UNIVERSITY of RWANDA

COLLEGE OF SCIENCE AND TECHNOLOGY

Regional Centre of Excellence in Biomedical Engineering and e-Health (CEBE)

DESIGN AND PROTOTYPING A MICROCONTROLLER-BASED WEARABLE DEVICE FOR EPILEPTIC SEIZURE DETECTION AND MONITORING

By:

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A Dissertation Submitted to the Regional Centre of Excellence in Biomedical Engineering and e-Health (CEBE), University of Rwanda as partial fulfilment of the requirements for the Master's Degree in Biomedical Engineering.

Supervised by:

Prof. Damien HANYURWIMFURA

And

Dr. Jean Felix MUKERABIGWI

DECLARATION

I, MUGAMBIRA Adalbert Alonso declare that this dissertation entitled "**Design and prototyping a microcontroller-based wearable device for epileptic seizure detection and monitoring**" is my original work based on research and prototype and has not been submitted for any other degree or professional qualification.

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CERTIFICATE

This is to certify that the project entitled "**Design and prototyping a microcontroller-based wearable device for epileptic seizure detection and monitoring**" is a record of original work done by MUGAMBIRA Adalbert Alonso (Reference number: 220020615), a MSc. Degree student in Biomedical Engineering.

This work has been submitted under the guidance of Prof. Damien HANYURWIMFURA and Dr. Jean Felix MUKERABIGWI

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ABSTRACT

One of the threats to our life is Seizure disorders which pose a significant challenge for individuals with epilepsy and their caregivers, as sudden episodes can occur at any time without warning, but traditional methods like paper-based diaries of seizure occurrence have proved to be inefficient in seizure monitoring. Wearable devices have emerged as an important cog in tracking and monitoring human daily life, hence early detection and timely intervention are crucial to minimizing the risks associated with seizures which motivated researchers to explore the use of wearable devices and biosensors like Electroencephalography (EEG), Electromyography (EMG), Electrocardiography (ECG), Gyroscopes and Accelerometers, but all the solutions explored in the literature are bulky with many wires and don't give the patient enough intended freedom. Our research focuses on the design and prototyping of a microcontroller-based wearable device for epileptic seizure detection by using wearable Myoware EMG sensor to measure muscle activity, and small sized ECG to detect heart rate**.** ESP8266 microcontroller collects data from the ECG sensor and another ESP8266 collects data from EMG sensor, then both data sets are sent to a remote IoT dashboard for data analysis and storage which uses a threshold control algorithm to identify patterns that are indicative of an impending seizure, then use an alerting system of the buzzer, OLED screen to warn the patient and an SMS gateway to send the status of the seizure detection to inform the caregiver that a seizure is about to occur with Global Positioning System (GPS) location of the patient. The proposed research has the prospective to revolutionize the way that seizures are detected and treated in Rwanda. By providing early warning of an impending seizure, the device could help prevent injuries and save the lives of people with epilepsy.

Keywords: *epilepsy, seizure, wearable device, microcontroller, biosensors.*

LIST OF ACRONYMS

IoT : Internet of Things

WHO : World Health Organization

CNS : Central Nervous System

SMS : Short Message Service

GPS : Global Positioning System

EMG : Electromyography

ECG : Electrocardiography

EEG : Electroencephalography

OLED: Organic Light-Emitting Diode

Wh/Kg: Watt Hours per Kilogram

ILAE: International league against epilepsy

SVM: Support Vector Machine

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1 GENERAL INTRODUCTION

1.1 Introduction

Epilepsy is a common neurological disorder that affects people of all ages and this chronic condition can be difficult to manage [1]. People with epilepsy often experience seizures, which can be unpredictable and disruptive because they lead to injuries, disability, and social isolation [2], and some correlation with depression has been shown in research which leads to a poorer quality of life for people with epilepsy [3].

In a survey conducted to estimate the popularity of epilepsy in the Rwandan community, it was approximated that epilepsy affecting the community at 0.7% of the population and based on the national census done in 2003, this translates to 59000 people affected by epilepsy [4]. A survey done in the northern part of Rwanda in 2018, showed that the lifetime prevalence of epilepsy was 36.2% in Kabarege site, 63.4% in Mwidagaduro site and 48.4% in Rutemba site meaning that it is rare for epilepsy to be treated in Rwandan rural areas [5].

This high prevalence of epilepsy proved to be costly in a study done at CARAES neuropsychiatric hospital in NDERA and this has become a big burden to the people with epilepsy where the total annual cost was 389.4 USD in 2020 which is a high cost for people from developing countries [6].

The proposed research will focus on the design and prototyping of a microcontroller-based wearable device for epileptic seizure detection. The device will be designed to be used in Rwanda, where the prevalence of epilepsy is high and the cost of medical treatments is often prohibitive [6].

The device will use a variety of physiological sensors to measure brain electrical activity via the heart and muscles. The data from these sensors will be used by a seizure detection algorithm to identify patterns that are associated with seizure occurrence. The proposed research has the potential to revolutionize the way that seizures are detected and treated in Rwanda, by providing early warning of an impending seizure, the device could help to avoid injuries and save lives.

1.2 Problem Statement

Traditional methods of monitoring seizures, such as paper-based seizure diaries, have limitations and can be unreliable. The advent of wearable technology and microcontrollers, as well as advancements in sensors and wireless communication, has created an opportunity to develop devices that can detect and monitor seizures in real-time, but the devices in literature are too much wired which impedes patients' freedom. This solution can be improved by using Biosensors and microcontrollers with wireless capability.

This device will provide people with epilepsy and their caregivers with more accurate and reliable information about seizure activity, which can lead to better seizure management and improved quality of life.

1.3 Research Questions

1. What are the current trends and advancements in seizure detection and monitoring technologies, particularly using wearable devices?
2. How do existing studies highlight the limitations of traditional seizure monitoring methods and the potential for improvement using wearable technology and wireless communication?
3. Which physiological signals, as outlined in existing research and clinical guidelines, are most relevant and reliable for the detection of seizures in individuals with myoclonic epilepsy?
4. How can the selected physiological signals be effectively measured and interpreted in the context of a wearable device for real-time seizure monitoring?
5. How does the developed prototype perform in terms of accuracy and reliability in detecting simulated seizure activity in a controlled laboratory setting?
6. What are the strengths and limitations of the wearable device based on the results obtained from the evaluation?

1.4 Objectives

1.4.1 General Objective

To develop a practical, cost-effective, and user-friendly wearable device that can accurately detect and monitor seizures in individuals with epilepsy.

1.4.2 Specific Objectives

1. To identify the most appropriate physiological signals to monitor for seizure detection, based on existing research and clinical guidelines.

2. To design and develop a prototype of the wearable device, including hardware components and software algorithms for data analysis and seizure detection.

3. To test the wearable device in detecting seizures in a laboratory setting, using simulated seizure activity.

1.5 Study Scope

By recognizing the presence of many types of epileptic seizures, this research project specifically focuses on detection of Myoclonic Seizures only, where we use software and hardware to build a system prototype.

1.6 Significance of the Study

The device is meant to help improve the quality of life for people with epilepsy in different ways:

Early warning of seizures: The device timely alerts users of an impending seizure, giving them time to take steps to prevent or mitigate the effects of a seizure. This includes finding a safe place to sit or lie down, and alerting caregivers.

Increased independence: The device gives people with epilepsy the confidence to live more independently, knowing that they will be monitored and given early warning of seizures. This translates into employment opportunities, social interaction, and an overall better quality of life.

1.7 Organization

This research study unfolds across five chapters, each with a distinct purpose contributing to the comprehensive understanding and impact of the project. In Chapter One, we begin with the Introduction, where the background of the research is unveiled, explaining the problem statement, objectives, research questions, and the study's significance. Chapter Two discusses the related literatures about seizure detection and monitoring technologies, with a focus on the promising field of wearable devices. In Chapter Three, we show the Research Methodology used, including the research process and design methods. Chapter Four discusses the Project Results, analyzing the outcomes of the accuracy and reliability evaluation of the developed prototype, while underlining any significant findings, patterns, or trends observed. Chapter Five provides the Conclusion and Recommendation, drawing the study to a close by briefly summarizing key findings, highlighting their implications, and anticipating the broader impact on epilepsy management, addressing the Challenges and Recommendations for future research on the developed wearable device.

2 LITERATURE REVIEW

The review of the related works will focus on the importance of wearable devices in modern times and also on the already exiting seizure detection systems that have been developed.

2.1 Epileptic Seizures

A seizure is a temporary disruption of neurologic activity due to anomalous neuronal firing in the brain which may be characterized by loss of awareness, confusion, body shaking or jerking, and if the seizures keep recurring unprovoked, the condition is called epilepsy [7].

The international league against epilepsy (ILAE) classifies epileptic seizures as focal seizures if they originate from one focal position in one hemisphere of the brain or generalized seizures if they start from both hemispheres at the same time [7][8].

2.1.1 Myoclonic Seizures

Myoclonic seizures refer to abrupt, brief, shock-like contractions that can differ in distribution and intensity which may result from either focal or generalized epilepsy [9].

The term myoclonic seizure is restricted to the events originating from the central nervous system (CNS) consisting of rapid muscle movements caused by an involuntary depolarization change [10].

2.2 Wearable Devices

Epilepsy is a prevalent neurological disorder that impacts individuals across various age groups, roots, socioeconomic backgrounds, and geographic regions. It is a condition that affects the brain and is distinguished by a persistent susceptibility to experiencing seizures. In addition, individuals with epilepsy may encounter a range of neurobiological, cognitive, psychological, and social harm as a result of recurrent seizures [1].

The occurrence of accidents and injuries is slightly higher in individuals with epilepsy compared to the overall population. This elevated risk is likely more common among patients with symptomatic epilepsy and frequent seizures, particularly when coupled with additional disabilities. Most of the accidents are minor in nature and happen within the home environment. The most frequent types of injuries experienced by epilepsy patients include bruises, cuts, fractures, and concussions [16].

The necessity for immediate and efficient interventions cannot be overemphasized when preventing neurological damage or brain injury. Unfortunately receiving essential services presents numerous challenges that can lead to prolonged wait times before seeing a doctor. Nonetheless, prehospital treatments have significantly proven to lower the severity of effects encountered during episodes of status epilepticus and boosted overall patient results [17].

A promising strategy for enhancing epilepsy management involves the creation of wearable devices capable of real-time detection and monitoring of seizures. Over the past few years, there has been an increasing focus on utilizing microcontroller-based wearable devices for this purpose due to their ability to provide continuous monitoring and immediate alerts when seizures occur [18].

Some of the advantages of wearable technologies are that they are compact, may be worn discretely in any setting, provide personalized data, and may be integrated via communication networks to enable remote monitoring. They also mention that wearable technology can be divided into two groups: primary, which operates independently and serves as a hub for other devices and/or information such as a wrist-worn fitness tracker, or a smartphone; and secondary, which records specific actions or carries out measurements and send them to a primary wearable device for analysis [19].

In their extensive analysis, Xiao-Fei Teng and co-authors present a thorough examination of the latest progress in wearable devices designed for monitoring vital signs. some developed devices for medical application include the earlobe device for blood flow change detection, a watch, a finger ring, a glove, a wrist-worn device, a jacket and a textile cloth, to mention but a few. The authors emphasize the obstacles and prospects associated with employing various sensor types and signal processing methods to identify changes in physiological parameters such as the fabrication of textiles with higher conductivity, the safety of electronic components, and ways of interfacing the components. The researchers particularly emphasize the significance of carefully selecting the most suitable physiological signals to monitor, taking into account existing research findings and clinical guidelines [20].

An example of the use of wearable devices in telemedicine, is where diseases like Hypertension and cardiovascular diseases can be monitored in elderly people remotely to combat the effect of chronic diseases where Electrocardiography (ECG) and personal digital assistants (PDAs) are used. The authors also point out the use of multisensory data fusion in military, remote sensing, and imaging applications, but they note that the application in bio-signal processing is still relatively new which indicates the need for engagement in wearable devices for medical purposes [21].

The role of wearable technology in enhancing the quality of life can also be exemplified by where a wearable smart shirt is used in monitoring vital signs of humans in an unnoticeable way. This plays an important role in tracking and monitoring situations like soldiers on the battlefield, mountain hiking, driving race cars, and small children monitoring. It contains a sensor for monitoring vital signs such as heart rate, respiration rate, electrocardiogram (ECG), body temperature, and pulse oximetry (SpO2) and can also record voice if a microphone is plugged, where a controller processes the information and sends it to the desired location for necessary use [22].

In addition to enabling the monitoring of physiological signals, wearable technology enables the replacement of missing body parts or the empowerment of weak limbs for the rehabilitation of stroke or Parkinson's disease patients with wearable robots that act as exoskeletons. Many of these wearable robots, like Kinetic Muscles's Hand Mentor, which uses games to encourage repetitive hand motions to help a patient with hemiparesis rewire her brain after a stroke, are already commercially available for stroke rehabilitation. However, current robotics technology is, of course, far beyond what is currently available [23].

2.3 Seizure Detection Systems

Escobar Cruz et al. developed a wearable glove with a mobile application and a support vector machine classifier based on cloud computing, by using an accelerometer, electromyography, electro-dermal activity electrodes, and a machine learning algorithm by support vector machine (SVM) which differentiates simulated tonic-clonic seizures that may be confused with convulsions. The limitation of the design is its bulky size and the use of a low-capacity battery which can be improved by using Li-Po battery of more capacity to work for more than 19 hours [24] .

A wearable epileptic seizure prediction Telemeter which bases on machine learning to detect the variability of heart rate was also proposed. The telemeter prototype uses a smartphone app and multivariate statistics to calculate the heart rate variability from an electrocardiogram (ECG) before the occurrence of seizures. It is a portable system with an accuracy of 85.7% but it needs a lot of data from many patients to be able to work properly. It can be improved by using more patients’ data to be more able to detect changes in normal state of the patients [25].

An Internet of Things (IoT) based monitoring system for epileptic patients focuses on tonic-clonic seizures. The system employs a combination of Electrocardiogram (ECG), Electromyogram (EMG), and accelerometer sensors to monitor heart rate, muscle spasms, and falls respectively, with a fuzzy logic algorithm to assess and classify seizure indicators and display the result on an IoT platform (Thing-Speak). It is an accurate system with an accuracy of more than 85%, but it is bulky and could be made an even better system by improving its portability, where small wireless sensors can be used, such as micro wireless ECG and wearable Nano EMG sensor [26].

A novel wearable device for automated real-time detection of epileptic seizures was also developed, which incorporates an accelerometer and vibration sensor for body movement detection, and a pulse oximeter for oxygen denaturation and heart rate sensing, and the combination of these parameters is valuable in detecting epileptic seizures. The prototype is a device with a high accuracy of more than 90%, but it lacks automation because pulse oximetry needs to work when the sensor is manually touched, it can also be made more portable by replacing the wired sensors with wireless sensors and also by extending the working time by considering a battery of higher capacity [27].

This research focuses on the use of wireless and smaller-sized sensors to design and prototype a microcontroller-based wearable device for epileptic seizure detection by using small-sized biosensors including micro ECG to detect heart rate and wearable Myoware EMG sensor to measure muscle activity with ESP8266 microcontrollers and remote IoT dashboard to run a threshold control algorithm to identify an impending seizure. It also uses an alerting system of buzzer, OLED display and an SMS gateway to send the Global Positioning System (GPS) location and the status of the seizure detection and also to inform the caregiver that a seizure is about to occur. This design will improve the portability of the device by reducing wires.

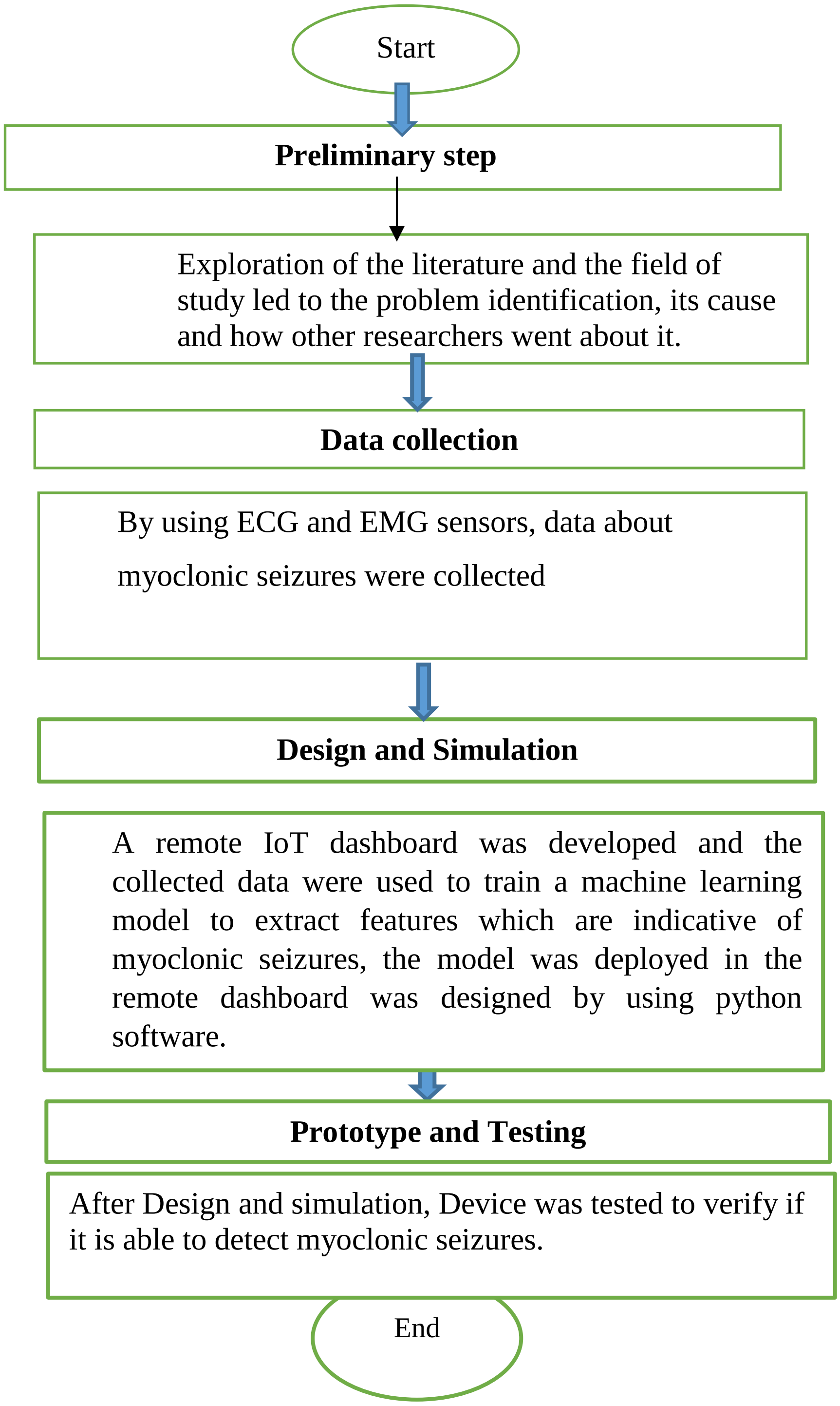
3 METHODOLOGY

The study involves not only the design and prototyping of the microcontroller-based wearable device for seizure detection and monitoring but also the implementation of advanced signal-processing algorithms. These algorithms enable the device to analyze physiological signals such as electromyography (EMG) and electrocardiography (ECG) data in real-time. Additionally, the device incorporates machine learning techniques to enhance its ability to detect and classify seizures accurately. By leveraging state-of-the-art technology, the wearable device aims to provide reliable and timely seizure detection, thereby improving the overall management and quality of life for individuals with epilepsy.

3.1 Research Process

In the research process for developing the microcontroller-based wearable device for epileptic seizure detection, it's imperative to ground our approach in existing literature. We draw upon a rich body of research exploring various aspects of seizure detection technologies, wearable device design, seizure prediction algorithms, user experience considerations, and ethical and regulatory frameworks. For instance, studies by Cook and Beniczky [28] have investigated the feasibility and accuracy of wearable EEG devices, informing our sensor selection and integration strategy. Additionally, works by Patel et al [29] and Bonato [30] offer insights into wearable sensor technologies and microcontroller programming methodologies, guiding our device design and prototyping efforts. Furthermore, research by Mormann et al. [31] and Subasi et al. [32] on seizure prediction algorithms informs our approach to real-time detection and alerting mechanisms. Considerations of user experience and acceptance, as explored by Peters et al. [33] and Bahrani et al. [34], are integrated into our study to ensure usability and user satisfaction. Moreover, insights from works by McDermott et al. [35] and Palacios-Garcia et al. [36] on ethical and regulatory considerations guide our approach to participant rights, informed consent, and data privacy. By leveraging existing research, our study aims to build upon established knowledge and methodologies, contributing to the advancement of seizure detection technology and ultimately improving outcomes for individuals living with epilepsy.

The research work followed these steps:


Start
Preliminary step
Exploration of the literature and the field of study led to the problem identification, its cause and how other researchers went about it.
Data collection
By using ECG and EMG sensors, data about myoclonic seizures were collected
Design and Simulation
A remote IoT dashboard was developed and the collected data were used to train a machine learning model to extract features which are indicative of myoclonic seizures, the model was deployed in the remote dashboard was designed by using python software.
Prototype and Testing
After Design and simulation, Device was tested to verify if it is able to detect myoclonic seizures.
End

3.2 Research Design Methods

3.2.1 Literature Review Method to Identify Physiological Signals

Objective: To identify the most appropriate physiological signals to monitor for seizure detection based on existing research and clinical guidelines.

Search strategy: A Comprehensive Literature review was used to distinguish among different physiological signals for seizure detection. The approach consisted of searches in information sources like PubMed and IEEE Xplore using keywords such as seizure detection, physiological signals, and epilepsy monitoring.

Inclusion and Exclusion Criteria: The included articles are published in peer-reviewed journals from the last 10 years to ensure updated and relevant information. In addition to old information, Sources with irrelevant topics were also excluded.

This included the extraction of data from various studies for details on a number of physiological signals used in seizure detection, how effective they were at identifying seizures and corresponding clinical outcomes. Data were synthesized from the literature to determine frequent and effective signals that can be measured using the physiological monitors suggested for incorporation in a wearable device.

3.2.2 High-Fidelity Prototyping Method for Design and Development of the Prototype

To design and develop a prototype of the wearable device, including hardware components and software algorithms for data analysis and seizure detection, high fidelity prototyping method was used. It was chosen because it results in a prototype of a wearable device which closely resembles the final product and is used to test its functionality.

The system requirements for a microcontroller-based wearable device for epileptic seizure detection are as follows:

3.2.2.1 Hardware

Microcontroller: Integrate the MyoWare Muscle Sensor Shields into the project to enable electromyography (EMG) recording for muscle activity detection.

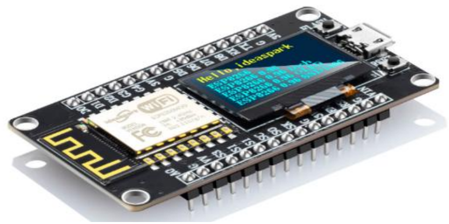


Figure 3.1: ESP Microcontroller

OLED Display (1.2 inch)

OLED stands for organic light-emitting diode. The "OLED 1.2 inch" is small in size, and it has a 1-inch diagonal. OLED has high contrast. The high contrast of OLED makes the device more readable. It has 128 x 32 individual white OLED pixels, and each one is turned on or off by the chip. The display makes its own light; no backlight is required. The high contrast of the OLED reduces the power required to run it. The OLED works under 3.3 volts.

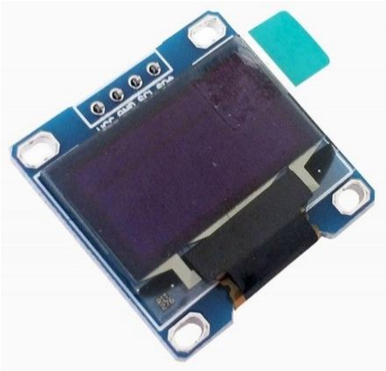


Figure 3.2: OLED Display

Sensors: Various sensors are used to detect physiological signals that are associated with seizures. These are

- **Wearable Myoware electromyography (EMG)** sensor to detect muscle activity, which can be used to detect convulsive seizures.

Single-supply - MyoWare won't need ± voltage power supplies! Unlike the previous sensor, it can now be plugged directly into 3.3V - 5V development boards.

Embedded Electrode Connectors - Electrodes now snap directly to MyoWare, getting rid of those pesky cables and making the MyoWare wearable!

RAW EMG Output - A popular request from grad students, the MyoWare now has a secondary output of the RAW EMG waveform.

Polarity Protected Power Pins - The #1 customer request was to add some protection so the sensor chips don't burn out when the power is accidentally connected backwards.

ON/OFF Switch - Speaking of burning out the board, Advancer Technologies also added an on-board power switch so you can test your power connections more easily. It's also handy for saving power.

LED Indicators - Advancer Technologies added two on-board LEDs one to let you know when the MyoWare's power is on and the other will brighten when your muscle flexes.

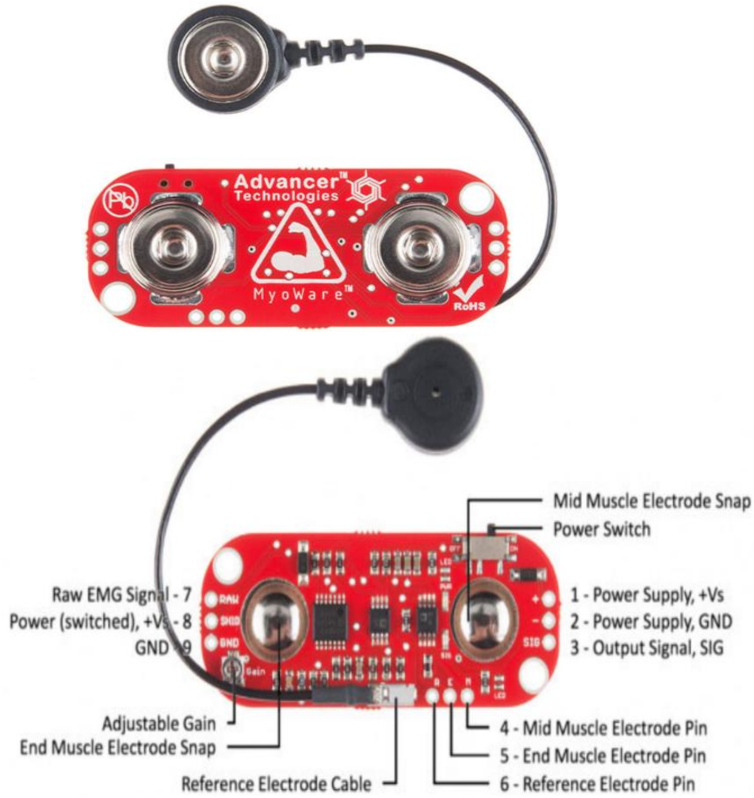


Figure 3.3: Myoware EMG Sensor

- **Small Size Electrocardiography (ECG)** Sensor to detect heart rate which is indicative of the effect of Seizures on autonomous Nervous System.

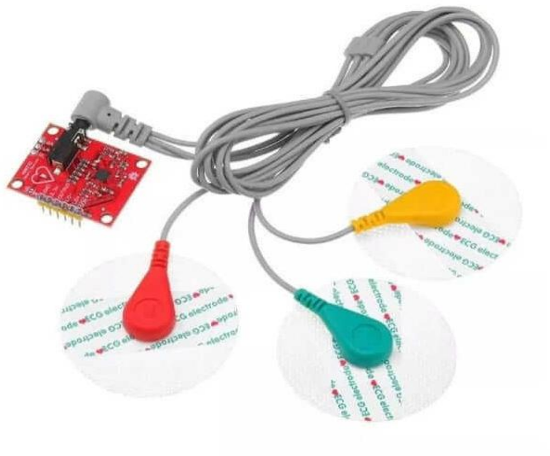


Figure 3.4: ECG Sensor

A buzzer (3 V–5 V), also called a beeper, is an audio signaling device. The buzzer may be electromechanical, piezoelectric, or mechanical. The main function of this device is to convert the signal from audio to sound, and it can be powered by a voltage of 35 volts. 5V.

Figure 3.5: Buzzer showing the source of power connections

The pin configuration in Figure 3.5 of the buzzer shows two pins. These pins are both positive and negative. The positive terminal of this is represented by to indicate that this is a positive terminal, use the "+" sign or a longer terminal. The GND terminal is connected to the positive terminal, which is represented by the '+' symbol. This terminal receives 5 volts of power.

Wireless communication: The wearable device is equipped with wireless communication module combining Wi-Fi and GPS capability, to transmit data to a remote monitoring system. This will enable real-time monitoring and alerts for seizures through mobile phones using Short Message Service.

Power supply: The power source will be rechargeable Coin cell batteries**,** the chemical composition of Coin cell batteries is also alkaline in nature. Apart from alkaline composition, lithium, and silver oxide chemicals are used to manufacture these batteries which are more efficient in providing steady and stable voltage in such small sizes. It has Power density of 270 Wh/Kg to provide power to the hardware components.

Figure 3.6: Coin cell batteries

Housing Case: The 3D-printed Polyvinylchloride housing will enclose the microcontroller and buzzer and will be worn on the arm.

3.2.2.2 Software:

We require software tools which are:

- **Arduino IDE**: For programming the microcontroller and developing the sensor control algorithm.
- **Python**: For additional software development tasks, such as data analysis and machine learning.
- **JavaScript (JS)**: For web-based interactions, applicable for developing additional functionalities for the wearable device's user interface or remote monitoring system.
- **SolidWorks**: For designing and modeling the housing case.

3.2.2.3 System Components

The sensors, including Myoware EMG sensor and micro ECG sensors, compose the sensing part which detects physiological signals related to seizures. The processing part is the microcontroller which will receive the output from sensors and process them using threshold control algorithm to determine whether a seizure has occurred. If a seizure is detected, the microcontroller sends the status to the Notification part of the LCD display and the buzzer to alert the patient and sends an alert containing the status of the patient and the GPS location through the SMS gateway to caregivers as shown in Figure 3.7.

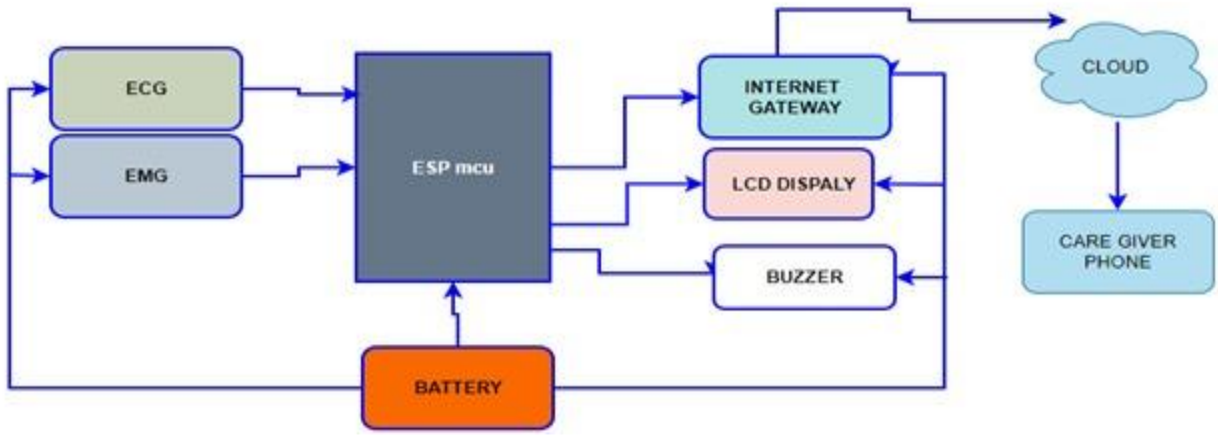


Figure 3.7: System Block Diagram

3.2.2.4 Seizure Detection Flow Chart

We set up a machine learning model that can accurately extract features and identify patterns in the physiological signals that are indicative of an impending seizure as the flow chart indicates in Figure 3.8

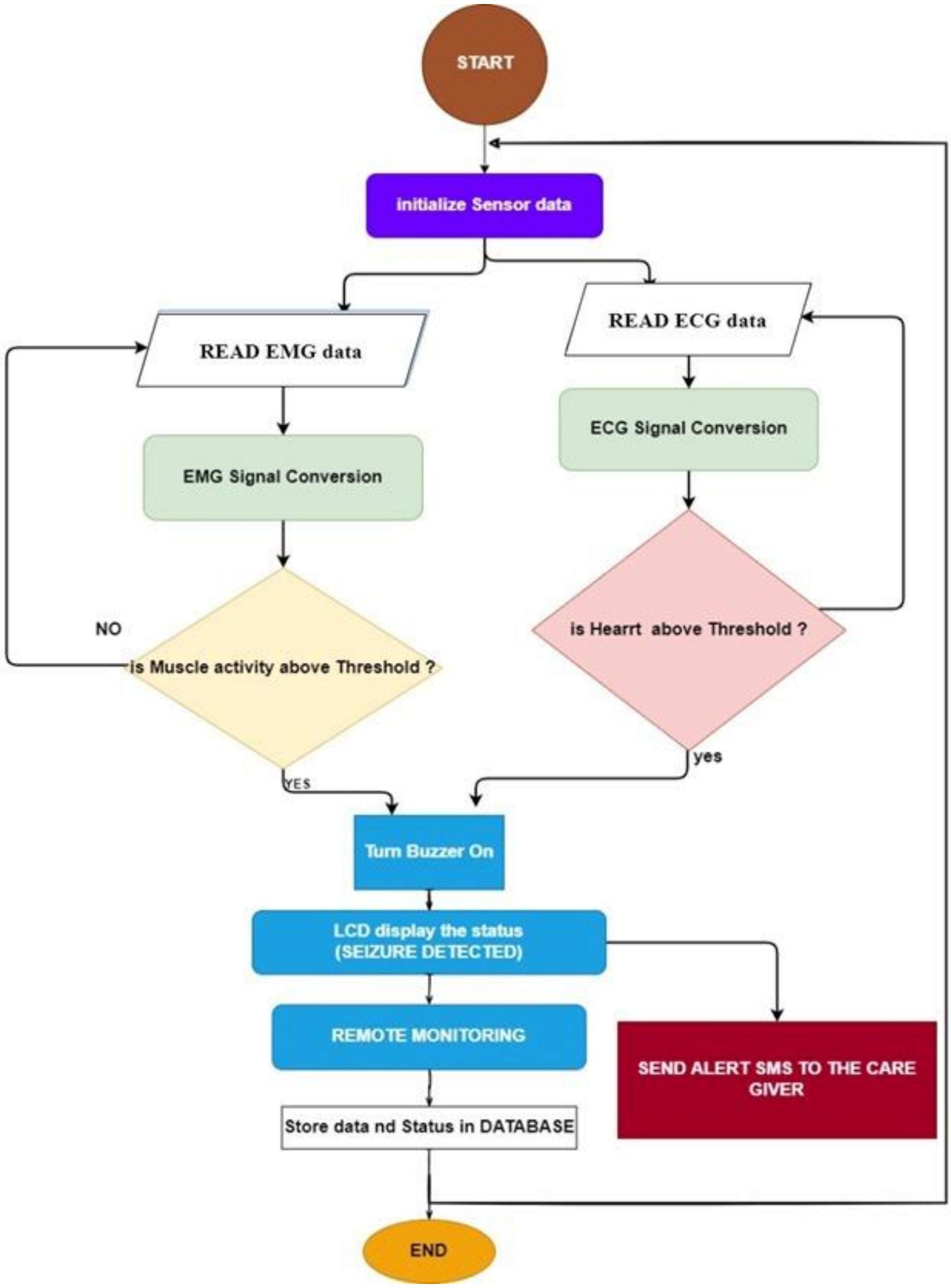


Figure 3.8: Seizure detection system flow chart

3.2.2.4.1 Machine learning model training codes

a) Conventional Neuron Network model training

```
    data.append([ecg, emg, label])

# Convert to DataFrame
df = pd.DataFrame(data, columns=['ecg', 'emg', 'label'])

# Prepare data for deep learning
X = np.array([np.vstack((row['ecg'], row['emg'])).T for _, row in df.iterrows()])
y = to_categorical(df['label'])

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Build CNN model
model = Sequential()
model.add(Conv1D(64, kernel_size=3, activation='relu', input_shape=(X_train.shape[1], X_train.shape[2])))
model.add(MaxPooling1D(pool_size=2))
model.add(Dropout(0.5))
model.add(Conv1D(128, kernel_size=3, activation='relu'))
model.add(MaxPooling1D(pool_size=2))
model.add(Dropout(0.5))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(2, activation='softmax'))

# Compile model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Train model
history = model.fit(X_train, y_train, epochs=20, batch_size=32, validation_split=0.2, verbose=1)
```

b) Support Vector Machine model training

```
# Support Vector Machine
print("\nSupport Vector Machine")
svm_model = SVC(kernel='rbf', random_state=42)
svm_model = evaluate_model(svm_model, X_train, y_train, X_test, y_test)
```

c) Logistic Regression model training

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train a Logistic Regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Predict on the test set
y_pred = model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

accuracy, conf_matrix, class_report
```

d) Feature extraction

```python
def extract_features(signal):
    return {
        'mean': np.mean(signal),
        'std': np.std(signal),
        'max': np.max(signal),
        'min': np.min(signal),
        'range': np.ptp(signal),
        'median': np.median(signal),
        'variance': np.var(signal)
    }

# Extract features for each sample
features = []
for index, row in df.iterrows():
    ecg_features = extract_features(row['ecg'])
    emg_features = extract_features(row['emg'])
    combined_features = {**ecg_features, **emg_features}
    combined_features['label'] = row['label']
    features.append(combined_features)

# Convert to DataFrame
features_df = pd.DataFrame(features)
```

[6]:

```python
features_df
```

[6]:

	mean	std	max	min	range	median	variance	label
0	0.002190	0.991749	2.657787	-3.206211	5.863999	0.011626	0.983567	0
1	0.042012	1.000164	2.837133	[illegible]	5.993782	0.038742	1.000328	0

3.2.2.5 System Working Principle

Participants are equipped with the wearable device, which is integrated with physiological sensors for data collection. Controlled experiments are then conducted to either induce simulated seizure activity by producing voluntary muscle spasms and increasing heart rate through exercising. Throughout the experiments, the wearable device continuously monitors physiological signals. Electromyography (EMG) sensor is attached to the upper arm and electrocardiography (ECG) sensor is attached to the chest to collect the data. These signals are processed in real-time and sent to a remote IoT dashboard in which a trained machine learning model was deployed to identify features indicative of seizure activity. Once the features indicative of myoclonic seizures are identified, the alert system is triggered to alert the patient and an SMS containing the GPS location and status of the patient is sent to the care giver.

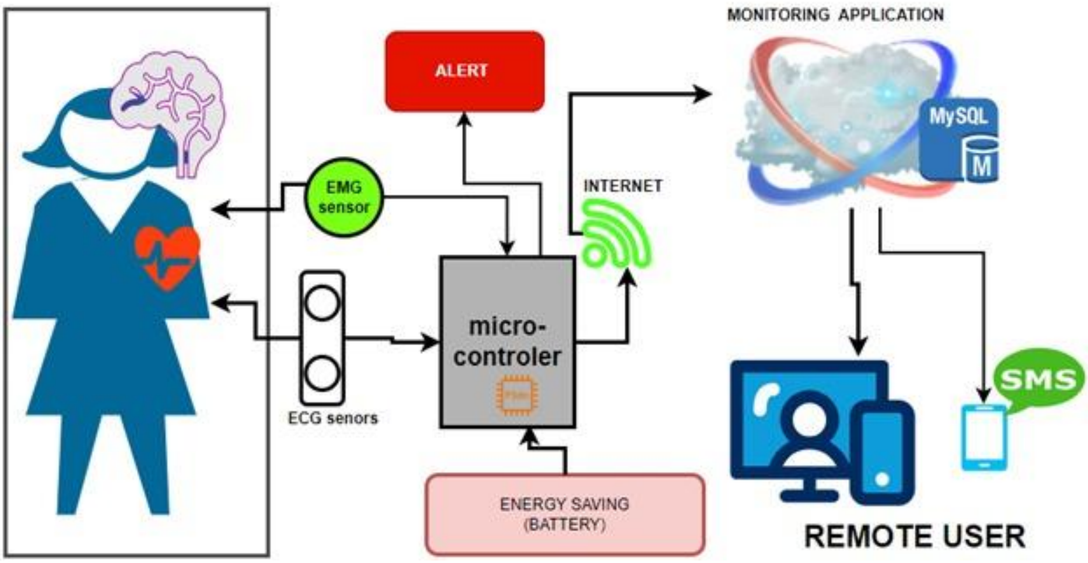


Figure 3.9: Working Principle of the System

3.2.3 Iterative Testing Method to Test the Prototype

To test the wearable device in detecting seizures in a laboratory setting, using simulated seizure activity, iterative prototype testing method was chosen due to its flexibility in allowing many rounds of testing one after another, to refine and optimize the device's performance.

In this regard, we iteratively tested the performance and accuracy of three different machine learning models, which are Logistic Regression model, Support Vector Machine model and Neuron networks training model.

4 PROJECT IMPLEMENTATION RESULTS AND DISCUSSION

4.1 RESULTS

4.1.1 Findings from Literature Review

4.1.1.1 Summary of Identified Signals

A seizure can be identified by monitoring a variety of physiological signals produced by the human body by using ECG, EEG, EMG, Motion, and audio/video recording. Among the mentioned signals, EEG is the most accurate of all because it directly shows the patterns of brain electrical activity where the seizures are shown by abrupt abnormal changes in the pattern. It also has high spatial and temporal resolution but it is a complicated procedure that requires experts to be done [11].

4.1.1.2 Application to Device Design

It is convenient to track myoclonic epilepsy by using a combination of other less accurate bio-signals such as EMG since Myoclonic seizures manifest in increased muscle activity[12], [13] and ECG because it was found that epilepsy affects the Autonomic Nervous System which controls involuntary processes of the body including the heart rate variability [14], [15].

In this research, we combine the change in heart rate and the electrical activity of the muscles as well as combination with IoT-based algorithms and machine learning for more accurate analysis.

4.1.2 Prototype and Testing Results

4.1.2.1 System Prototype

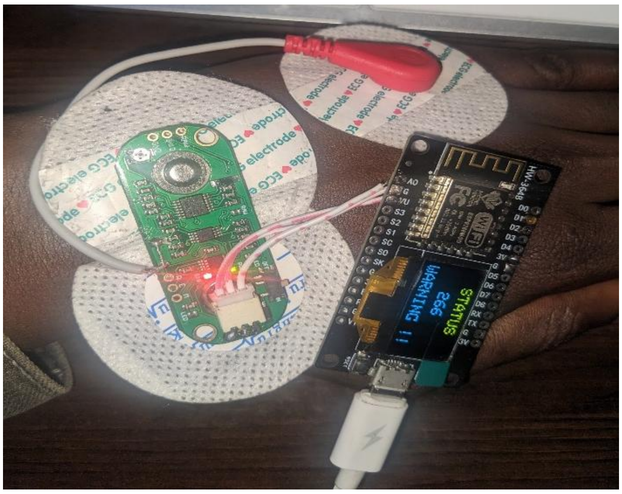


Figure 4.1: EMG Part of prototype

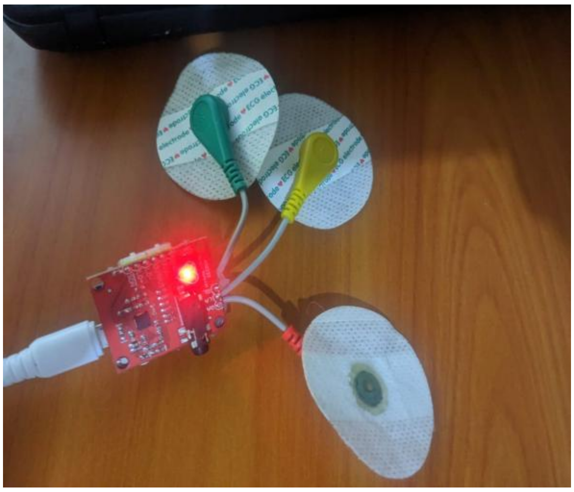


Figure 4.2: ECG Part of prototype

4.1.2.2 Sensor data plotting

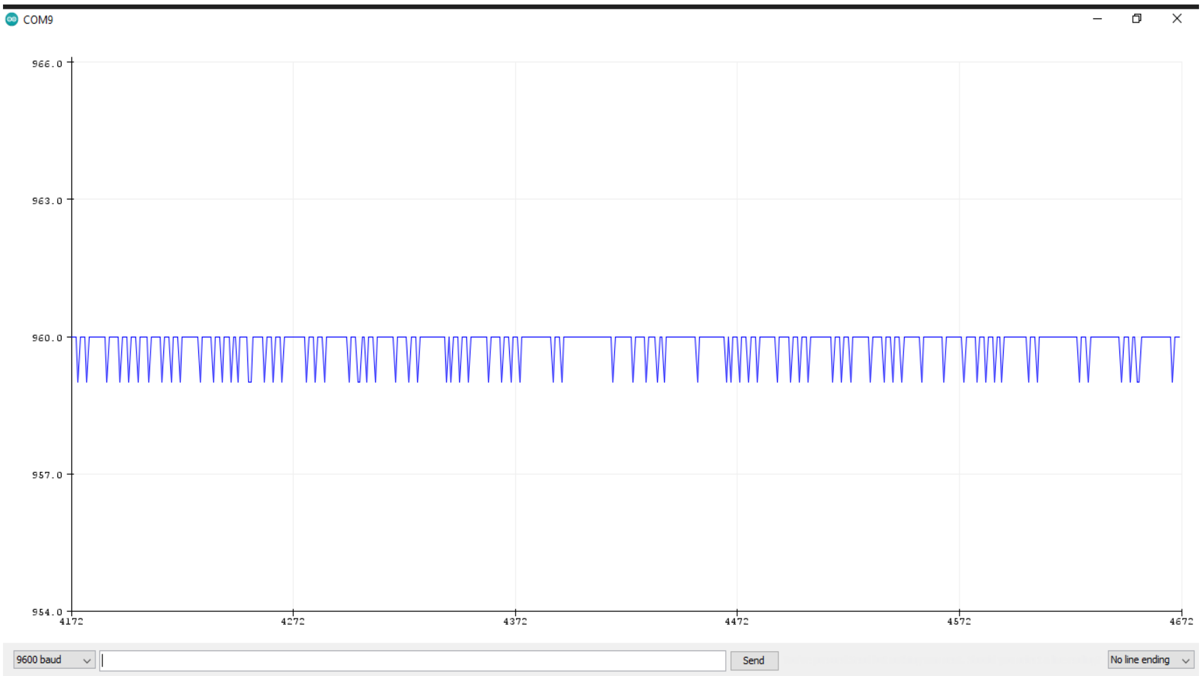


Figure 4.3: Sensor value represented in Serial Plotter

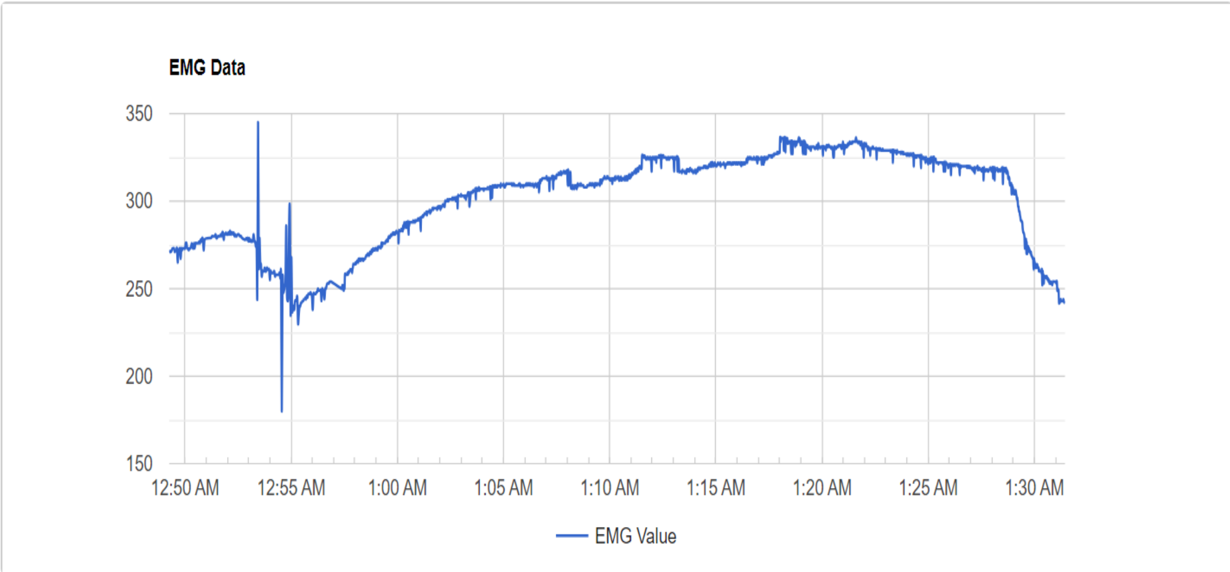


Figure 4.4: Sensor value variations on Remote dashboard

4.1.2.3 Sensor value variations on Remote dashboard

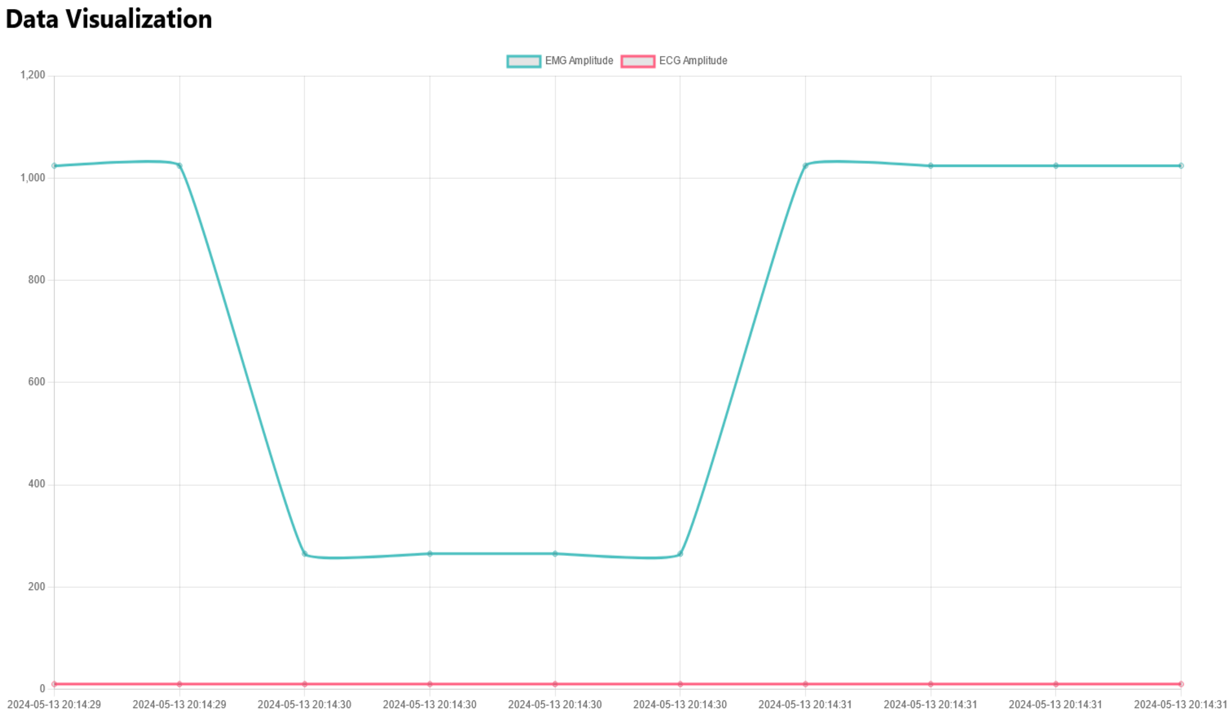


Figure 4.5: Sensor Value variations on remote dashboard

4.1.2.4 Data presented on Tabular format

Data from CSV

TIMESTAMP	EMG AMPLITUDE	ECG RHYTHM
2024-05-13 20:14:29	1024	10
2024-05-13 20:14:29	1024	10
2024-05-13 20:14:30	265	10
2024-05-13 20:14:30	265	10

Figure 4.6: Data presented on Tabular format

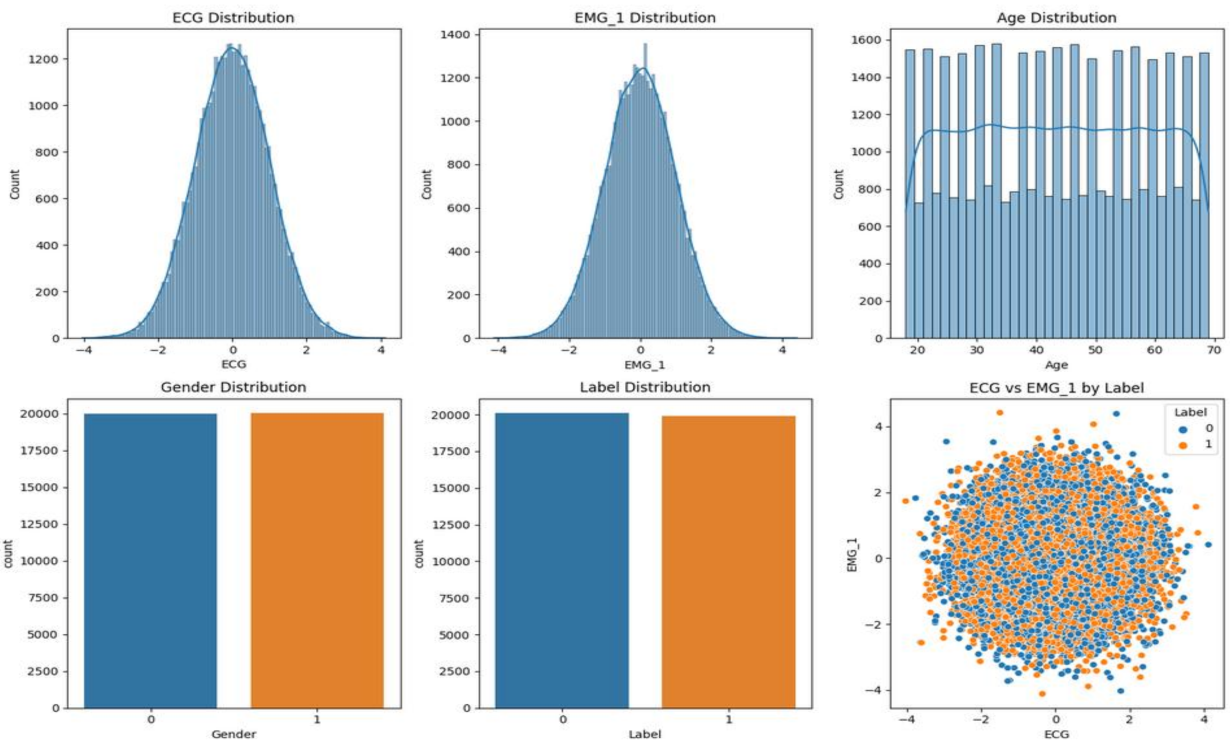
4.1.2.5 Data preprocessing

Out[5]:

	EMG_1	ECG	Age	Gender	Address	Label
0	-0.363527	0.743368	61	1	1	1
1	0.041656	0.420283	23	0	2	0
2	-0.907021	-0.489900	66	0	3	1
3	-1.436346	0.235257	62	0	2	1
4	1.140401	0.747606	41	1	2	1

Figure 4.7: Dataset

4.1.2.6 Data Visualization before Feature Extraction



Out[6]:

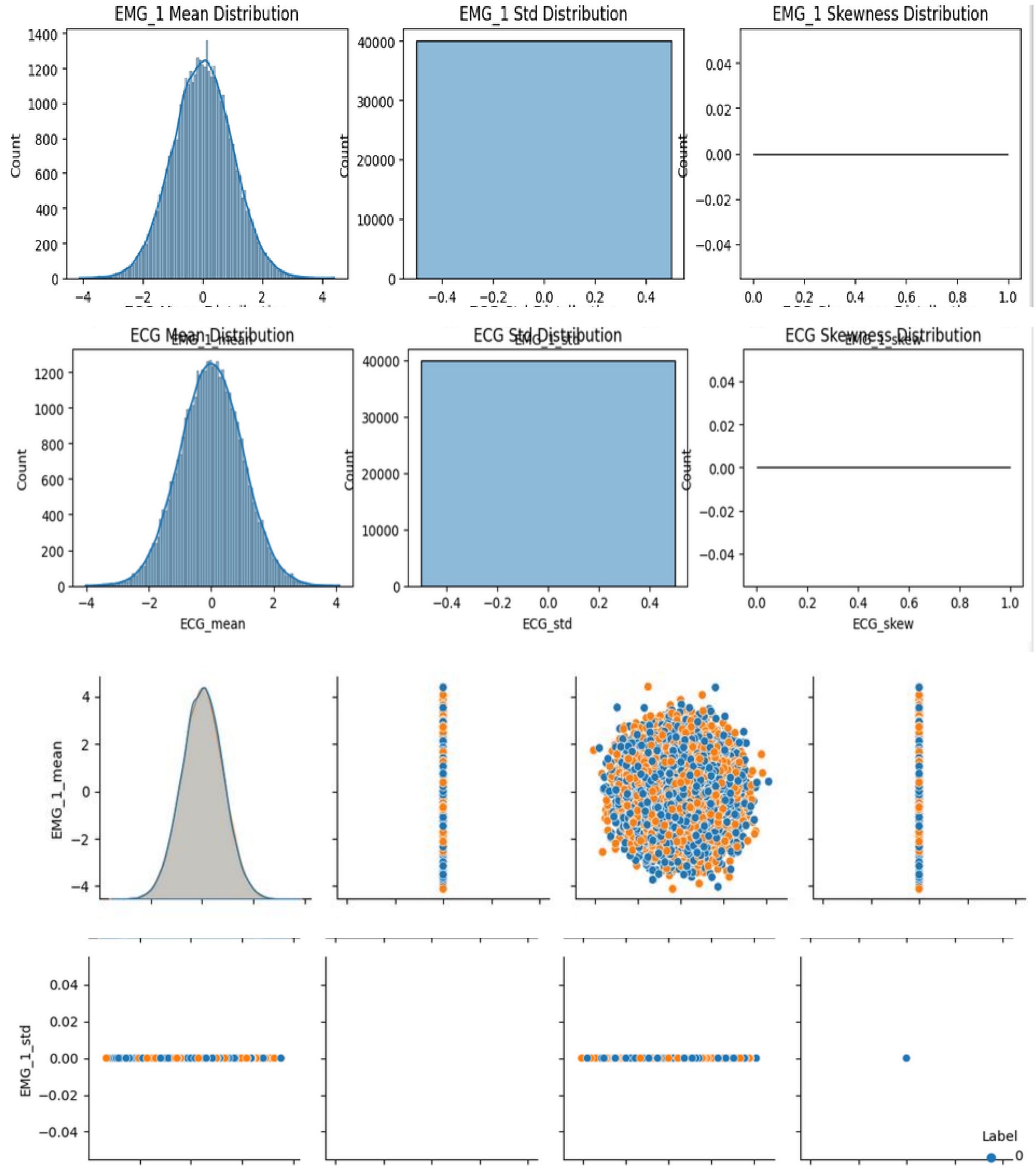
	EMG_1_mean	EMG_1_std	EMG_1_var	EMG_1_skew	EMG_1_kurt	EMG_1_max	EMG_1_min	EMG_1_rms	EMG_1_peak2peak	ECG_mean	...
0	-0.363527	0.0	0.0	NaN	NaN	-0.363527	-0.363527	0.363527	0.0	0.743368	...
1	0.041656	0.0	0.0	NaN	NaN	0.041656	0.041656	0.041656	0.0	0.420283	...
2	-0.907021	0.0	0.0	NaN	NaN	-0.907021	-0.907021	0.907021	0.0	-0.489900	...
3	-1.436346	0.0	0.0	NaN	NaN	-1.436346	-1.436346	1.436346	0.0	0.235257	...
4	1.140401	0.0	0.0	NaN	NaN	1.140401	1.140401	1.140401	0.0	0.747606	...

5 rows x 21 columns

EMG_1_peak2peak	ECG_mean	...	ECG_var	ECG_skew	ECG_kurt	ECG_max	ECG_min	ECG_rms	ECG_peak2peak	Age	Gender	Label
0.0	0.743368	...	0.0	NaN	NaN	0.743368	0.743368	0.743368	0.0	61	1	1
0.0	0.420283	...	0.0	NaN	NaN	0.420283	0.420283	0.420283	0.0	23	0	0
0.0	-0.489900	...	0.0	NaN	NaN	-0.489900	-0.489900	0.489900	0.0	66	0	1
0.0	0.235257	...	0.0	NaN	NaN	0.235257	0.235257	0.235257	0.0	62	0	1
0.0	0.747606	...	0.0	NaN	NaN	0.747606	0.747606	0.747606	0.0	41	1	1

Figure 4.8: Data Extracted from training set

4.1.2.7 Graphical representation of extracted features



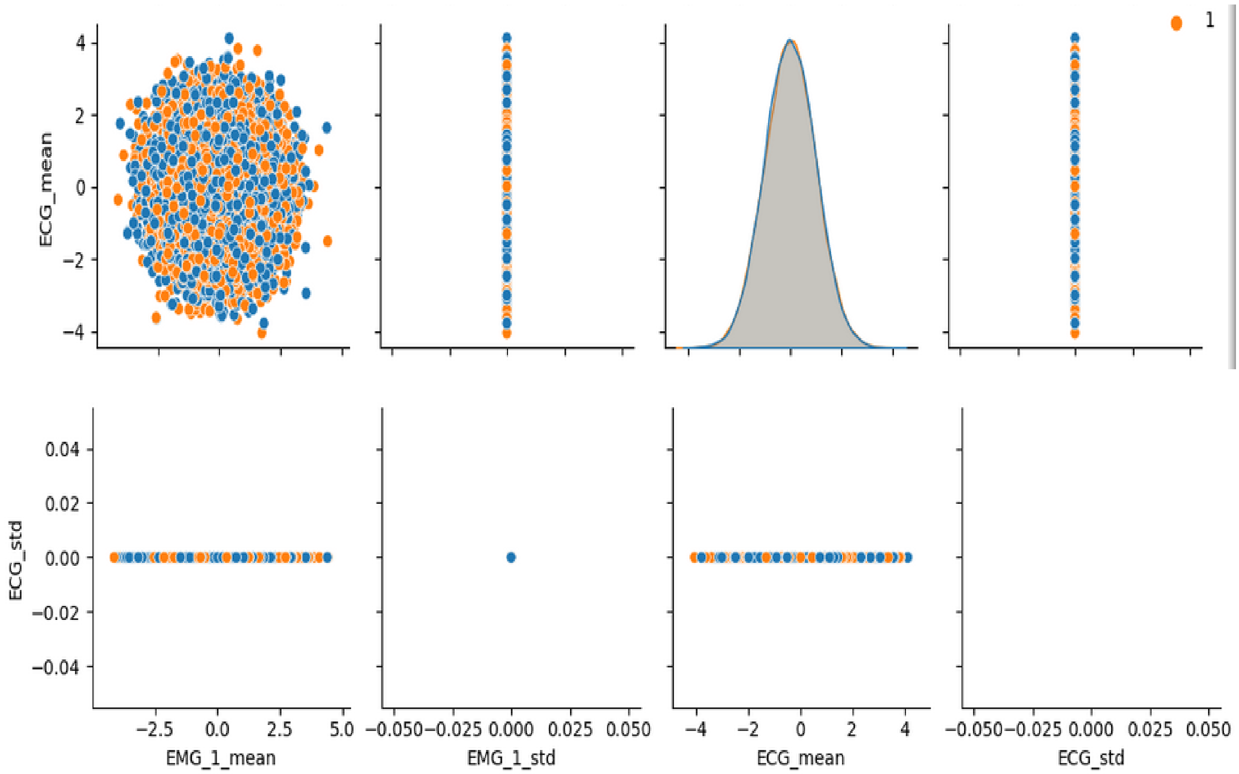


Figure 4.9: visualization of feature extraction

4.1.2.8 Training Logistic Regression Model Results

Accuracy: 0.49875
Confusion Matrix:

[1999 2050]
[1960 1991]

Classification Report:				
	precision	**recall**	**f1-score**	**support**
0	0.50	0.49	0.50	4049
1	0.49	0.50	0.50	3951
accuracy			0.50	8000
macro avg	0.50	0.50	0.50	8000
weighted avg	0.50	0.50	0.50	8000

4.1.2.9 Training Support Vector Machine Model Results

Accuracy: 0.487125
Confusion Matrix:

[1486 2563]
[1540 2411]

Classification Report:				
	Precision	recall	f1-score	support

0	0.49	0.37	0.42	4049
1	0.48	0.61	0.54	3951
Accuracy:			0.49	8000
Macro avg:	0.49	0.49	0.48	8000
Weighted avg:	0.49	0.49	0.48	8000

4.1.2.10 Neuron Networks Training Model Results

```
Accuracy: 0.502
Confusion Matrix:

 [2524 1525]
 [2459 1492]
```

Classification Report:				
	Precision	recall	f1-score	support
0	0.51	0.62	0.56	4049
1	0.49	0.38	0.43	3951
Accuracy			0.50	8000
Macro avg	0.50	0.50	0.49	8000
Weighted avg	0.50	0.50	0.49	8000

Table 4.1: Summarized Sensor Read Data

Device ID	3	Device ID	3
Patient Name	4	Patient Name	4
Age	62	Age	62
Gender	2	Gender	2
Timestamp	6996	Timestamp	6996
Value	7029	Value	7029

Mean Value	25.002756696960592	
Median Value	24.95595197026311	
Standard Deviation of Value	4.9871315350975784	
Mean Age by Gender		
Gender		
Female 48.470535		
Male 48.419512		
Name	Age, dtype	float64

4.1.3 Prediction results snippets from IoT dashboard


```
{"prediction":0,"prediction_prob":[1.0,0.0],"timestamp":"2024-05-13 23:40:41"},
{"prediction":0,"prediction_prob":[1.0,0.0],"timestamp":"2024-05-13 23:40:56"},
{"prediction":0,"prediction_prob":[1.0,0.0],"timestamp":"2024-05-13 23:41:00"},
{"prediction":0,"prediction_prob":[1.0,0.0],"timestamp":"2024-05-13 23:41:04"},
{"prediction":0,"prediction_prob":[1.0,0.0],"timestamp":"2024-05-13 23:41:09"},
{"prediction":1,"prediction_prob":[0.0,1.0],"timestamp":"2024-05-13 23:43:23"},
{"prediction":1,"prediction_prob":[0.0,1.0],"timestamp":"2024-05-13 23:43:26"},
{"prediction":1,"prediction_prob":[0.0,1.0],"timestamp":"2024-07-12 15:15:28"},
```


Figure 4.10: Results of predicting two classes

Figure 4.11: Emergency SMS received with Location address

4.2 DISCUSSION

The evaluation of three machine learning models; Logistic Regression, Support Vector Machine (SVM), and Neural Network showed insights into their performance on a given dataset. In Table 4.2, we summarize their results based on accuracy, confusion matrix, and classification metrics such as precision, recall, and F1-score.

Table 4.2: Comparison of Logistic Regression, Support Vector Machine, and Neuron Network Models

Metric	Logistic Regression	Support Vector Machine	Neuron Network
Accuracy	0.49875	0.487125	0.502
Confusion Matrix	$\begin{bmatrix} 1999 & 2050 \\ 1960 & 1991 \end{bmatrix}$	$\begin{bmatrix} 1486 & 2563 \\ 1540 & 2411 \end{bmatrix}$	$\begin{bmatrix} 2524 & 1525 \\ 2459 & 1492 \end{bmatrix}$
Class 0 Precision	0.50	0.49	0.51
Class 0 Recall	0.49	0.37	0.62
Class 0 F1-score	0.50	0.42	0.56
Class 1 Precision	0.49	0.48	0.49

Class 1 Recall	0.50	0.61	0.38
Class 1 F1-score	0.50	0.54	0.43
Macro Avg Precision	0.50	0.49	0.50
Macro Avg Recall	0.50	0.49	0.50
Macro Avg F1-score	0.50	0.48	0.49
Weighted Avg Precision	0.50	0.49	0.50
Weighted Avg Recall	0.50	0.49	0.50
Weighted Avg F1-score	0.50	0.48	0.49

Class 1 = Seizure detected

Class 0 = No seizure detected

Confusion matrix = $\begin{bmatrix} TN & FP \\ FN & TP \end{bmatrix}$

Where TN = True negative, meaning that the model correctly predicted class 0

FN = False negative, meaning that the model wrongly predicted class 0

TP = True positive, meaning that the model correctly predicted class 1

FP = False Positive meaning that the model wrongly predicted class 1

4.2.1 Accuracy

The accuracy metric indicates the ratio of correctly predicted instances to the total instances.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

The Neural Network achieved the highest accuracy at 0.502, followed closely by Logistic Regression with an accuracy of 0.498, and the SVM model with an accuracy of 0.487. While these accuracies are close to 50%, which suggests performance similar to random guessing, the Neural Network demonstrates a slight edge.

4.2.2 Confusion Matrix

The confusion matrix provides a detailed breakdown of the model predictions. For Logistic Regression, the matrix $\begin{bmatrix} 1999 & 2050 \\ 1960 & 1991 \end{bmatrix}$ shows a balanced but significant number of misclassifications for both classes. The SVM model's confusion matrix $\begin{bmatrix} 1486 & 2563 \\ 1540 & 2411 \end{bmatrix}$ indicates that it struggles more with predicting class 0 but performs slightly better for class 1. The Neural Network, with a confusion matrix $\begin{bmatrix} 2524 & 1525 \\ 2459 & 1492 \end{bmatrix}$ performs better at predicting class 0 compared to class 1.

4.2.3 Precision, Recall, and F1-score

Precision, recall, and F1-score provide deeper insights into model performance.

- Precision is the ratio of correctly predicted positive observations to the total predicted positives.

  $Precision = \frac{TP}{TP+FP}$

- Recall is the ratio of all correctly predicted positive observations to all observations in the class.

  $Recall = \frac{TP}{TP+FN}$

- F1-score is the weighted average of precision and recall.

  $F1 - score = 2\left(\frac{precision \times recall}{precision + recall}\right)$

For Logistic Regression, the precision for class 0 is 0.50, recall is 0.49, and F1-score is 0.50. Similarly, for class 1, the precision is 0.49, the recall is 0.50, and F1-score is 0.50. These balanced metrics indicate mediocre performance. The SVM model shows a precision of 0.49 for class 0 and 0.48 for class 1, with a recall of 0.37 and 0.61, respectively. The F1-scores are 0.42 for class 0 and 0.54 for class 1, suggesting that SVM is better at predicting class 1. The Neural Network has a precision of 0.51 for class 0 and 0.49 for class 1, with recalls of 0.62 and 0.38, respectively. Its F1-scores are 0.56 for class 0 and 0.43 for class 1, indicating its strength in identifying class 0 instances.

4.2.4 Averages

Considering macro and weighted averages for precision, recall, and F1-score, all models show similar results. Logistic Regression, SVM, and Neuron Networks have macro and weighted averages around 0.49 to 0.50, reflecting their balanced but moderate overall performance.

4.2.5 Summary

In summary, while all three models; Logistic Regression, SVM, and Neural Network demonstrate performance close to random guessing, the Neural Network shows a slight advantage in terms of accuracy and is particularly effective at predicting class 0. However, the overall moderate performance of all models suggests a need for further tuning, enhanced data preprocessing, or the adoption of more advanced modeling techniques to achieve better results.

4.3 Comparison with existing solutions

The aim of this research was to develop a wearable device that improves the freedom of the user, since the devices in the literature were bulky with many wires around the user's body. Our prototype is a more portable and flexible device as it is about half of the size with wires which reduces the burden from the user.

5 CONCLUSION AND FUTURE WORK

5.1 CONCLUSION

In summary, the design of a microcontroller-based wearable device for epilepsy detection and monitoring is a viable project that could significantly impact the lives of people with epilepsy as evidenced by the high-fidelity prototype that we designed in this research. The device could help improve the quality of life for people with epilepsy in a number of ways, including early warning of seizures, improved treatment, and increased independence. The technology is still in the early stages of development, and due to the use of simulated data, the accuracy is still low but further research and development by collecting real-life data will result into a highly accurate wearable device revolutionizing the way epilepsy is treated and monitored.

5.2 CHALLENGES FACED

The biggest challenge faced was the inaccessibility of the open-source wireless micro Encephalography sensor (uECG) which we could not be able to buy from the manufacturers because of the war in Ukraine, and this was the core of the solution to the identified gap. We tried to solve the challenge by replacing it with a wireless ECG manufactured by SICHIRAY, but its data were encrypted and could not be accessed for further processing.

This challenge was solved by using a second Wi-Fi enabled microcontroller interfaced with an ECG with reduced form factor to be able to communicate wirelessly with other components of the prototype.

5.3 FUTURE WORK

For future research, we plan to enhance our prototype by collecting real-world data to improve the accuracy of the wearable device.

We also plan to purchase the wireless uECG sensor to further reduce the form factor and reduce the number of microcontrollers.

REFERENCES

[1] E. Beghi, “The Epidemiology of Epilepsy,” *Neuroepidemiology*, vol. 54, no. 2, pp. 185–191, 2020, doi: 10.1159/000503831.

[2] F. Sebera *et al.*, “Effectiveness of community health workers on identification and mobilization of persons living with epilepsy in rural Rwanda using a validated screening tool,” *Hum. Resour. Health*, vol. 20, no. 1, p. 10, Dec. 2022, doi: 10.1186/s12960-022-00704-5.

[3] F. Sebera *et al.*, “Association of depression and epilepsy in Rwanda: A prospective longitudinal study,” *Epilepsy Behav.*, vol. 138, p. 108993, 2023, doi: 10.1016/j.yebeh.2022.108993.

[4] V. Simms, O. Atijosan, H. Kuper, A. Nuhu, D. Rischewski, and C. Lavy, “Prevalence of epilepsy in Rwanda: a national cross-sectional survey,” *Trop. Med. Int. Heal.*, vol. 13, no. 8, pp. 1047–1053, Aug. 2008, doi: 10.1111/j.1365-3156.2008.02108.x.

[5] P. Dedeken *et al.*, “High prevalence of epilepsy in Northern Rwanda: Exploring gender differences,” *Brain Behav.*, vol. 11, no. 11, Nov. 2021, doi: 10.1002/brb3.2377.

[6] D. E. Teuwen *et al.*, “Epilepsy-Related Direct Medical and Direct Non-Medical Cost in Adult Patients Living with Epilepsy at a Tertiary Neurology Center in Rwanda,” *Clin. Outcomes Res.*, vol. 15, pp. 15–27, Jan. 2023, doi: 10.2147/CEOR.S382030.

[7] E. L. Johnson, “Seizures and Epilepsy,” *Med. Clin. North Am.*, vol. 103, no. 2, pp. 309–324, 2019, doi: 10.1016/j.mcna.2018.10.002.

[8] R. S. Fisher, “The New Classification of Seizures by the International League Against Epilepsy 2017,” *Curr. Neurol. Neurosci. Rep.*, vol. 17, no. 6, pp. 1–6, 2017, doi: 10.1007/s11910-017-0758-6.

[9] P. Striano and V. Belcastro, “Treatment of myoclonic seizures,” *Expert Rev. Neurother.*, vol. 12, no. 12, pp. 1411–1418, 2012, doi: 10.1586/ern.12.90.

[10] I. E. Leppik, “Classification of the Myoclonic Epilepsies,” *Epilepsia*, vol. 44, no. SUPPL. 11, pp. 2–6, 2003, doi: 10.1046/j.1528-1157.44.s11.4.x.

[11] T. Kim *et al.*, “Epileptic Seizure Detection and Experimental Treatment: A Review,” *Frontiers in Neurology*, vol. 11. 2020. doi: 10.3389/fneur.2020.00701.

[12] S. Beniczky, I. Conradsen, and P. Wolf, “Detection of convulsive seizures using surface electromyography,” *Epilepsia*, vol. 59, no. December 2017, pp. 23–29, 2018, doi: 10.1111/epi.14048.

[13] S. Beniczky, I. Conradsen, O. Henning, M. Fabricius, P. Wolf, and P. Uldall, “Real-time detection of tonic-clonic seizures using a wearable EMG device,” *Neurology*, vol.

90, no. 5, pp. e428--e434, 2018.

[14] J. Jeppesen *et al.*, "O-45 Automated seizure detection for epilepsy patients using wearable ECG-device," *Clin. Neurophysiol.*, vol. 130, no. 7, 2019, doi: 10.1016/j.clinph.2019.04.360.

[15] J. Jeppesen *et al.*, "Seizure detection based on heart rate variability using a wearable electrocardiography device," *Epilepsia*, vol. 60, no. 10, pp. 2105–2113, 2019, doi: 10.1111/epi.16343.

[16] T. Tomson, E. Beghi, A. Sundqvist, and S. I. Johannessen, "Medical risks in epilepsy: a review with focus on physical injuries, mortality, traffic accidents and their prevention," *Epilepsy Res.*, vol. 60, no. 1, pp. 1–16, Jun. 2004, doi: 10.1016/J.EPLEPSYRES.2004.05.004.

[17] J. M. Pellock, "Overview: Definitions and Classifications of Seizure Emergencies," *J. Child Neurol.*, vol. 22, no. 5_suppl, pp. 9S-13S, May 2007, doi: 10.1177/0883073807303064.

[18] E. Bruno *et al.*, "Wearable technology in epilepsy: The views of patients, caregivers, and healthcare professionals," *Epilepsy Behav.*, vol. 85, pp. 141–149, Aug. 2018, doi: 10.1016/J.YEBEH.2018.05.044.

[19] A. Godfrey, V. Hetherington, H. Shum, P. Bonato, N. H. Lovell, and S. Stuart, "From A to Z: Wearable technology explained," *Maturitas*, vol. 113, pp. 40–47, Jul. 2018, doi: 10.1016/j.maturitas.2018.04.012.

[20] Xiao-Fei Teng, Yuan-Ting Zhang, C. C. Y. Poon, and P. Bonato, "Wearable Medical Systems for p-Health," *IEEE Rev. Biomed. Eng.*, vol. 1, pp. 62–74, 2008, doi: 10.1109/RBME.2008.2008248.

[21] K. Hung, Y. T. Zhang, and B. Tai, "Wearable medical devices for tele-home healthcare," in *The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, pp. 5384–5387. doi: 10.1109/IEMBS.2004.1404503.

[22] Sungmee Park and S. Jayaraman, "Enhancing the quality of life through wearable technology," *IEEE Eng. Med. Biol. Mag.*, vol. 22, no. 3, pp. 41–48, May 2003, doi: 10.1109/MEMB.2003.1213625.

[23] J. J. Rutherford, "Wearable Technology," *IEEE Eng. Med. Biol. Mag.*, vol. 29, no. 3, pp. 19–24, May 2010, doi: 10.1109/MEMB.2010.936550.

[24] N. Escobar Cruz, J. Solarte, and A. Gonzalez-Vargas, "Automated Epileptic Seizure Detection System Based on a Wearable Prototype and Cloud Computing to Assist People with Epilepsy," *Commun. Comput. Inf. Sci.*, vol. 916, pp. 204–213, 2018, doi:

10.1007/978-3-030-00353-1_18.

[25] T. Yamakawa *et al.*, "Wearable epileptic seizure prediction system with machine-learning-based anomaly detection of heart rate variability," *Sensors (Switzerland)*, vol. 20, no. 14, pp. 1–16, 2020, doi: 10.3390/s20143987.

[26] S. Hassan, E. Mwangi, and P. K. Kihato, "IoT based monitoring system for epileptic patients," *Heliyon*, vol. 8, no. 6, p. e09618, 2022, doi: 10.1016/j.heliyon.2022.e09618.

[27] M. Habtamu *et al.*, "A novel wearable device for automated real-time detection of epileptic seizures," *BMC Biomed. Eng.*, vol. 5, no. 1, pp. 1–9, 2023, doi: 10.1186/s42490-023-00073-7.

[28] S. Beniczky, P. Karoly, E. Nurse, P. Ryvlin, and M. Cook, "Machine learning and wearable devices of the future," *Epilepsia*, vol. 62, no. S2, pp. S116–S124, 2021, doi: 10.1111/epi.16555.

[29] S. Patel, H. Park, P. Bonato, L. Chan, and M. Rodgers, "A review of wearable sensors and systems with application in rehabilitation," *J. Neuroeng. Rehabil.*, vol. 9, no. 1, p. 21, 2012.

[30] P. Bonato, "Advances in wearable technology and its medical applications," in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10*, 2010. doi: 10.1109/IEMBS.2010.5628037.

[31] F. Mormann, R. G. Andrzejak, C. E. Elger, and K. Lehnertz, "Seizure prediction: the long and winding road," *Brain*, vol. 130, no. 2, pp. 314–333, 2007.

[32] A. Subasi and M. I. Gursoy, "EEG signal classification using PCA, ICA, LDA and support vector machines," *Expert Syst. Appl.*, vol. 42, no. 3, pp. 1121–1127, 2015.

[33] D. Peters, R. A. Calvo, and R. M. Ryan, "Designing for motivation, engagement and wellbeing in digital experience," *Front. Psychol.*, vol. 9, p. 797, 2018.

[34] N. Bahrani, G. Wilson, R. Patibanda, and N. Raghunath, "Towards understanding and measuring user acceptance of wearable devices," *Int. J. Hum. Comput. Interact.*, vol. 36, no. 5, pp. 459–468, 2020.

[35] M. P. McDermott and E. Roessler, "Ethical considerations for wearable devices," *Handb. Clin. Neurol.*, vol. 160, pp. 429–437, 2019.

[36] A. M. Palacios-García, M. L. Alonso-Álvarez, and R. Losada-Del Pozo, "Data protection in the era of wearables: a systematic review," *Pers. Ubiquitous Comput.*, vol. 25, no. 1, pp. 125–139, 2021.

APPENDICES

Appendix 1: The Utilized Codes

A. Code for Communication between EMG part and Remote IoT dashboard

```
#include <ESP8266WiFi.h>
#include <Wire.h>
#include <Adafruit_GFX.h>
#include <Adafruit_SSD1306.h>
#include <ESP8266HTTPClient.h>
#include <WiFiManager.h>
#include <ArduinoJson.h>

// WiFi credentials
char ssid[32];     // Your WiFi SSID
char password[64]; // Your WiFi password
// API endpoint URL
const char* serverUrl = "http://192.168.170.102:5000/dataemg/"; // Replace with
your API endpoint
int Buzzer=D7;
// Define OLED parameters
#define SCREEN_WIDTH 128 // OLED display width, in pixels
#define SCREEN_HEIGHT 64 // OLED display height, in pixels
#define OLED_RESET    -1 // Reset pin # (or -1 if sharing Arduino reset pin)

// Define sampling parameters
#define SAMPLE_RATE 500 // Sampling rate in Hz
#define BAUD_RATE 115200 // Serial baud rate
#define INPUT_PIN A0 // Analog input pin for EMG signal

// Initialize OLED display
Adafruit_SSD1306 display(SCREEN_WIDTH, SCREEN_HEIGHT, &Wire, OLED_RESET);

float lastSignal = 0;

void connectToWiFi();
float signalFilter(float input);
void plotSignal(float signal);
void sendDataToAPI(float signal, const char* deviceType);

void setup() {
  // Initialize serial communication
  Serial.begin(BAUD_RATE);
   pinMode(Buzzer,OUTPUT);
  // Initialize OLED display
  Wire.begin(D5, D6);  // SDA pin = D5, SCL pin = D6
  if (!display.begin(SSD1306_SWITCHCAPVCC, 0x3C)) {
```

```
    Serial.println(F("SSD1306 allocation failed"));
    while (true);
  }
//  delay(20);  // Pause for 2 seconds
  display.clearDisplay();
  display.setTextSize(1);      // Normal 1:1 pixel scale
  display.setTextColor(SSD1306_WHITE); // Draw white text

  // Connect to Wi-Fi
  connectToWiFi();
}

void loop() {
  // Read EMG signal
  float signal;
  signal = analogRead(INPUT_PIN);
  signal = signalFilter(signal);
  Serial.println(signal);
  plotSignal(signal);

  // Send data to API
  sendDataToAPI(signal, "EMG");

  // Delay

      // Adjust delay time as needed
}

// Function to connect to WiFi
void connectToWiFi() {
  WiFiManager wifiManager;
  // Reset settings - Uncomment the line below to reset WiFi settings
  //wifiManager.resetSettings();
  // Custom parameters for WiFiManager
  WiFiManagerParameter custom_ssid("ssid", "WiFi SSID", ssid, 32);
  WiFiManagerParameter custom_password("password", "WiFi Password", password,
64);

  wifiManager.addParameter(&custom_ssid);
  wifiManager.addParameter(&custom_password);

  // Connect to WiFi using stored credentials or create AP to configure WiFi
  wifiManager.autoConnect("net__link"); // Change "net__link" to your desired AP
name

  // Copy WiFi credentials from WiFiManager parameters to global variables
  strncpy(ssid, custom_ssid.getValue(), 32);
  strncpy(password, custom_password.getValue(), 64);
```

```
  Serial.println("Connected to Wi-Fi");
  Serial.print("IP Address: ");
  Serial.println(WiFi.localIP());
}

// EMG signal filtering function (placeholder)
float signalFilter(float input) {
  return input; // Placeholder, implement your filtering logic here
}

// Function to plot signal on OLED display
void plotSignal(float signal) {
  static int xOffset = 0;
  static int lastY = 0;
  int newY = map(signal/100, 0, 1023, SCREEN_HEIGHT - 1, 0);

  // Draw line between previous and current point
  display.drawLine(xOffset - 1, lastY, xOffset, newY, SSD1306_WHITE);

  // Display signal value as text
  display.setTextSize(2); // Set text size
  display.setCursor(4, 0); // Set cursor position
  display.setTextColor(SSD1306_WHITE); // Set text color
  display.print("EMG: "); // Print text
  display.print(signal/100); // Print signal value

  display.display();

  // Update lastY and xOffset for next iteration
  lastY = newY;
  xOffset++;

  // If xOffset reaches the end of the screen, reset xOffset and clear display
  if (xOffset >= SCREEN_WIDTH) {
    xOffset = 0;
    display.clearDisplay();
  }
}

// Function to send data to API
void sendDataToAPI(float signal, const char* deviceType) {
  HTTPClient http;
  WiFiClient client;

  // Create JSON object
  StaticJsonDocument<200> jsonDoc;
  jsonDoc["signal_data"] = signal/100;
```

```
  jsonDoc["device_type"] = deviceType;
  String jsonData;
  serializeJson(jsonDoc, jsonData);

  // Send a POST request to the server with the JSON data
  http.begin(client, serverUrl);
  http.addHeader("Content-Type", "application/json");
  int httpResponseCode = http.POST(jsonData);

  // Check for response
  if (httpResponseCode > 0) {
    String response = http.getString();
    Serial.print("HTTP Response code: ");
    Serial.println(httpResponseCode);
    Serial.print("Response message: ");
    Serial.println(response);
    display.setTextSize(1); // Set text size
  display.setCursor(0, 44); // Set cursor position
  display.setTextColor(SSD1306_WHITE); // Set text color
  display.print(response); // Print text
   // Print signal value

  display.display();
    if(response=="danger")
    {
      digitalWrite(Buzzer,HIGH);
//      delay(500);

    }else{
          digitalWrite(Buzzer,LOW);
//      delay(500);
    }
  } else {
    Serial.println("Error sending POST request");
  }

  // End HTTP connection
  http.end();
}
```

B. Code for Communication between ECG part and Remote IoT dashboard

- `#include <ESP8266WiFi.h>`
- `#include <Wire.h>`
-
- `#include <SoftwareSerial.h>`

```
#include <ArduinoJson.h> // Include the ArduinoJson library
#include <ESP8266HTTPClient.h> // Include the HTTPClient library

// WiFi credentials
const char* ssid = "Ada";      // Your WiFi SSID
const char* password = "88888888"; // Your WiFi password
const char* serverUrl = "http://192.168.170.102:5000/ecg_data"; // Replace with your server URL

int ecgValue;

void setup() {
  // Initialize serial communication:
  Serial.begin(9600);
  pinMode(A0, INPUT);
  connectToWiFi();
}

void loop() {
  ecgValue = analogRead(A0);
  Serial.println(ecgValue);
  sendEcgData(ecgValue);
//  delay(1000); // Adjust delay as needed
}

void sendEcgData(int ecgValue) {
  WiFiClient client;
  HTTPClient http;

  // Create a JSON object to hold the ECG data
  StaticJsonDocument<200> jsonDocument;
  jsonDocument["ecg_data"] = ecgValue/10;

  // Serialize the JSON object to a string
  String jsonStr;
  serializeJson(jsonDocument, jsonStr);

  // Send POST request to server
  http.begin(client, serverUrl);
  http.addHeader("Content-Type", "application/json");
  int httpCode = http.POST(jsonStr);

  Serial.print("HTTP POST Response Code: ");
  Serial.println(httpCode);

  if (httpCode > 0) {
    String payload = http.getString();
    Serial.println(payload);
```

```
  } else {
    Serial.println("Error sending request");
  }

  http.end();
}

void connectToWiFi() {
  Serial.println("Connecting to Wi-Fi...");
  WiFi.begin(ssid, password);
  int attempts = 0;
  while (WiFi.status() != WL_CONNECTED && attempts < 10) {
    delay(1000);
    Serial.println("Connecting...");
    attempts++;
  }
  if (WiFi.status() == WL_CONNECTED) {
    Serial.println("Connected to Wi-Fi");
    Serial.print("IP Address: ");
    Serial.println(WiFi.localIP());
  } else {
    Serial.println("Failed to connect to Wi-Fi");
  }
}

```