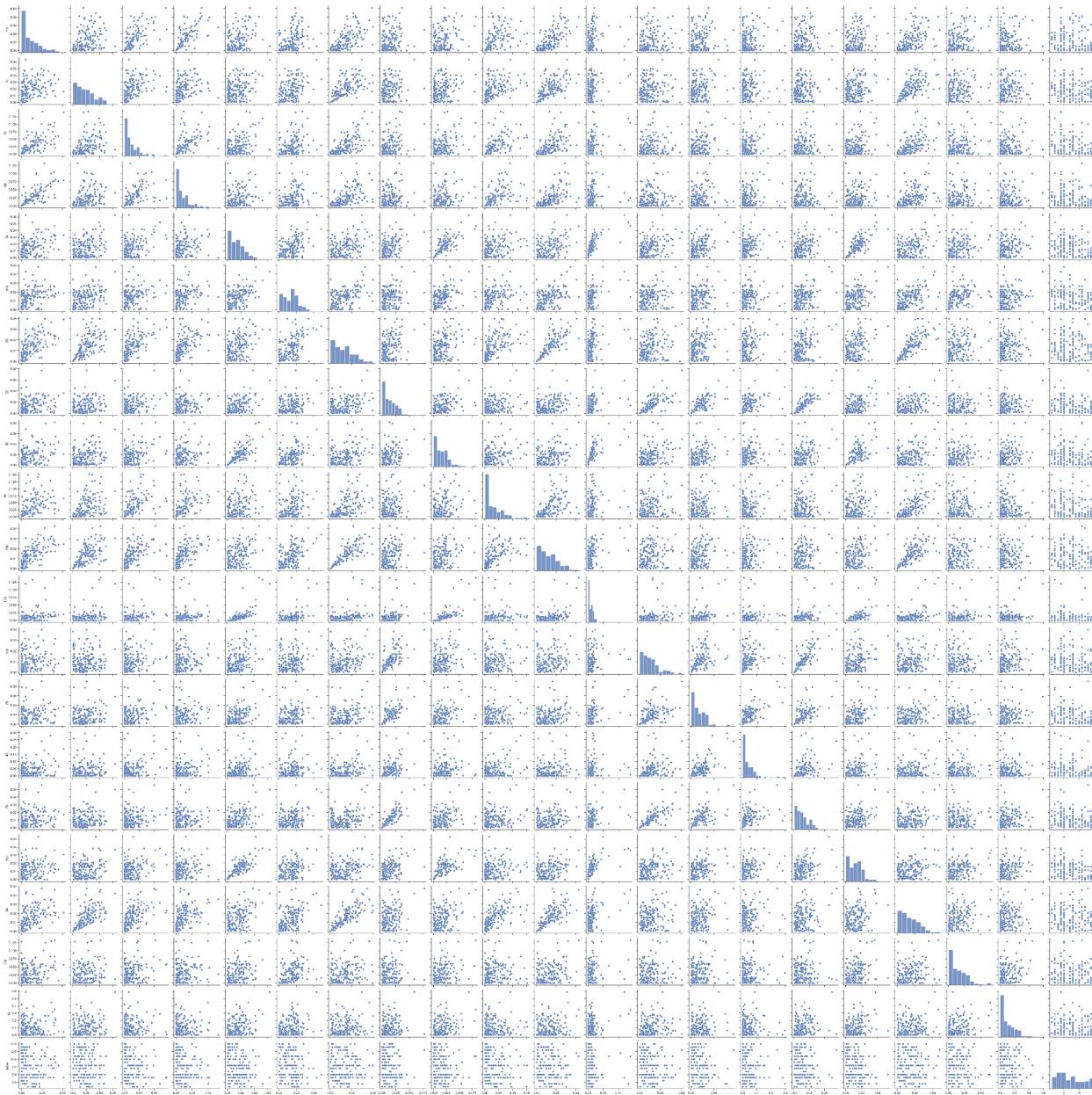


Figure 37: Seaborn Pairplot



From the seaborn pairplot and the heatmap, one can spot the correlation between features and the relationship between features and the labels. From here, one can analyze and choose better features to use. However, through all the comparisons, there seemed to be no significant amount of increase in accuracy. So, the same model, with all 129 features, was used.

5.2.11. ML integration

The ML model is uploaded to the AWS server for the integration with Android Studio. In order to do that, the ML model must be uploaded to the EC2 instance on the AWS server.

Figure 38: Upload ML to EC2 instance

```
C:\Users\hjk0811>scp -i D:/111/SC404NK.pem D:/111/sv.py ubuntu@ec2-18-219-199-125.us-east-2.compute.amazonaws.com:/home/ubuntu/
sv.py                                         100%   20KB 236.4KB/s  00:00
```

Then a connection is set up between the S3 bucket and the EC2 instance, so we can receive the json file that Android Studio sent to S3 bucket and copy that file from S3 to EC2, then the Python code is run that uses the model we generate and the json file that just copied from S3 bucket. Then the ML model will generate a result also in json format named in sample.json with hit region, overall speed, impact speed on each axis, and angle on each axis.

Figure 39: Example output on EC2 instance

```
{'region': 5, 'speedoverall': 111.13424204987409, 'speedimpactx': 7.008683989028049, 'speedimpacty': -1.8077591576900351, 'speedimpactz': 4.918215736480965, 'anglex': -3.157455447482602, 'angley': -7.916609345424729, 'anglez': 5.546042036210611}
ubuntu@ip-172-31-26-208:~$
```

Then we will copy the generated json file from the EC2 instance to the S3 bucket.

5.3. Machine Learning Validation

5.3.1. Validation for actual hit on the bat

For the validation of the ML subsystem, we tried to hit the ball with the bat and chalk with the physical location that the hit was landing as the result. We validated and put one of each hit on each region on the whole system report. The ML is mostly predicting region 5 and 8 since this is the data it had the most of. Figure 40 is an example of hitting on region 8 that we did and the corresponding output that the ML output on EC2 instance of the AWS server. It correctly predicted region 8 as its collision with an overall speed of 116.78 m/s and an angle of -4.76 degrees in the z axis which runs along the bat and corresponds to the tilt of the bat.

Figure 40: Hit location on the bat and ML output on EC2 console



```
{'region': 8, 'speedoverall': 116.7838632602981, 'speedimpactx': -3.32490632562539, 'speedimpacty': 1.3805229020235064, 'speedimpactz': 2.1654700671956717, 'anglex': 2.9829337109604133, 'angley': 1.167147824558429, 'anglez': -4.762309629048121}
ubuntu@ip-172-31-26-208:~$
```

5.3.2. ML integration on EC2 Validation

To validate if the ML successfully uploaded to EC2, we tested if the ML is outputting the same results on the EC2 server and running with Colab.

Figure 41: Same ML output on EC2 and Colab

```
aws Services Search
[5, 0.011637187942433075, 1, 0.0847813352191
2, 2, 0.45906602430419465, 1, 0.100096581085
, 8, 0.040538618579817165, 3, 0.030582994202
78288174, 4, 0.15972921632924725, 6, 0.31421
94517424792, 6, 0.04760392637896483, 9, 0.02
.26873079705588226, 9, 0.08037045964908925,
42, 12, 0.015184294780793527, 34, 0.05049417
5989217841304, 22, 0.012927768833583302, 13,
34, 0.050494175928878504, 28, 0.01093017524
15
['1', '2', '3', '4', '5', '6', '7', '8', '9'
'0', '31', '32', '33', '34', '35', '36', '37'
'8', '59', '60', '61', '62', '63', '64', '65'
'6', '87', '88', '89', '90', '91', '92', '93'
'12', '113', '114', '115', '116', '117', '118
/home/ubuntu/.local/lib/python3.10/site-pac
sion 1.1.1. This might lead to breaking code
https://scikit-learn.org/stable/model_persis
warnings.warn(
/home/ubuntu/.local/lib/python3.10/site-pac
sion 1.1.1. This might lead to breaking code
https://scikit-learn.org/stable/model_persis
warnings.warn(
[8]
ubuntu@ip-172-31-26-208:~$ i-0e077b8ce580c678d (SC404)
PublicIPs: 18.219.199.125 PrivateIPs: 172.31.26.208
```

```
list_of_features.append(spedFiveT[i])
print(list_of_features)
print(list_of_labels)

[9, 0.011637187942433075, 1, 0.0847813352191105, 1, 0.03752700460896405, 1, 0.04536443340566516
15

[10] usseqId=1101
usseqId[0]=list_of_features

[11] columnNames=['1','2','3']
for i in range(4,121):
    columnNames.append(str(i))

print(columnNames)
df = pd.DataFrame(arrayId, columns = columnNames)

[12] df2 = df[['20', '31', '77', '118', '55', '102', '58', '106', '98', '16']]

[13] from joblib import Parallel, delayed
import joblib

# Load the model from the file
clf_from_joblib = joblib.load('/content/drive/MyDrive/filename.pkl')

# Use the loaded model to make predictions
print(clf_from_joblib.predict(df2))
```

5.4. Subsystem Conclusion

The Machine Learning subsystem is able to receive the data and do the process needed like normalizing, windowing, speed and angle calculation, FFT, PSD, peak energy detection,

Smart Cricket Bat

total energy calculation, angular impulse calculation, feature extraction, training, and testing. In order to have better accuracy, we still need to do much more data. With a lot of validations we did, the ML can predict region 5 and region 8 really well, because they have the most amount of data. Region 4 and 7 are also having considerable results since they also have more data than the others. As a result, the ML subsystem has the ability to transform the necessary data to give feedback for users to see their impact region on the bat. The downside is it can only predict region 5 and region 8 much better than the others.

Smart Cricket Bat

Gavin Dahl, Jiakai Hu, Pablo Barron, Nolapat Pipitvitayakul

FULL SYSTEM REPORT

Draft – 1
20 November 2022

SYSTEM REPORT

FOR

Smart Cricket Bat

PREPARED BY:

Author Date

APPROVED BY:

Project Leader Date

John Lusher II, P.E. Date

T/A Date

Change Record

Rev.	Date	Originator	Approvals	Description
1	11/20/2022	Gavin Dahl		First Draft

Table of Contents

Table of Contents	3
List of Figures	4
1.1. Introduction	6
1.2. System Details	7
1.3. System Validation	8
1.4. System Conclusion	23

List of Figures

Figure 1: Hit Location 15	8
Figure 1a: Marked Physical Collision on Hit Location 15	8
Figure 1b: Hit Data Plots After Preprocessing of Machine Learning	8
Figure 1c: Screenshot of Output Hit Location from Machine Learning	8
Figure 1d: Output shown in App	8
Figure 2: Hit Location 14	9
Figure 2a: Marked Physical Collision on Hit Location 14	9
Figure 2b: Hit Data Plots After Preprocessing of Machine Learning	9
Figure 2c: Screenshot of Output Hit Location from Machine Learning	9
Figure 2d: Output shown in App	9
Figure 3: Hit Location 13	10
Figure 3a: Marked Physical Collision on Hit Location 13	10
Figure 3b: Hit Data Plots After Preprocessing of Machine Learning	10
Figure 3c: Screenshot of Output Hit Location from Machine Learning	10
Figure 3d: Output shown in App	10
Figure 4: Hit Location 12	11
Figure 4a: Marked Physical Collision on Hit Location 12	11
Figure 4b: Hit Data Plots After Preprocessing of Machine Learning	11
Figure 4c: Screenshot of Output Hit Location from Machine Learning	11
Figure 4d: Output shown in App	11
Figure 5: Hit Location 11	12
Figure 5a: Marked Physical Collision on Hit Location 11	12
Figure 5b: Hit Data Plots After Preprocessing of Machine Learning	12
Figure 5c: Screenshot of Output Hit Location from Machine Learning	12
Figure 5d: Output shown in App	12
Figure 6: Hit Location 10	13
Figure 6a: Marked Physical Collision on Hit Location 10	13
Figure 6b: Hit Data Plots After Preprocessing of Machine Learning	13
Figure 6c: Screenshot of Output Hit Location from Machine Learning	13
Figure 6d: Output shown in App	13
Figure 7: Hit Location 9	14
Figure 7a: Marked Physical Collision on Hit Location 9	14
Figure 7b: Hit Data Plots After Preprocessing of Machine Learning	14
Figure 7c: Screenshot of Output Hit Location from Machine Learning	14
Figure 7d: Output shown in App	14
Figure 8: Hit Location 8	15
Figure 8a: Marked Physical Collision on Hit Location 8	15
Figure 8b: Hit Data Plots After Preprocessing of Machine Learning	15
Figure 8c: Screenshot of Output Hit Location from Machine Learning	15
Figure 8d: Output shown in App	15
Figure 9: Hit Location 7	16
Figure 9a: Marked Physical Collision on Hit Location 7	16

Figure 9b: Hit Data Plots After Preprocessing of Machine Learning	16
Figure 9c: Screenshot of Output Hit Location from Machine Learning	16
Figure 9d: Output shown in App	16
Figure 10: Hit Location 6	17
Figure 10a: Marked Physical Collision on Hit Location 6	17
Figure 10b: Hit Data Plots After Preprocessing of Machine Learning	17
Figure 10c: Screenshot of Output Hit Location from Machine Learning	17
Figure 10d: Output shown in App	17
Figure 11: Hit Location 5	18
Figure 11a: Marked Physical Collision on Hit Location 5	18
Figure 11b: Hit Data Plots After Preprocessing of Machine Learning	18
Figure 11c: Screenshot of Output Hit Location from Machine Learning	18
Figure 11d: Output shown in App	18
Figure 12: Hit Location 4	19
Figure 12a: Marked Physical Collision on Hit Location 4	19
Figure 12b: Hit Data Plots After Preprocessing of Machine Learning	19
Figure 12c: Screenshot of Output Hit Location from Machine Learning	19
Figure 12d: Output shown in App	19
Figure 13: Hit Location 3	20
Figure 13a: Marked Physical Collision on Hit Location 3	20
Figure 13b: Hit Data Plots After Preprocessing of Machine Learning	20
Figure 13c: Screenshot of Output Hit Location from Machine Learning	20
Figure 13d: Output shown in App	20
Figure 14: Hit Location 2	21
Figure 14a: Marked Physical Collision on Hit Location 2	21
Figure 14b: Hit Data Plots After Preprocessing of Machine Learning	21
Figure 14c: Screenshot of Output Hit Location from Machine Learning	21
Figure 14d: Output shown in App	21
Figure 15: Hit Location 1	22
Figure 15a: Marked Physical Collision on Hit Location 1	22
Figure 15b: Hit Data Plots After Preprocessing of Machine Learning	22
Figure 15c: Screenshot of Output Hit Location from Machine Learning	22
Figure 15d: Output shown in App	22

1.1. Introduction

The smart cricket bat will acquire data during the user's swing and give feedback to the user on how to further improve their swing. The system gathers data through the inertial measurement unit mounted at the handle of the bat, where it is transmitted to the consumer app via a microcontroller with a Bluetooth module. The data transferred to the app is then uploaded to the machine learning algorithm to be processed and then returns to the user the characteristics of the swing and what can be done to improve. The system is broken down into the power, control, app, and machine learning subsystems, each of which was designed and rigorously tested. Since each subsystem was validated to be working correctly and fulfilling all requirements, there is a clear path to integration for these subsystems into the full system specified in the Conops, FSR, and ICD.

1.2. System Details

The system as a whole has three main components, the actual sensing device that attaches to the bat handle, the user interface application, and the machine learning algorithm in the cloud. The first component consists of a PCB that holds an ATmega328p microcontroller that interfaces with two main modules, the MPU-6050 inertial measurement unit and the HC-05 Bluetooth module, and the charging circuit that connects to and charges the 3.7V 500 mAh Li-Po battery. This PCB and the corresponding Li-Po battery are what make up the sensing unit. The sensing unit uses its bluetooth to connect to any device available, which in this case will be the user's phone, which acts as the middle man between the data measurement device and the machine learning algorithm. The important data that the sensing device will deliver to the phone and whether it gets sent to the machine learning depends on what the user requests, there are 4 options available to them: connecting to the device, getting battery life of the device, calibrating the device, and starting or stopping the sending of IMU data. When sending data to the machine learning, the MCU sends 7 data points that the machine learning needs to properly derive the characteristics of the swing, those points being the time the current data was obtained at, the 3 values for the 3 axes of the gyroscope, and the 3 values for the 3 axes of the accelerometer. The data is sent from the application to the cloud as a compressed json file to then be processed (as of now this is done manually through a few simple terminal commands in the AWS database, however in future iterations the goal is to have quick automatic processing). First, the machine learning algorithm does preprocessing to the data collected with normalizing, chunking, FFT, PSD, peak energy detection, total energy calculation, and angular impulse calculation. Through this process, the 7 data points generated will transform into 129 features for each data collected. Then, these features will be used in the ML model training with the same process in the AWS server and produce the output with the predicted hit region, swing speed, and angles as a json file. Then, the json file is sent to the application for the user to view and interact with. The application has a home screen with buttons that will lead the user to a page that will have the output value from the machine learning that corresponds to said button. For example, if the user wants to see the swing speed and tilt after their swing, they simply touch the "speed/tilt" button and are taken to the page that will then display the speed and tilt of the bat (along the z-axis) that the machine learning algorithm calculated in meters per second and degrees, respectively.

1.2. System Validation

Hit Location 15 Data

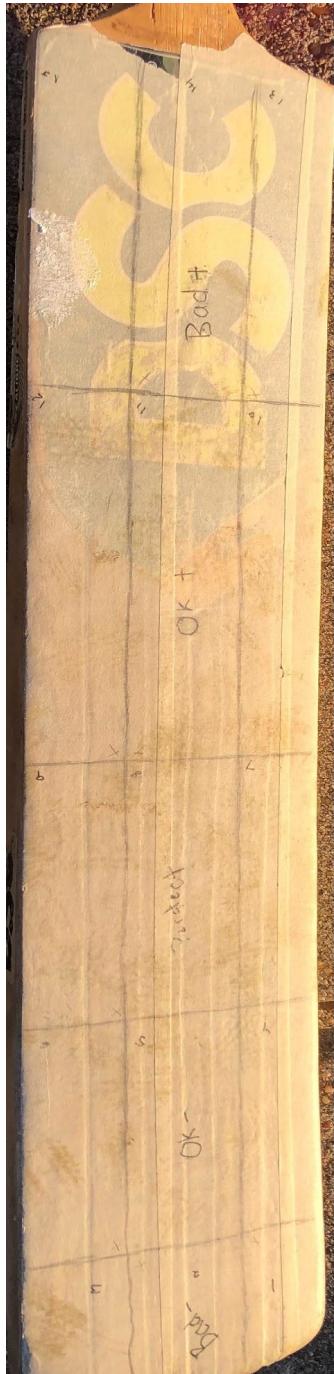


Figure 1a: Marked Physical Collision on Hit Location 15

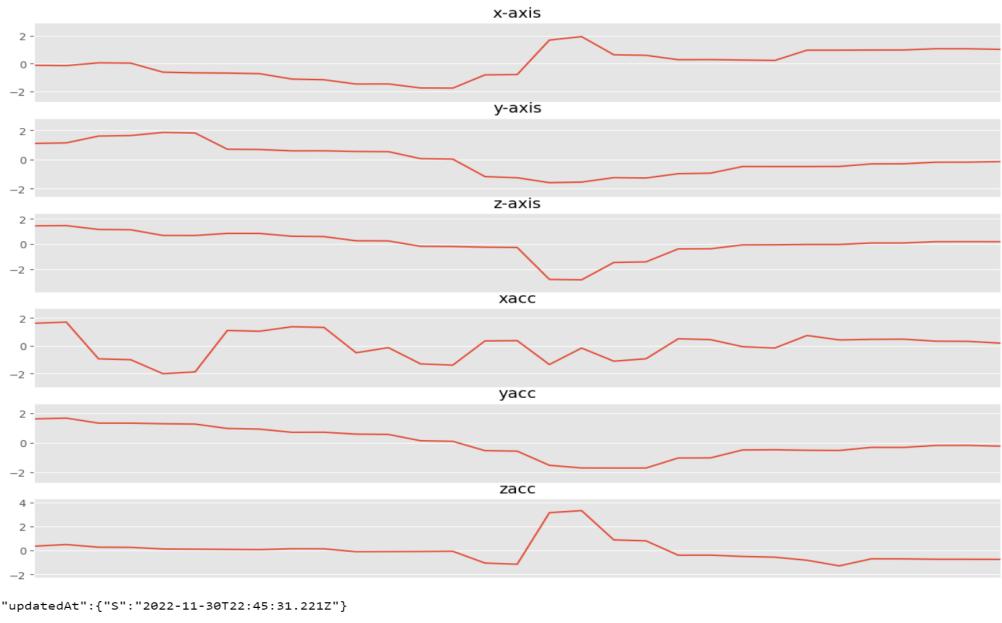


Figure 1b: Hit Data Plots After Preprocessing of Machine Learning

```
{'region': 5, 'speedoverall': 50.01299521124484, 's  
378861072409553, 'angleY': -0.4826150188041244, 'an  
ubuntu@ip-172-31-26-208:~$
```

Figure 1c: Screenshot of Output Hit Location from Machine Learning

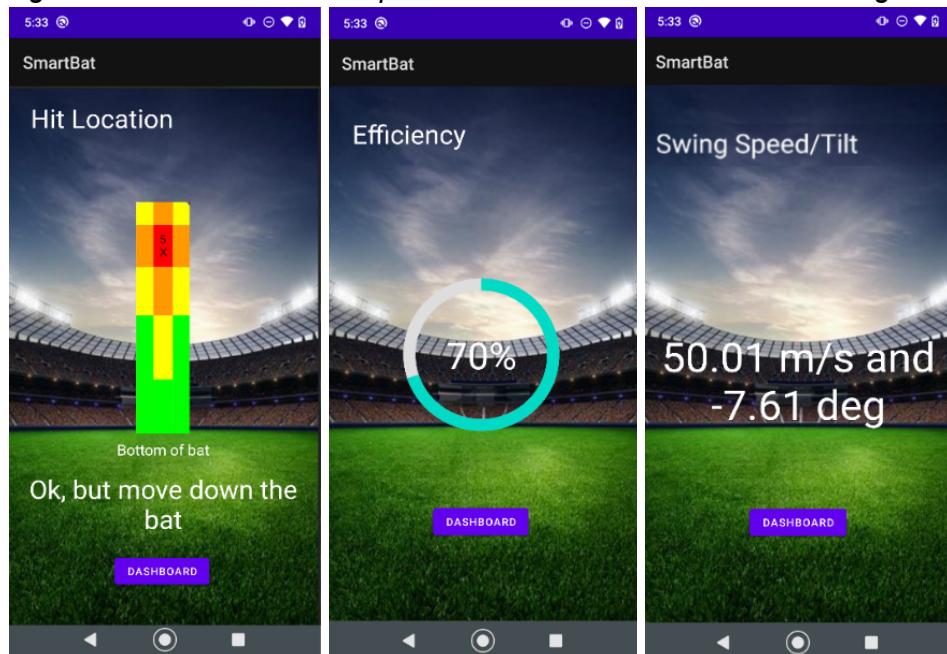


Figure 1d: Output shown in App

Hit Location 14 Data

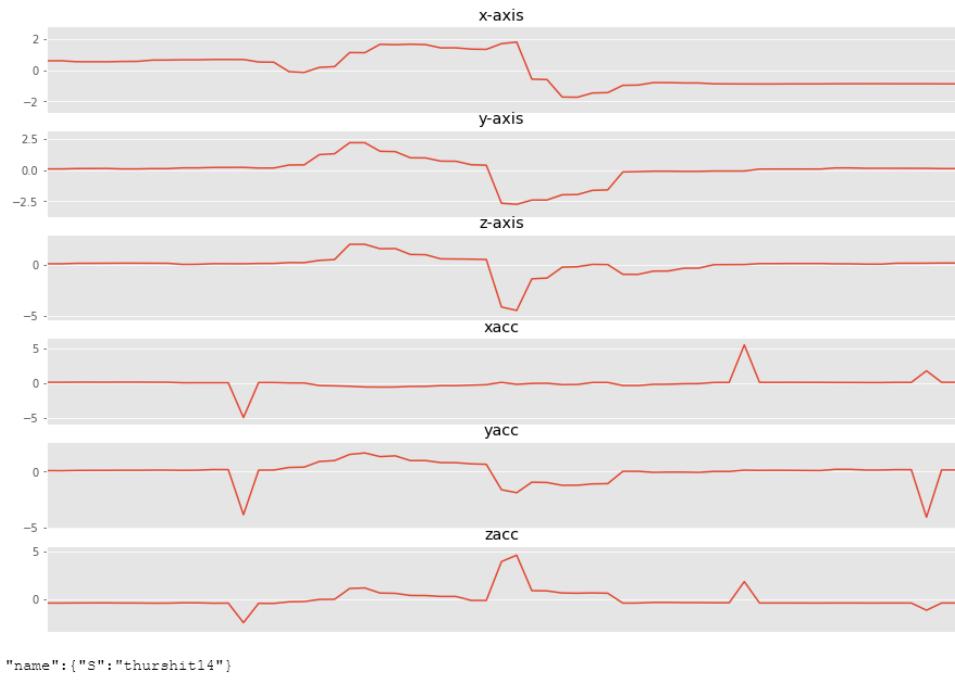


Figure 2b: Hit Data Plots After Preprocessing of Machine Learning

```
{'region': 5, 'speedoverall': 89.96263917038004, 'speedimpactx': 0
458639434195035, 'angley': -0.5952277331718819, 'anglez': 0.0}
ubuntu@ip-172-31-26-208:~$
```

Figure 2c: Screenshot of Output Hit Location from Machine Learning

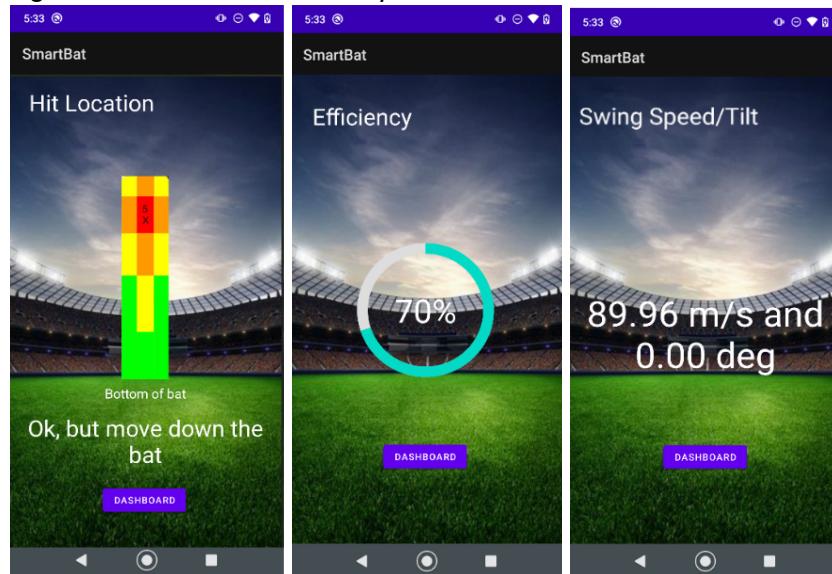


Figure 2d: Output shown in App

Figure 2a: Marked Physical Collision on Hit Location 14

Hit Location 13 Data

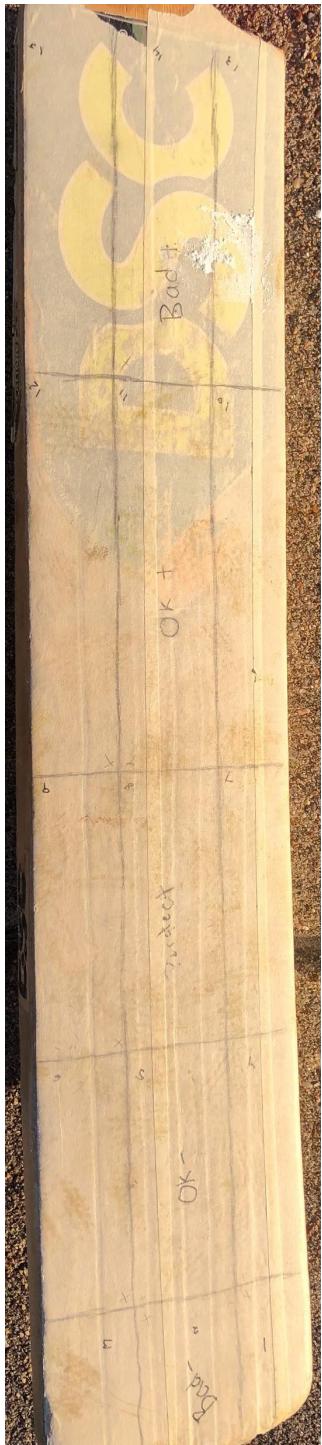


Figure 3a: Marked Physical Collision on Hit Location 13

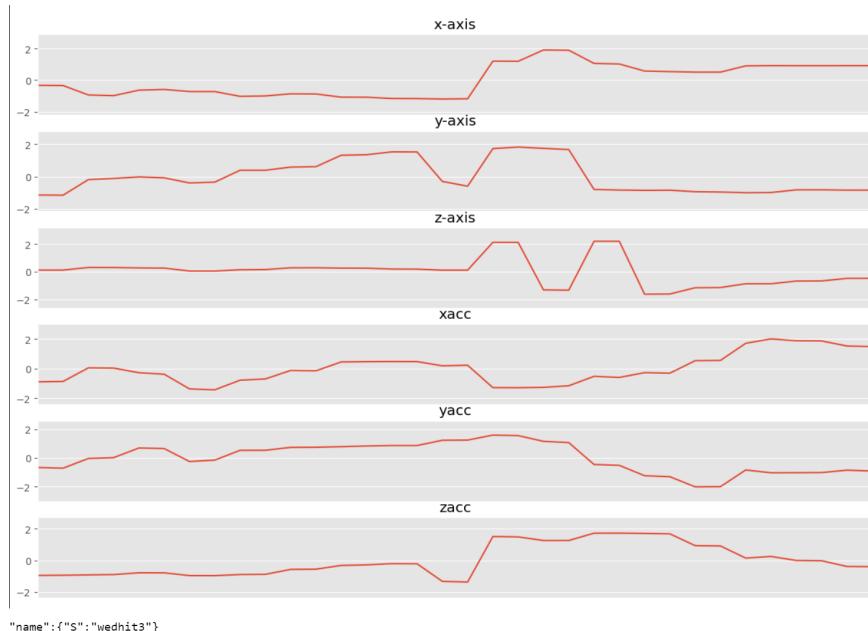


Figure 3b: Hit Data Plots After Preprocessing of Machine Learning

```
{'region': 5, 'speedoverall': 73.90951274024205, 'angley': -1.320558542410429, 'anglez': 5.988970394}
```

ubuntu@ip-172-31-26-208:~\$

Figure 3c: Screenshot of Output Hit Location from Machine Learning

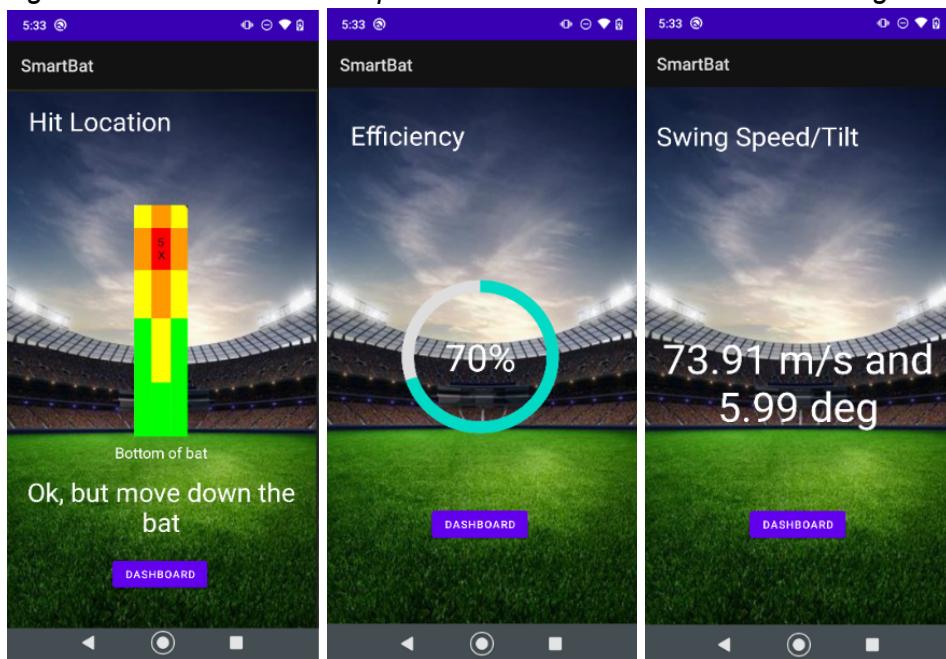


Figure 3d: Output shown in App

Hit Location 12 Data

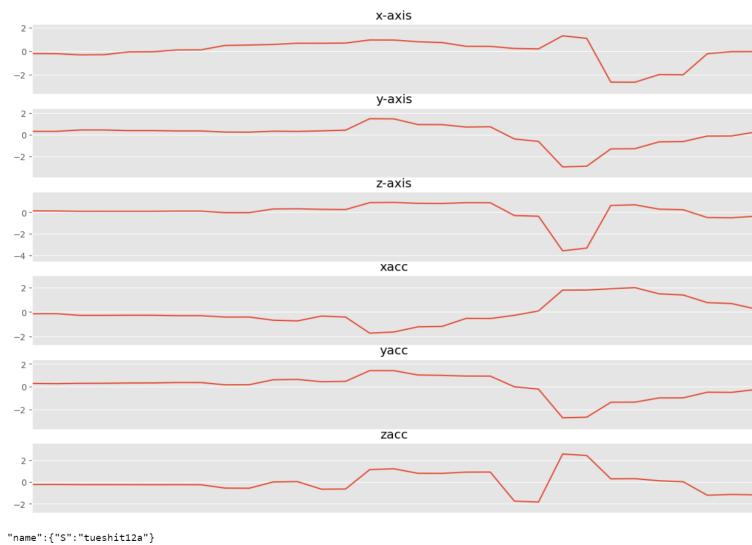
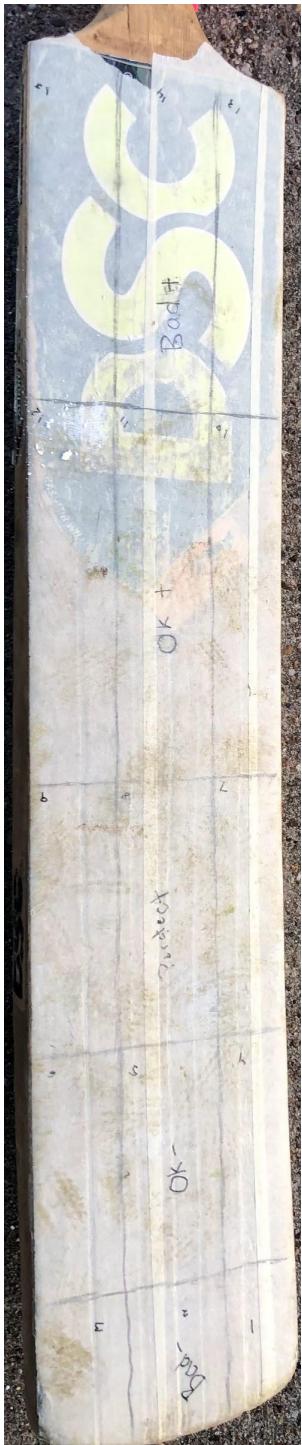


Figure 4b: Hit Data Plots After Preprocessing of Machine Learning

```
10.018882694162259, 0.018882694162259, 0.018882694162259,
{'region': 8, 'speedoverall': 120.10625823515609, 'speedin
.3184722127196475, 'angley': -8.485130688920975, 'anglez': ubuntu@ip-172-31-26-208:~$ █
```

Figure 4c: Screenshot of Output Hit Location from Machine Learning

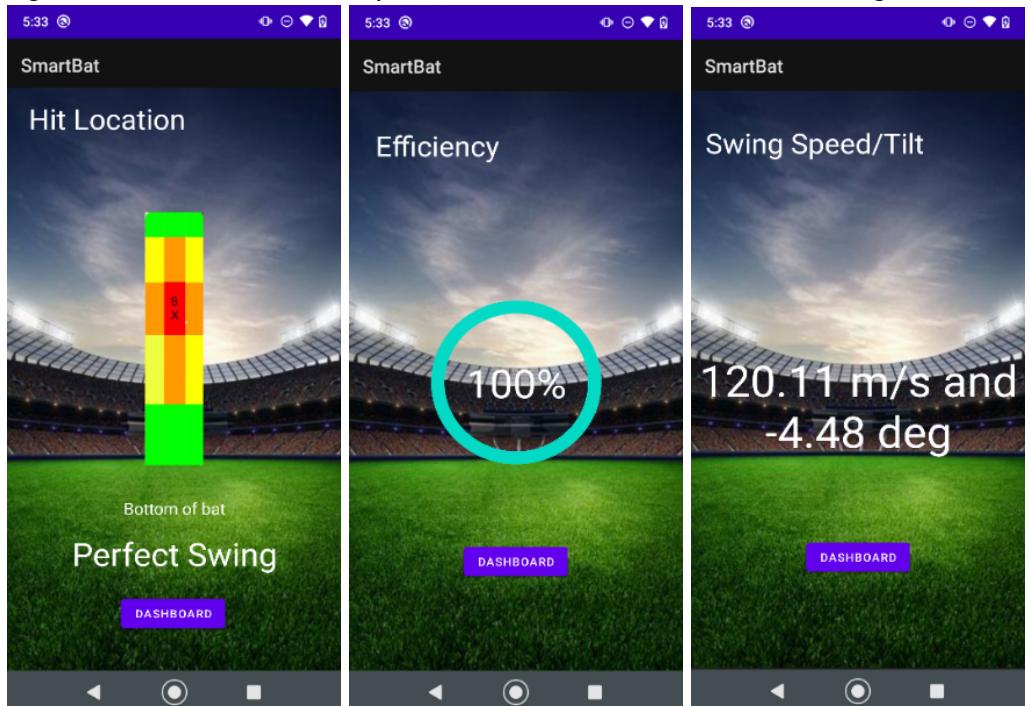


Figure 4a: Marked Physical Collision on Hit Location 12

Figure 4d: Output shown in App

Hit Location 11 Data

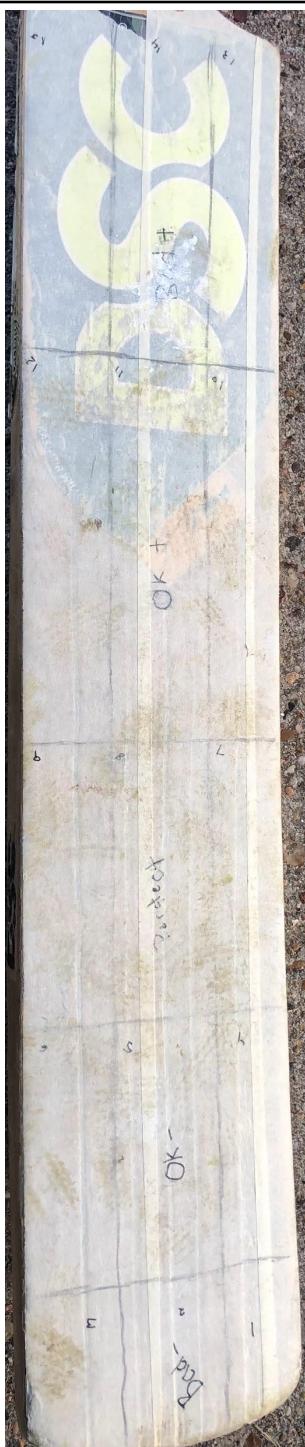


Figure 5a: Marked Physical Collision on Hit Location 11

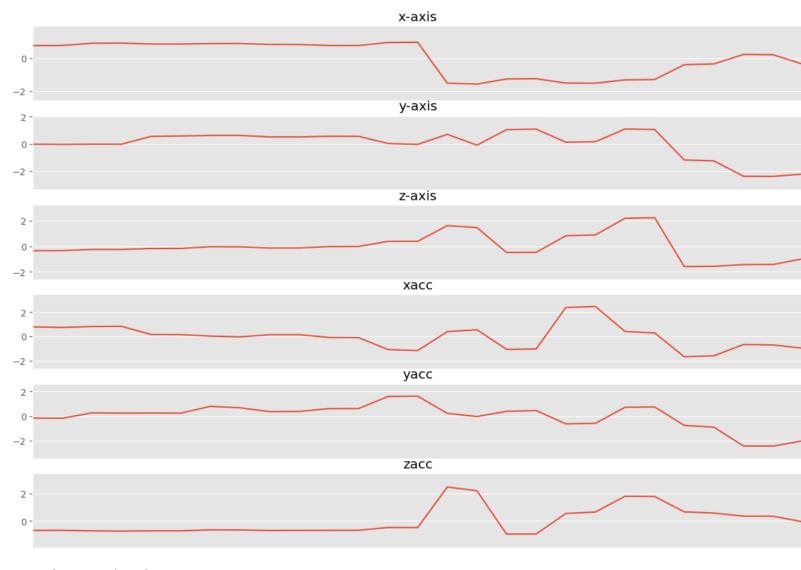


Figure 5b: Hit Data Plots After Preprocessing of Machine Learning

```
{'region': 8, 'speedoverall': 182.2760676083122,
328980352957, 'angley': -2.4056969162116832, 'ang
ubuntu@ip-172-31-26-208:~$
```

Figure 5c: Screenshot of Output Hit Location from Machine Learning

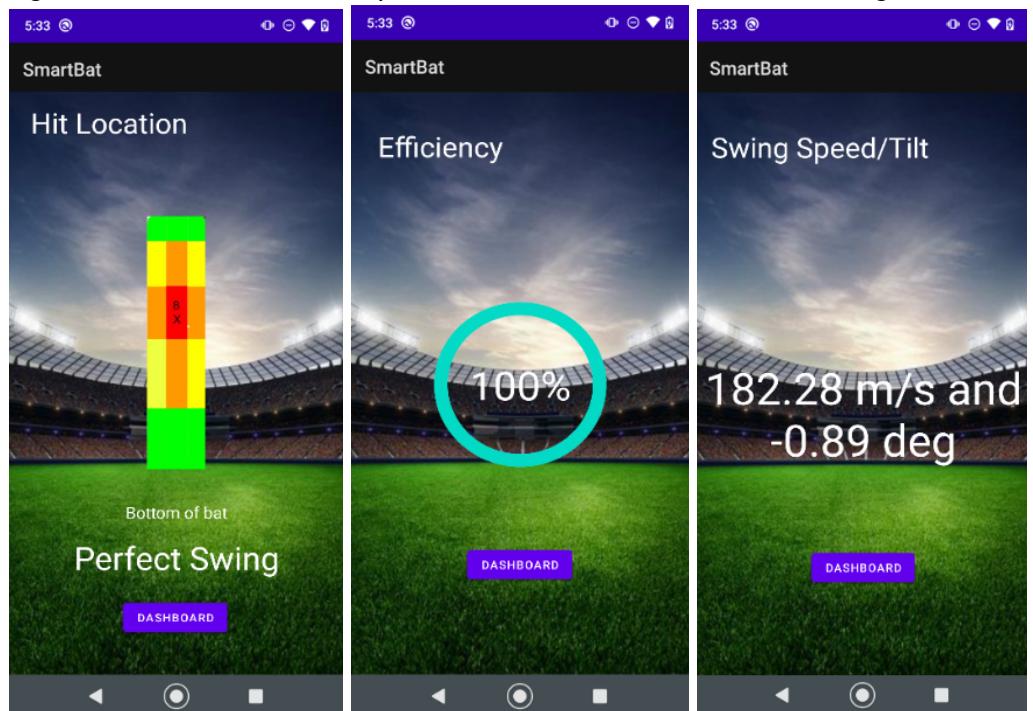


Figure 5d: Output shown in App

Hit Location 10 Data

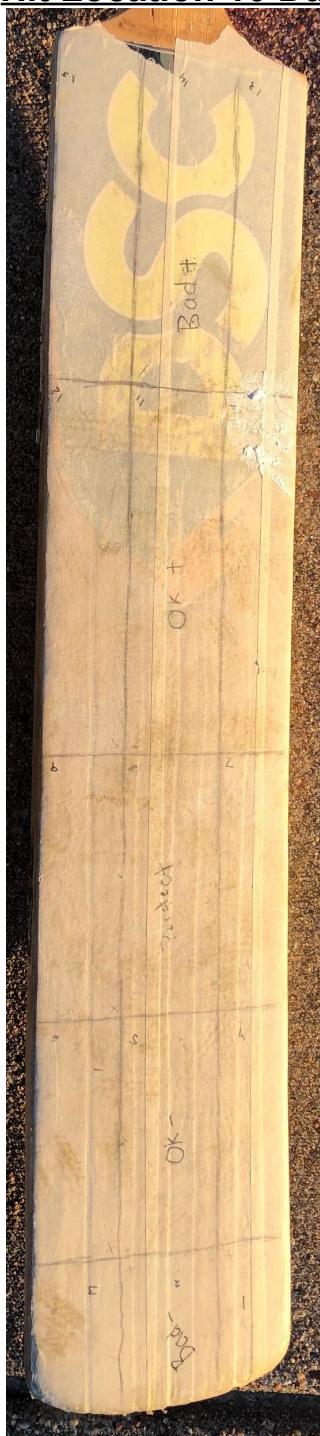


Figure 6a: Marked Physical Collision on Hit Location 10

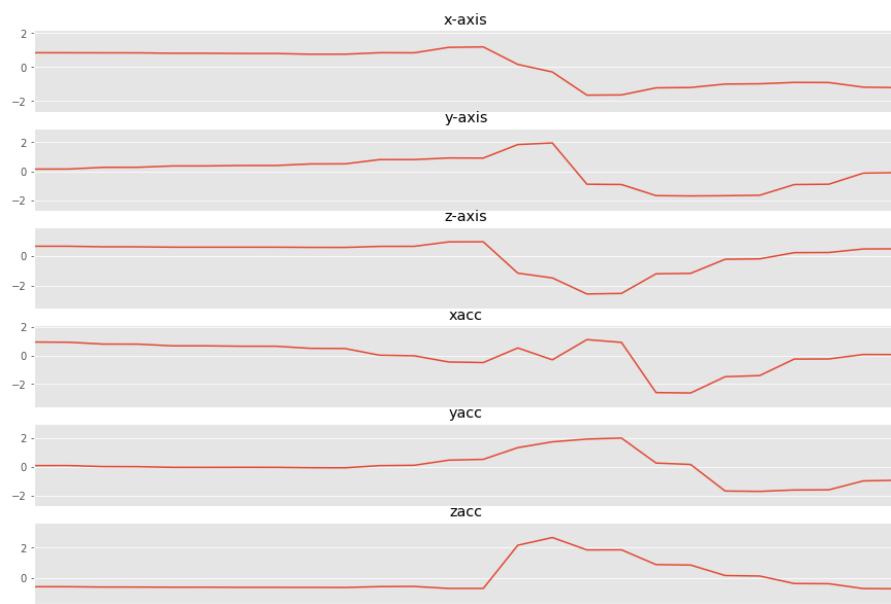


Figure 6b: Hit Data Plots After Preprocessing of Machine Learning

```
{'region': 5, 'speedoverall': 127.19032056037128, 'speedimpac  
69859327460608, 'angley': -2.1123514074571523, 'anglez': -7.1  
ubuntu@ip-172-31-26-208:~$
```

Figure 6c: Screenshot of Output Hit Location from Machine Learning

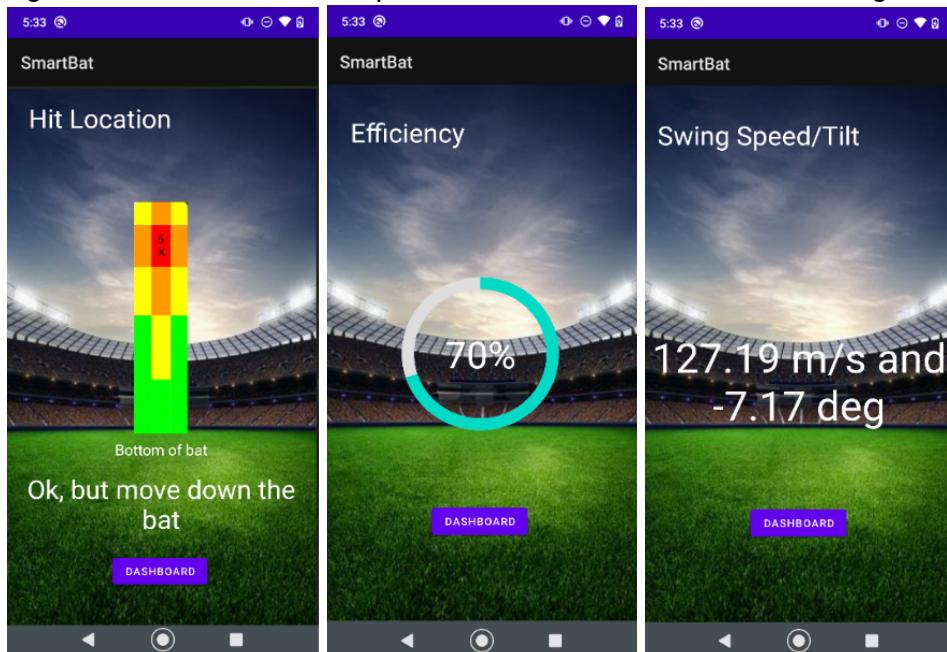


Figure 6d: Output shown in App

Hit Location 9 Data

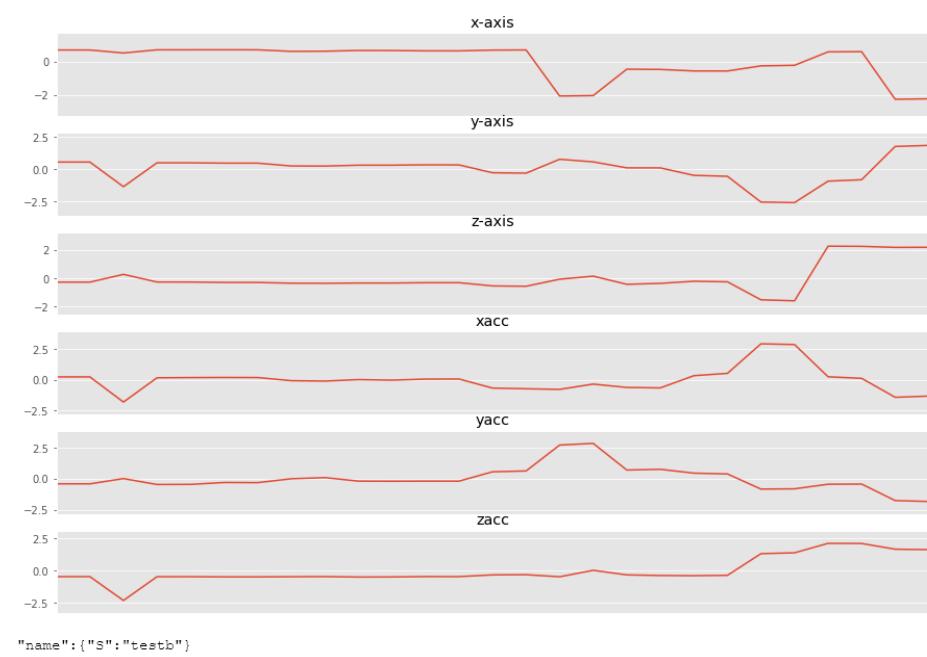


Figure 7b: Hit Data Plots After Preprocessing of Machine Learning

```
{'region': 5, 'speedoverall': 119.31773775093124, 'speedimpactx': 2.9976214870757939777945, 'angley': -5.034752402260575, 'anglez': 3.62209360058705} ubuntu@ip-172-31-26-208:~$
```

Figure 7c: Screenshot of Output Hit Location from Machine Learning

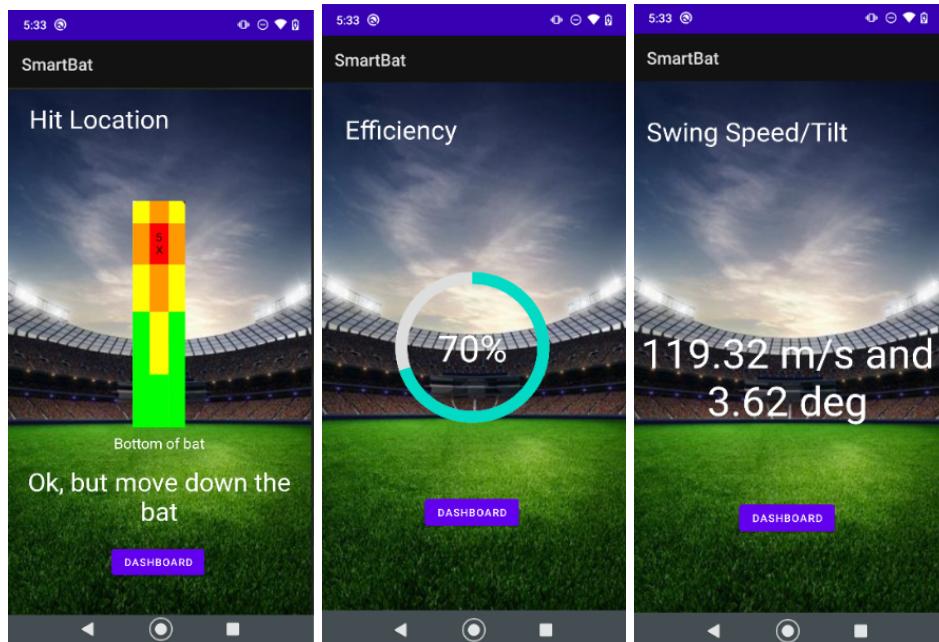


Figure 7a: Marked Physical Collision on Hit Location 9

Figure 7d: Output shown in App

Hit Location 8 Data

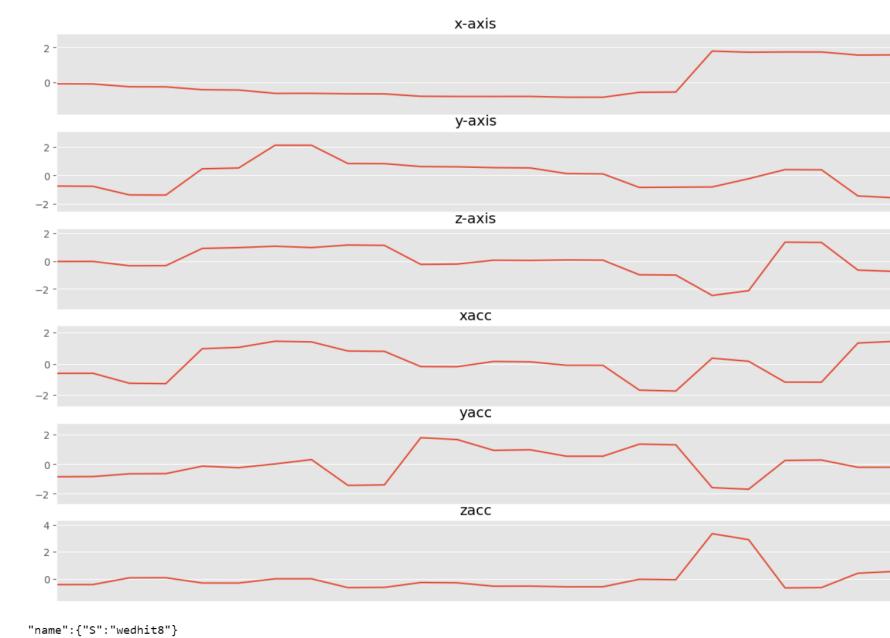
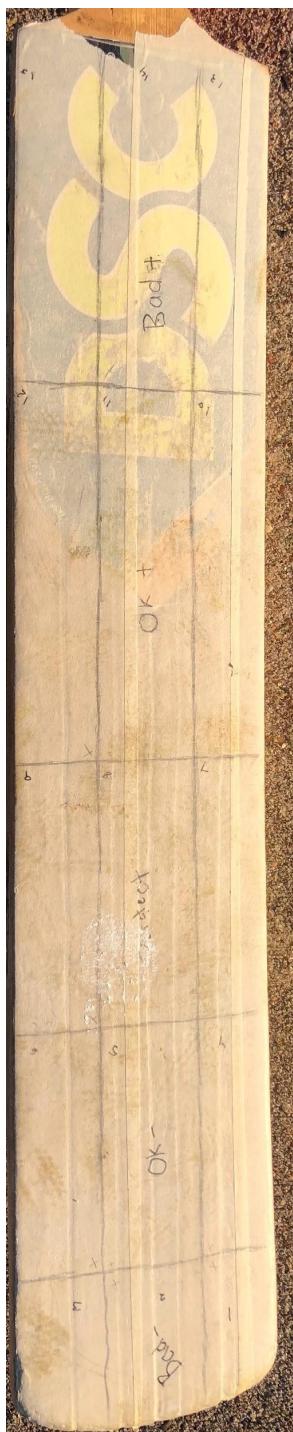


Figure 8b: Hit Data Plots After Preprocessing of Machine Learning

```
{'region': 8, 'speedoverall': 116.7838632602981, 'speedimpact': 337109604133, 'angley': 1.167147824558429, 'anglez': -4.76215535515, 'anglex': 0.0, 'batid': 1, 'ip': '172.31.26.208', 'port': 5000, 'model': 'MLModel', 'version': '1.0', 'platform': 'Ubuntu', 'language': 'Python', 'script': 'hitlocation.py', 'name': {"S": "wedhit8"}}
```

Figure 8c: Screenshot of Output Hit Location from Machine Learning

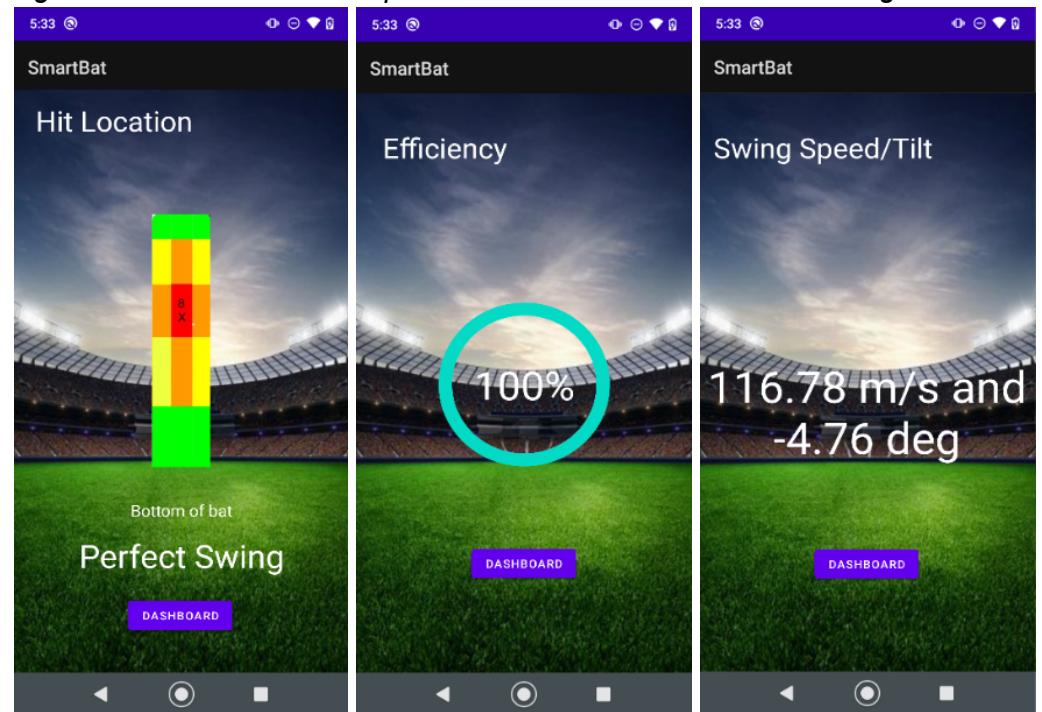


Figure 8a: Marked Physical Collision on Hit Location 8

Figure 8d: Output shown in App

Hit Location 7 Data

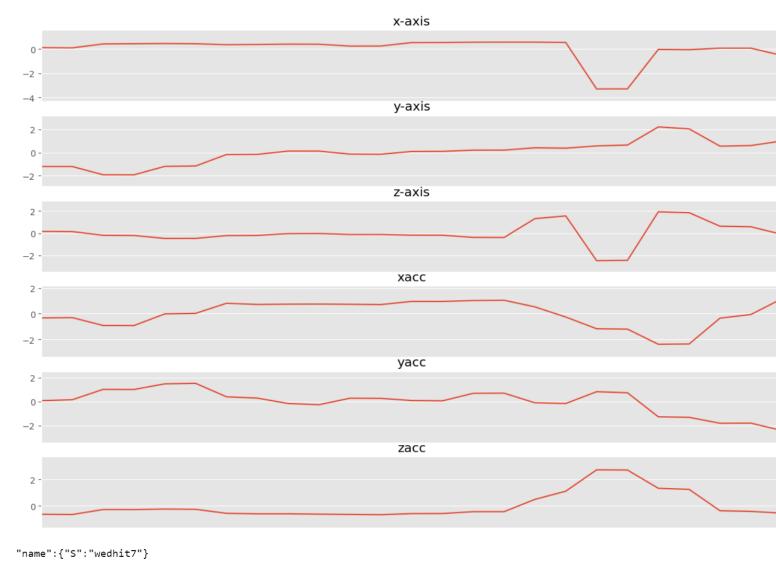


Figure 9b: Hit Data Plots After Preprocessing of Machine Learning

```
{'region': 8, 'speedoverall': 134.1742842304  
44009197668416, 'angleY': 8.4416406636497, '  
ubuntu@ip-172-31-26-208:~$
```

Figure 9c: Screenshot of Output Hit Location from Machine Learning

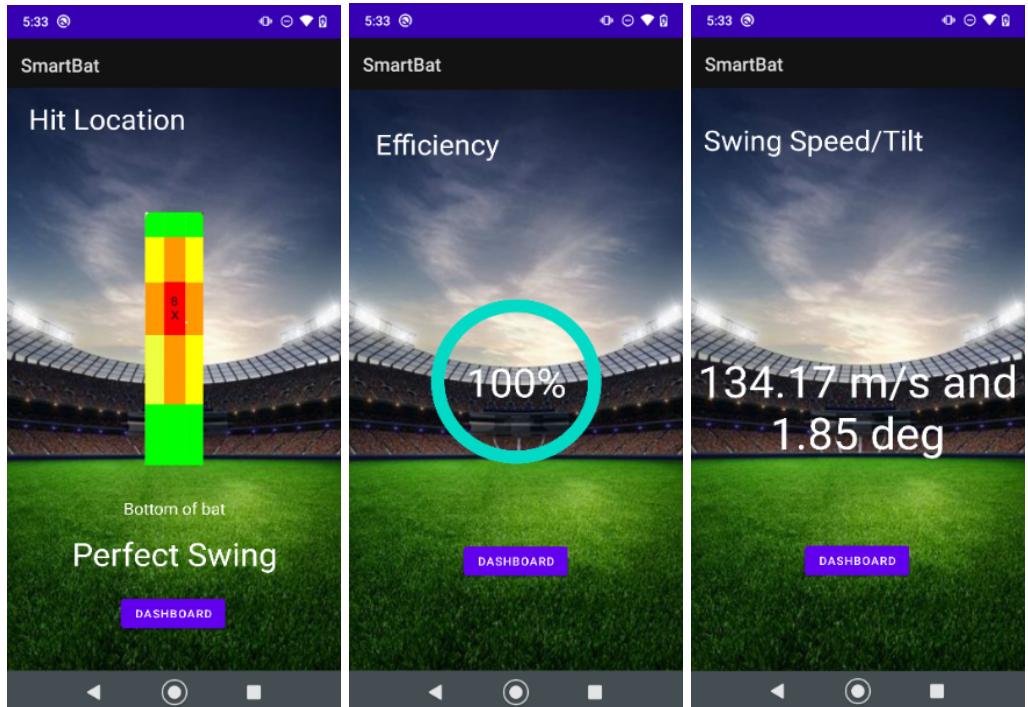


Figure 9a: Marked Physical Collision on Hit Location 7

Figure 9d: Output shown in App

Hit Location 6 Data



Figure 10a: Marked Physical Collision on Hit Location 6

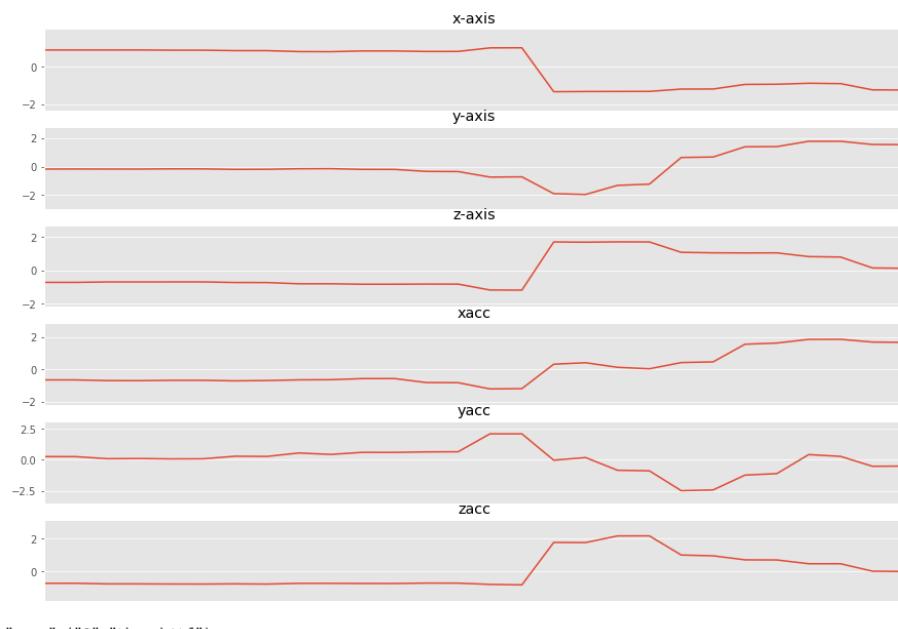


Figure 10b: Hit Data Plots After Preprocessing of Machine Learning

```
{'region': 8, 'speedoverall': 166.078434119252168575837134, 'angley': 3.150132820649097, ubuntu@ip-172-31-26-208:~$}
```

Figure 10c: Screenshot of Output Hit Location from Machine Learning

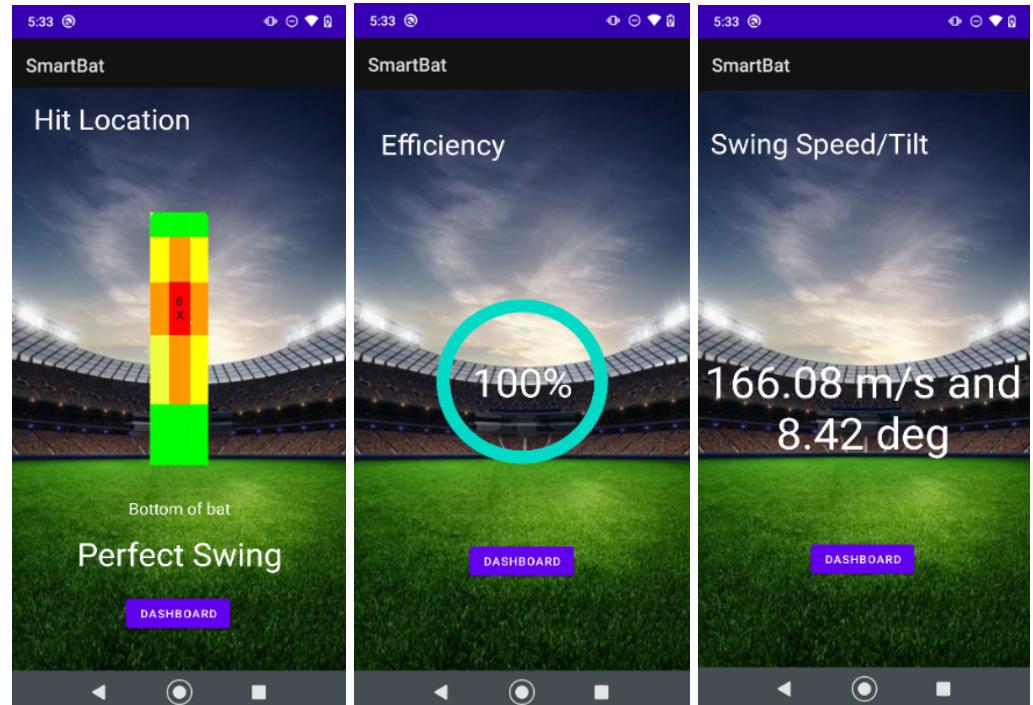


Figure 10d: Output shown in App

Hit Location 5 Data

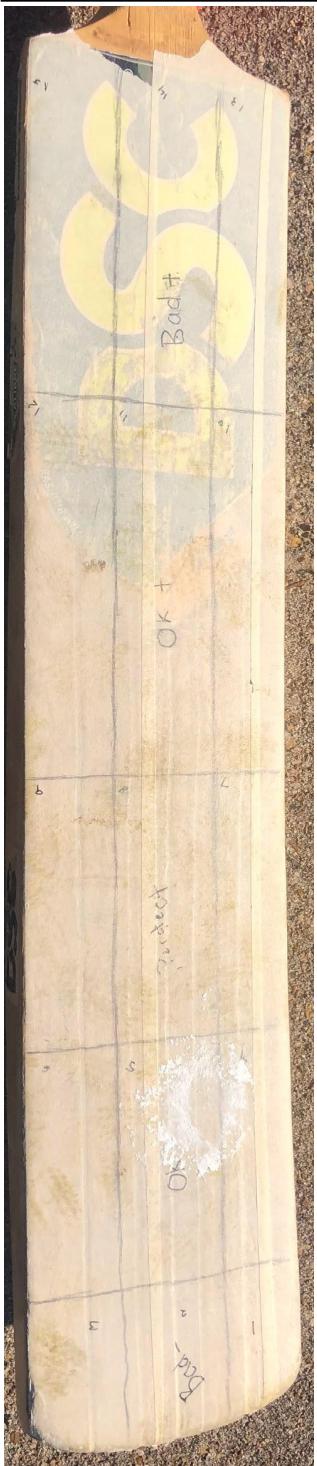


Figure 11a: Marked Physical Collision on Hit Location 5

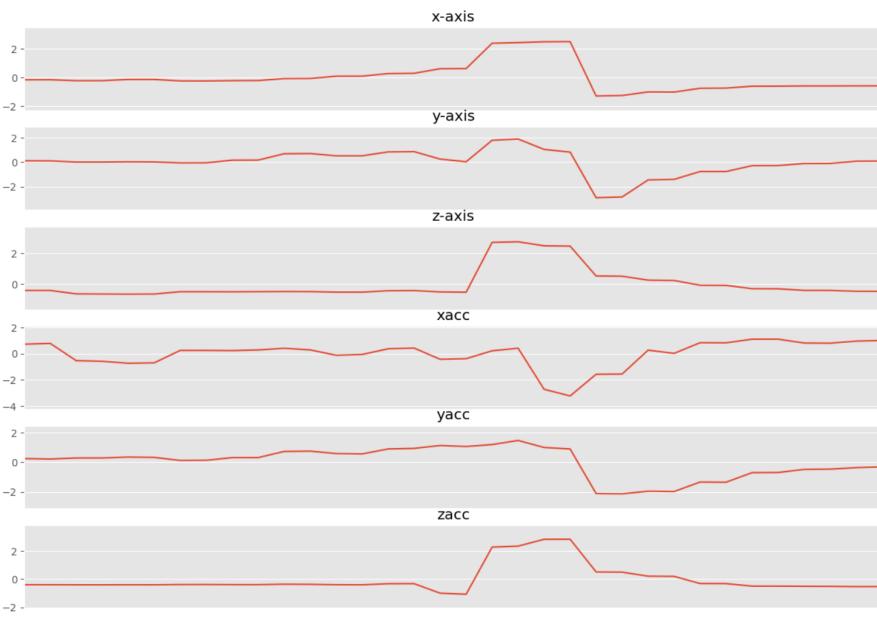


Figure 11b: Hit Data Plots After Preprocessing of Machine Learning

```
{'region': 5, 'speedoverall': 111.13424204987409, 'speedtest': 7455447482602, 'angley': -7.916609345424729, 'anglez': 1.5708},  
ubuntu@ip-172-31-26-208:~$
```

Figure 11c: Screenshot of Output Hit Location from Machine Learning

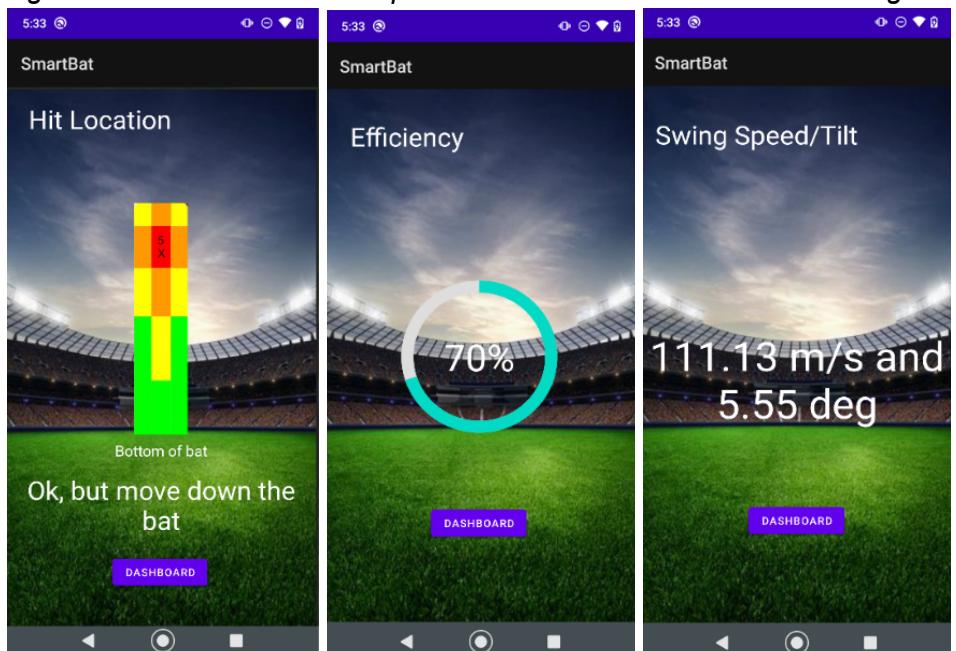


Figure 11d: Output shown in App

Hit Location 4 Data

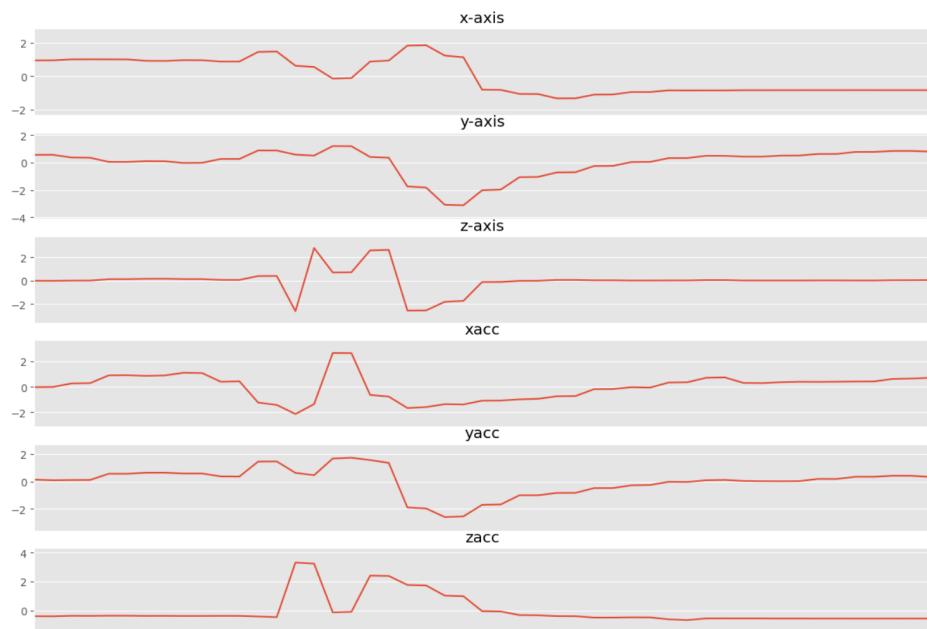


Figure 12b: Hit Data Plots After Preprocessing of Machine Learning

```
"name": {"S": "wedhit4"}  
{'region': 5, 'speedoverall': 179.63365069705063, 'speed': 46809272407164, 'angley': 5.7132027492102235, 'anglez': 0}
```

Figure 12c: Screenshot of Output Hit Location from Machine Learning

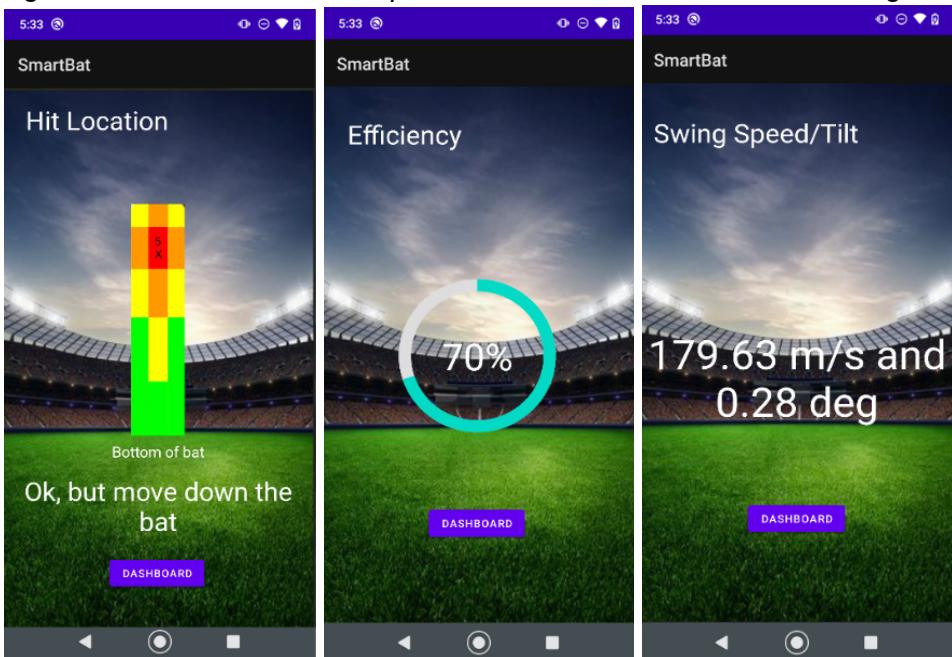


Figure 12a: Marked Physical Collision on Hit Location 4

Figure 12d: Output shown in App

Hit Location 3 Data



Figure 13a: Marked Physical Collision on Hit Location 3

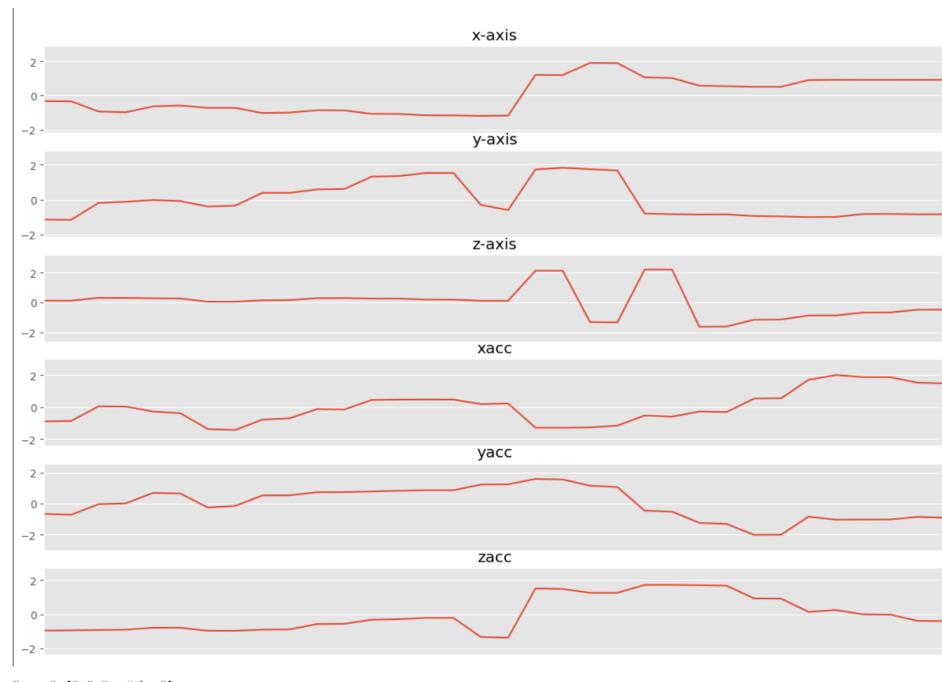


Figure 13b: Hit Data Plots After Preprocessing of Machine Learning

```
{'region': 5, 'speedoverall': 247.5920759560976, '99797915793, 'angley': -5.691397204630443, 'anglez: ubuntu@ip-172-31-26-208:~$ }
```

Figure 13c: Screenshot of Output Hit Location from Machine Learning

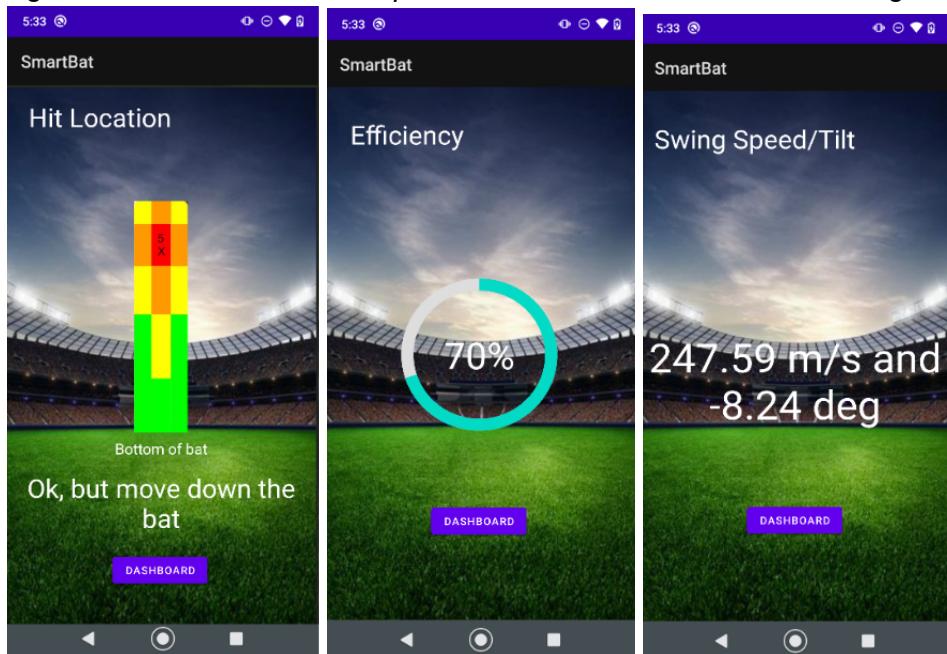


Figure 13d: Output shown in App

Hit Location 2 Data

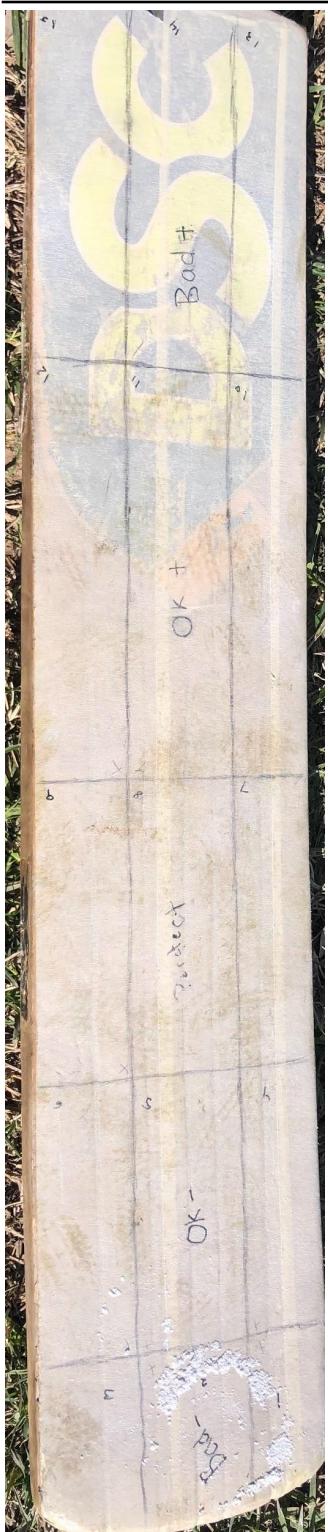


Figure 14a: Marked Physical Collision on Hit Location 2

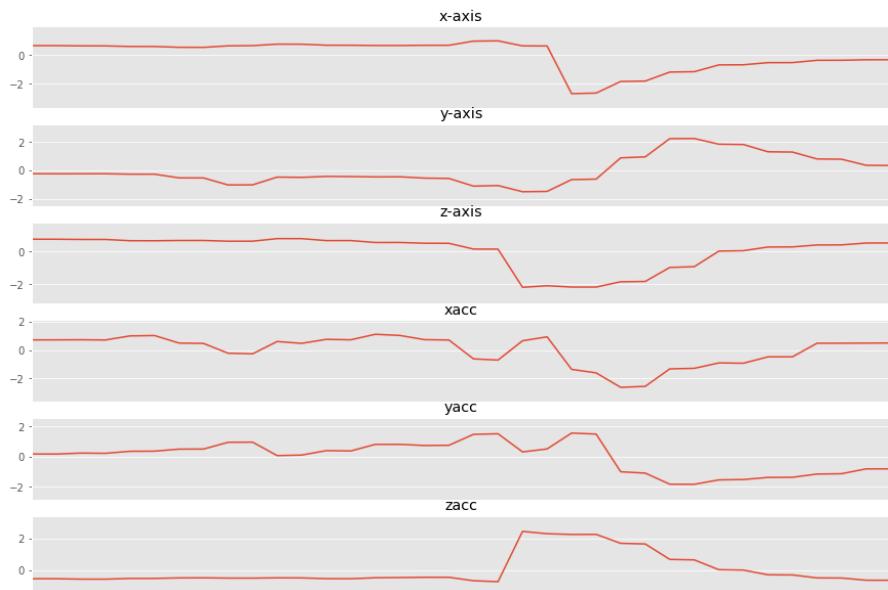


Figure 14b: Hit Data Plots After Preprocessing of Machine Learning

```
{"region": 5, 'speedoverall': 175.15418673414578, '178238132846536, 'angley': 9.529245245475083, 'angle': 1.66, 'ubuntu@ip-172-31-26-208:~$ }
```

Figure 14c: Screenshot of Output Hit Location from Machine Learning

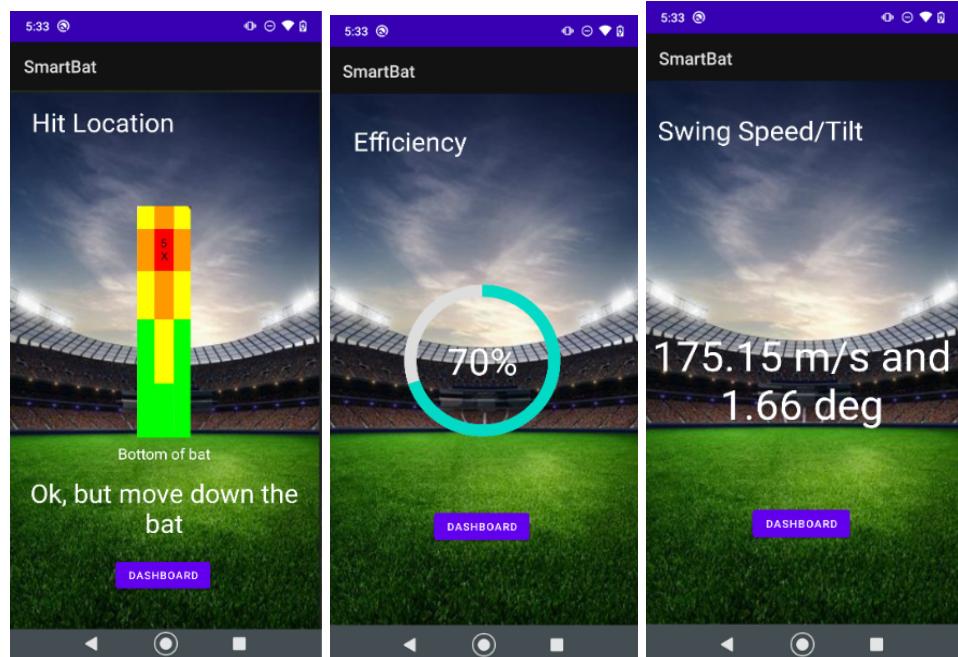


Figure 14d: Output shown in App

Hit Location 1 Data

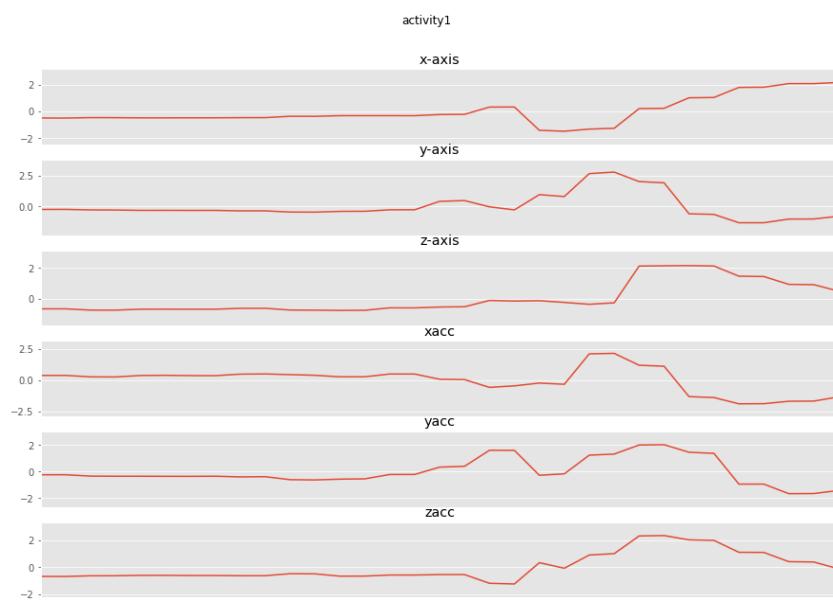


Figure 15b: Hit Data Plots After Preprocessing of Machine Learning

```
10.01151000071551001, 10.01151000071551001, 10.01151000071551001
{'region': 8, 'speedoverall': 149.4660881613284, 'speed8017654318054, 'angley': 1.8019440519001186, 'anglez': 1
ubuntu@ip-172-31-26-208:~$
```

Figure 15c: Screenshot of Output Hit Location from Machine Learning

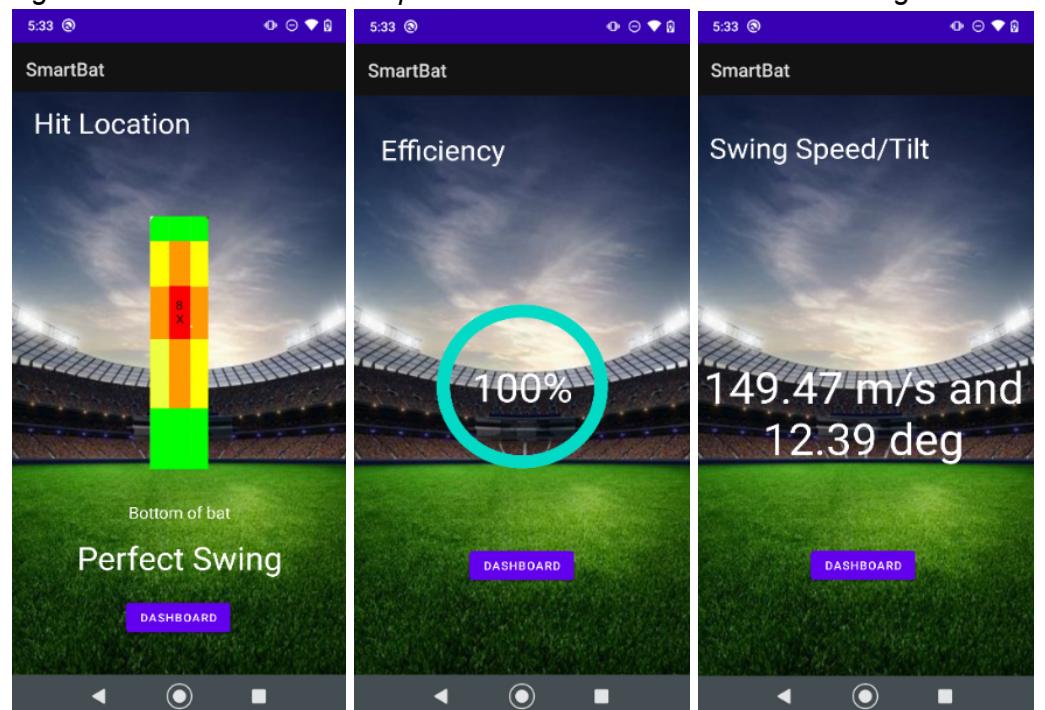


Figure 15a: Marked Physical Collision on Hit Location 1

Figure 15d: Output shown in App

System validation was done by simply using the device as a normal user would, using chalk on the ball to mark where on the bat the ball struck, and comparing that location to the output of the system, i.e. the hit location found by the machine learning algorithm. By looking at all the figures above, one can see that the output region calculated by the machine learning model is not correct for most regions and is always either location 5 or 8. This is because of a lack of training data for the machine learning model, the largest group of data acquired were 5 and 8 as they are the most commonly hit regions on a cricket bat. Throughout the prediction of our model on test set data, and further enhanced by validations and the tests we did, we found that an actual hit on region 5 and region 8 can be predicted correctly. So, we think by increasing the training set the overall accuracy of all other regions would increase. Although accuracy is important, our sponsor for this project has said that high accuracy is not the main goal of the project as much as getting a working “proof of concept”. That is being able to go from collecting data on the MCU to being processed by machine learning to being output on the phone app. And this validates that the device created is able to at least deliver the impact and rotational data from a given swing to a machine learning algorithm in the cloud, and deliver an output to a user friendly app with some accuracy.

1.4. System Conclusion

Overall, our fully integrated system was able to meet all but one requirement placed by our sponsor. Our sponsor set a requirement for the duration from gathering swing data to viewing the calculated results from the ML to take no longer than one minute. However, due to some complications with integration of the ML with the app, exporting data from our AWS Amplify GraphQL API to EC2 instance that runs the ML model takes approximately 8 minutes. This exporting process is out of our control since the latency of exporting is controlled by AWS. Once the ML model has completed processing our data, the user is able to view their swing results at their discretion by pressing the designated buttons. In the future we would have wanted for this exporting process to be done automatically to substantially reduce our total run time. Aside from run time, our system was successful in meeting the weight and dimension requirements. These requirements were put in place to allow our device to be as least intrusive to the user during the swing. If the device is too heavy or too big it would significantly affect how the user swings the cricket bat. Our device also met all bluetooth requirements which include a connection range of at least 100 ft and the MCU is controlled by the app via bluetooth. We were able to successfully establish a connection range of at least 220 ft and communicated with the MCU via bluetooth with a press of a button. The app is able to start and stop data receiving, calibrate the device, and determine battery life of the system via trigger signals sent to the MCU through bluetooth. Lastly, our sponsor set a requirement for the battery life to last at least 2 hours to allow the user to complete a full practice session. Our device is able to last about 6 hours on a full battery. Once the user has concluded their practice session, the user can recharge the device via a simple USB connection. If the battery was fully discharged, charge time to full battery will take approximately 7 hours.