Development of wearable sensors for continuous monitoring and early diagnosis of neuromuscular disease

SIDDHI 2.0

Content

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Summer Internship for Data-Driven Healthcare Innovations

Section 1: Project Report

- Team: Include Name, Branch/Year/Affiliation, Picture, Email, Role in the project
- Introduction and Motivation: Introduction to the project and reasoning why this project is important?
- Problem Definition: What is the specific problem to be solved?
- User Requirement: What is the specific deliverable expected from the solution?
- Technology Background: What is the general solution approach in literature?
- Gaps/Challenges: What aspects are unaddressed in literature for this problem?
- Data Description: What is the data, data source, data collection frequency, etc.?
- Proposed Solution: What is the overall solution you are proposing?
- Project Tasks: What are the specific tasks that need to be accomplished?
- Task-wise Methodology: For each task, what is the final methodology followed?
- Task-wise Results/Conclusion: For each task, what are the achieved outcomes?
- Demonstration Video: Compilation of the developed solution into a demonstration video (max. 90 seconds)

Section 2: Weekly Updates (Use this section to document all efforts)

- Week 1 Updates
- …
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Section 3: Solution-at-a-Glance (Compilation of the developed solution within 2 slides)

Project Report

Team

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Introduction and Motivation

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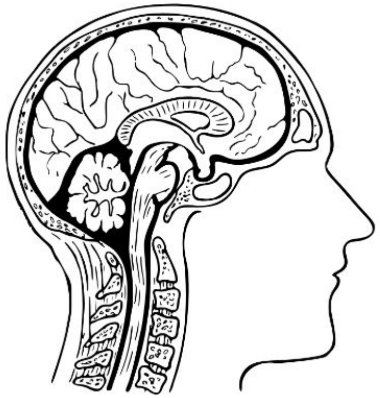
Neuromuscular Disorders in India

A worrisome condition that is increasingly Showing its presence in medical studies in India



Definition

Understanding the issue!

Neuromuscular disorders affect the nerves controlling voluntary muscles and the muscles themselves, leading to impaired muscle function, movement, and coordination. They can result from genetic mutations, autoimmune responses, infections, or other causes.

Neuromuscular diseases (NMDs) affect **15 million people globally**.

Symptoms

Include muscle weakness, cramps, tremors, numbness, and difficulties with movement, balance, and coordination.

Once the disease progresses, the effects can not be undone, neuromuscular disorders can cause PERMANENT IMPAIRMENT if not detected early and is stopped from progressing

Important

The Impact on Individuals

The seriousness of these conditions is underscored by their profound impact on mobility, independence, and quality of life.

Early detection enables timely therapy, improving outcomes and reducing long-term disability and socioeconomic burden.

The Shocking Truth!

Healthcare infrastructure often lacks specialized diagnostics and treatments for these disorders, leading to delayed or inaccurate diagnoses and suboptimal management.

Problem Definition

Neuromuscular disorders(NMDs) are a group of conditions that affect the nerve and muscle, that cause muscle weakness, atrophy, and paralysis. What's alarming is that there is no way to reverse neuromuscular disorder effects. In such a situation it becomes very crucial to detect the disease early and stop it from progressing further. Failure to do this can lead to worsening of conditions and permanent disability. Often when one begins to notice the symptoms and visits a healthcare professional, the problems already mount up and the treatment becomes difficult. Current healthcare infrastructure, especially in India, lacks severely in timely diagnosis. Instruments to detect presence of NMDs are often bulky, only present in hospitals, and can be handled by trained professionals hence only people experiencing symptoms can utilize the functionality of these machines. This misses out on a large share of people, otherwise healthy but maybe showing early signs of NMDs. Only if these detection devices were portable, easy to use, and its results easy to comprehend, these early signs can also be spotted early on. Not just early detection, these portable devices can also be utilized in rehabilitation of patients recovering from NMDs, the effect of medications, therapy can be monitored remotely by healthcare professionals, without the need of frequent hospital visits. Hence we propose to develop such a portable device with IoT and Machine Learning at its core leveraging diagnostic capabilities of Surface Electromyography(sEMG).

User Requirement

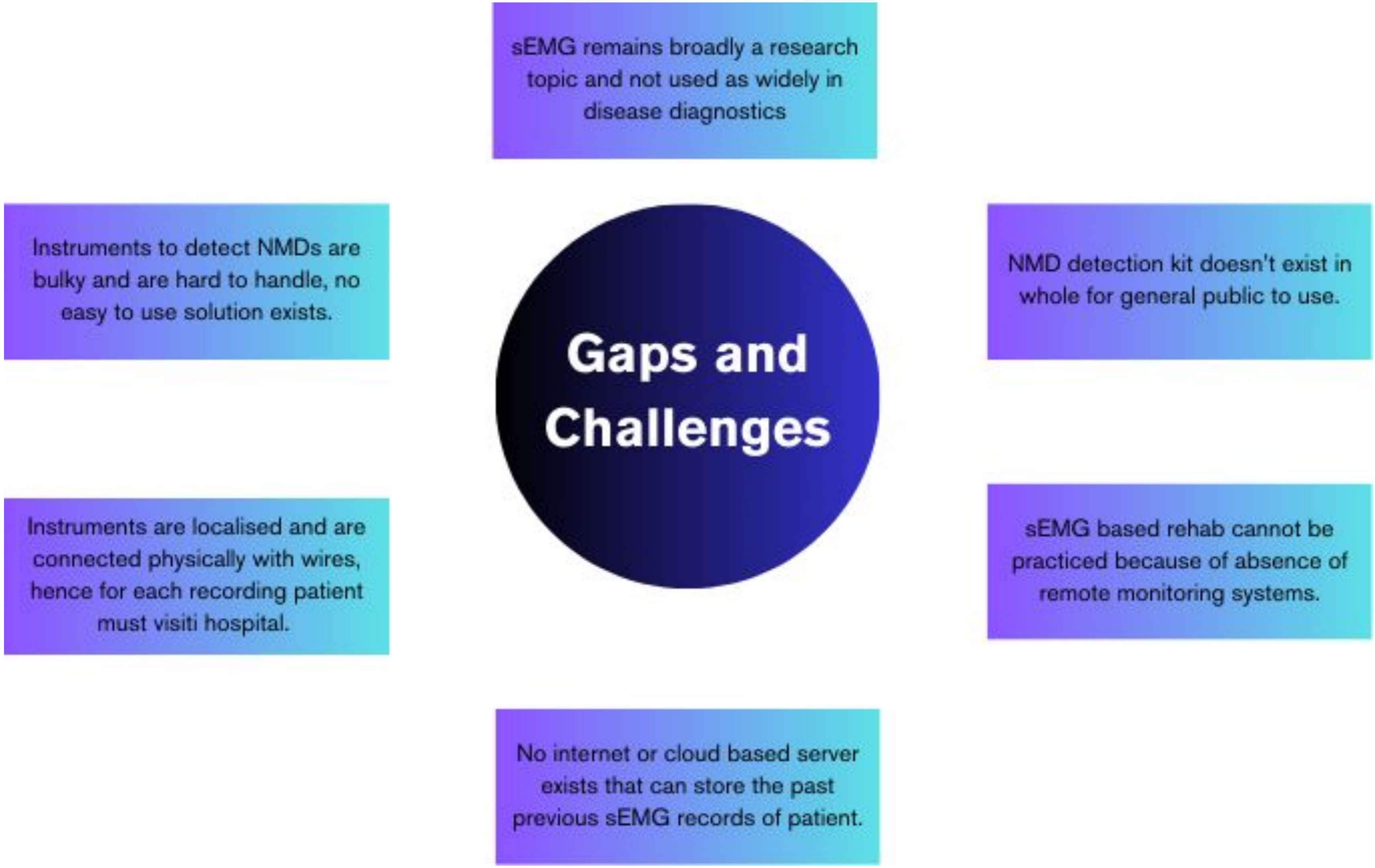
An efficient monitoring system that is convenient to the patient and leads to early detection with reasonable accuracy can pose to be a strong contender for solving the problem of Neuromuscular Diseases.
Our solution prioritizes user-friendliness, portability, and remote diagnostics. Upon receiving raw EMG signal data from the surface sensors , providing a non invasive and easy to use method , it processes the signal and gives out a processed EMG wave visualisation for consultation to medical practitioners through the application.
Further the machine learning algorithm will predict whether the EMG data is indicative of certain possibilities of Neuromuscular diseaThere is an unmet need for portable, easy-to-use devices that can detect early signs of NMDs before symptoms become severe. Such devices would enable proactive healthcare, identifying potential cases even among those not yet experiencing major symptoms. These devices should not only be portable and user-friendly but also provide clear and actionable results that both users and healthcare professionals can easily interpret. This would allow early intervention, improving treatment outcomes and potentially delaying or preventing severe disability.

Moreover, these devices could also play a pivotal role in the rehabilitation of NMD patients. By monitoring patients remotely, healthcare providers can track the effectiveness of medications and therapies without requiring frequent hospital visits. This approach would enhance the efficiency of rehabilitation programs and reduce the burden on patients and healthcare infrastructure.
ses and the application will provide a dashboard for the user with several parameters . Also the feature of patient registration and hence patient history monitoring can be done using the application

Technology Background

- Non-invasive methods like sEMG are commonly used in clinical and research purposes, lacking application in disease diagnostics. Thus sEMG sensors to be used for data collection.
- Signal Processing techniques like Filtering (using of High-pass, Low-pass, Band-pass etc filters) remove noise, Rectification and smoothing of EMG signals to make them easier to analyze, and Normalization method to standardize the EMG signals to account for the difference between subjects or conditions. These techniques are used for preprocessing currently, before the signal is fed into machine learning models.
- Previous works on feature extraction included the time domain, frequency domain and Time-Frequency analysis, providing some powerful insights on the amplitude and frequency characteristics.
- Use of Classification algorithms, like SVM, k-NN, Decision Tree, Random Forest have been covered in research papers
- No hardware based application or complete software package has been developed that leverages ML algorithms.
- Our previous work of SIDDHI 1.0 gives us an algorithm, and an ML backed platform to run diagnostic tests baked on sEMG data.

Gaps and Challenges



Data Description

The Electromyography Analysis of Hand Activities - DataBase 1 (EMAHA-DB1) is a comprehensive dataset designed to facilitate the study of surface electromyography (sEMG) signals collected during various activities of daily life (ADL). The dataset aims to provide valuable insights into understanding neuromuscular disorders, limb disabilities, aging effects, and neuromotor deficits. It can also aid in the development of prosthetic devices, realistic biomechanical hands, and rehabilitation therapies. This dataset is particularly useful for classification studies and statistical analysis of sEMG signals.

25 healthy subjects (22 males, 3 females) with no history of upper limb pathology. The average age is 28 years.

Setup and Acquisition Protocol

- Activities: 22 different hand activities, each performed 10 times by each subject.
- Recording Device: 5-channel Noraxon Ultium wireless sEMG sensor setup.
- Electrode Placement: Self-adhesive Ag/AgCL dual electrodes placed at five key muscle sites on the right arm, according to the atlas in chapter 17 of Criswell (2010):
    1. Brachioradialis (BR)
    2. Flexor carpi radialis (FCR)
    3. Flexor carpi ulnaris (FCU)
    4. Biceps Brachii (BB)
    5. Abductor Pollicis Brevis (APB)
- Session Details: Each session lasted up to one hour, including familiarization with the protocol and video demonstrations. Each activity consisted of an action phase, a release phase (if applicable), and a rest phase. Activities were performed for up to 10 seconds with a 5-second rest between repetitions and a 30-second rest between different activities.

Data Description

Data File Structure

- Folders: Training data and test data.
- Trials: Activities are separated into trials [2, 5, 7] for test data.
- MAT Files: Each subject's data is stored in a MATLAB file with the following columns:
  1. sEMG data from 5 channels
  2. Sub_activity (0: rest, 1: action, 2: release)
  3. Movement (label for 21 activities)
  4. Repetition index (1 to 10)
  5. Trial index (1 to 210)
  6. Manually generated activity component segmentation index

Data Description

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Activity Details:

Sl.NO	Activity name	No. of repetitions	Total time (s)	Trial Length
1	Tossing a coin	10	8	16000
2	Finger Snapping	10	8	16000
3	Pulling draw(Empty)	10	8	16000
4	Pulling draw(weight)	10	8	16000
5	Pulling draw-palmar view(Empty)	10	8	16000
6	Pulling draw-palmar view(weight)	10	8	16000
7	Pushing draw (Empty)	10	8	16000
8	Pushing draw (weight)	10	8	16000
9	Hand clasping	10	8	16000
10	Hand clapping	10	8	16000


Action 1 : Coin Tossing


Action 2 : Finger Snapping


Action 3 : Pulling Draw(Empty)


Action 4 : Pulling Draw(Heavy)


Action 5 : Pulling Draw(Empty) (Palmar View)


Action 6 : Pulling Draw(Heavy) (Palmar View)


Action 7 : Pushing Drawer (Empty)


Action 8 : Pushing Drawer (Heavy)


Action 9 : Hand Clasping


Action 10 : Hand Clapping

Proposed Solution

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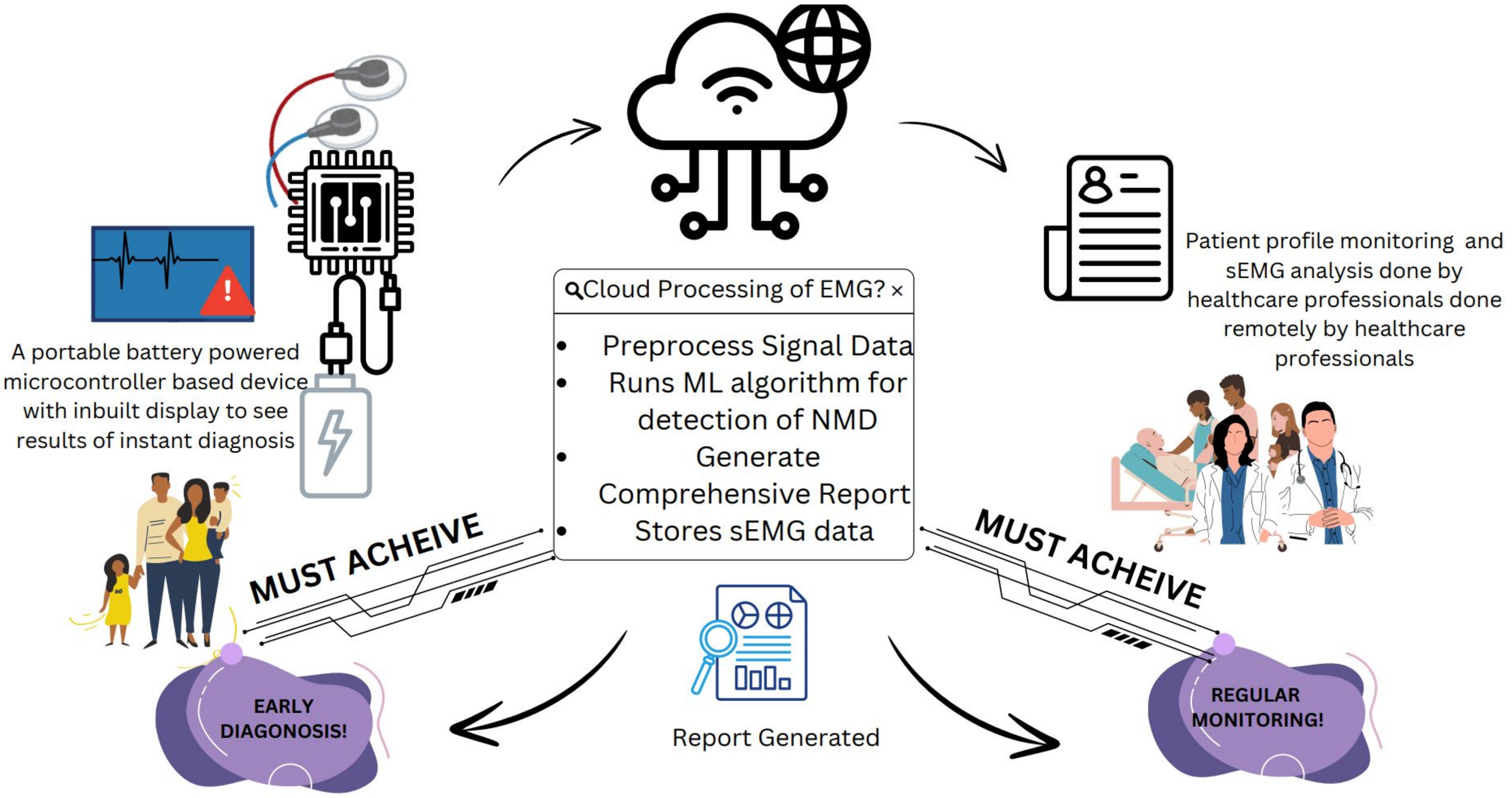
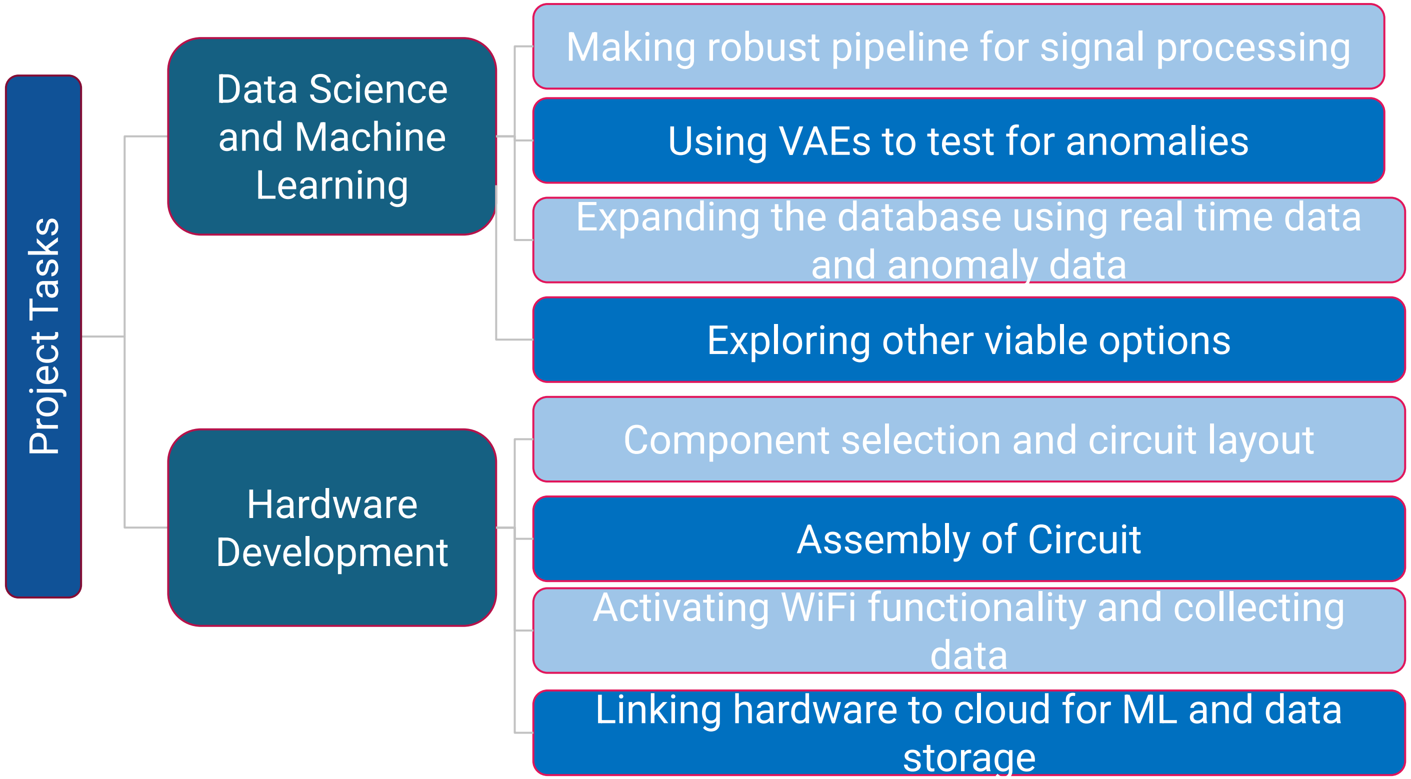


Project Tasks

The entire problem statement consists of focusing on broadly two ends, the data science portion and the hardware development portion, which has further classifications into sub-tasks.



Data Science and Machine Learning: Methodology

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Exploring other ML algorithms

Exploring other ML algorithms like VAEs, to make a better predicament on the anomaly in given dataset

Expanding Database

We aim to expand the current database of EMAHA Database, with real time data as well as explore sources to get real anomaly data from patients

Publishing the model

Publishing model in cloud.

Robust Pipeline for Signal Processing

Making a robust pipeline for signal processing, which will detect muscle activity and accordingly categorise out noise and quality data

Data Science and Machine Learning: Methodology

1. **Expanding Database:**
   To achieve the objective of expanding the database, the first step would be to collaborate with healthcare institutions, research labs, and clinics to access anonymized patient data related to muscle anomalies or other conditions of interest. This can involve building partnerships with these organizations to obtain high-quality, real-time data. Additionally, crowdsourcing data through wearable devices, such as EMG sensors and fitness trackers used by volunteers, would help enrich the dataset. Creating a secure cloud system to collect and store this data is critical for seamless access and real-time analysis. In cases where certain types of anomalies are underrepresented, synthetic data generation algorithms can be developed to simulate these conditions, helping to balance the dataset.

2. **Signal Processing:**

   Developing algorithms for muscle activity detection is critical to identifying muscle contractions, relaxation phases, and abnormal activities like tremors. These algorithms can be designed for real-time processing to handle data as it is recorded, ensuring quick categorization and analysis.

Data Science and Machine Learning: Methodology

3. Exploring other ML algorithms:

Autoencoders can be used to reduce the dimensionality of the dataset while retaining critical features, which is particularly helpful when dealing with large datasets. Variational Autoencoders (VAEs) can help detect anomalies by identifying data points that deviate from typical patterns, leveraging their latent space to generate new data points. Since the data may be time-series in nature, algorithms like Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks can be utilized to capture temporal dependencies. Implementing Explainable AI (XAI) ensures that the model's predictions, particularly in critical healthcare applications, can be interpreted and understood. Transfer learning can also accelerate the model-building process by fine-tuning pre-trained models on the current dataset.

4. Publishing in Cloud:

A robust cloud infrastructure, such as AWS, Google Cloud, or Microsoft Azure, is key to ensuring scalability, real-time processing, and storage.

Data Science and Machine Learning: Results

Hardware Development: Methodology

Component selection and circuit layout

The sensor is the primary component to be selected. Its peripherals, i.e power regulators and inverters must be chosen. A power supply and a microcontroller needs to be chosen and a layout needs to be made.

Assembly of Circuit

Primary level circuit needs to be assembled to see the functioning of sensor with microcontroller and gathered peripherals.

Activating WiFi functionality and collecting data

The device should be capable of being disconnected from wired sources and should be able to send data over WiFi to a computing system.

Linking hardware to cloud for ML and data storage

The data has to be stored over a cloud service and processing needs to be done on it. Further it has to be fed into ML algorithms for decision making and results need to be returned to device.

Hardware Development: Methodology

1) Sensor:

Techtonics EMG Muscle Sensor Module V3.0 is the primary sensor that we aim to use in this device. To use this sensor, the user must have three electrodes connected to the subject's body.
The reference electrode should be placed on an inactive section of the body, such as the bony portion of the elbow, shin or forearm. This electrode should be connected to the black or brown cable.
The two other electrodes should be placed along the muscle selected to be measured. The second electrode should be placed along the mid-length of the muscle; this electrode should be connected to the red cable. The required power supply is ideally ±5 V.

2) Power Source:

A 12 V rechargeable Li ion battery can be used to power up the microcontroller, the sensor and the OLED display. For the sensor and the microcontroller the voltage needs to be converted to nearly 5V and some peripheral integrated circuits like Voltage Inverter Circuit, Voltage Controller circuit need to be attached to the power source.

Hardware Development: Methodology

3) Microcontroller:

We plan to utilize ESP32 as our microcontroller, utilizing its dual core processor for simultaneous sending and receiving of data on cloud. It has inbuilt WiFi, and hence can wirelessly send and receive data. With a clock frequency of 80-240Mhz, it would be quick and ideally suited to our application.

4) OLED display:

A display screen following either I2C or serial communication protocol, with display size greater than 1 inch may be used for this application to display the signal, display the instructions and the results.

Hardware Development: Methodology

5) Cloud Server:

A server capable of file handling, data preprocessing , IoT compatible and applying machine learning model needs to be used.

The following tasks are the be done by the server:

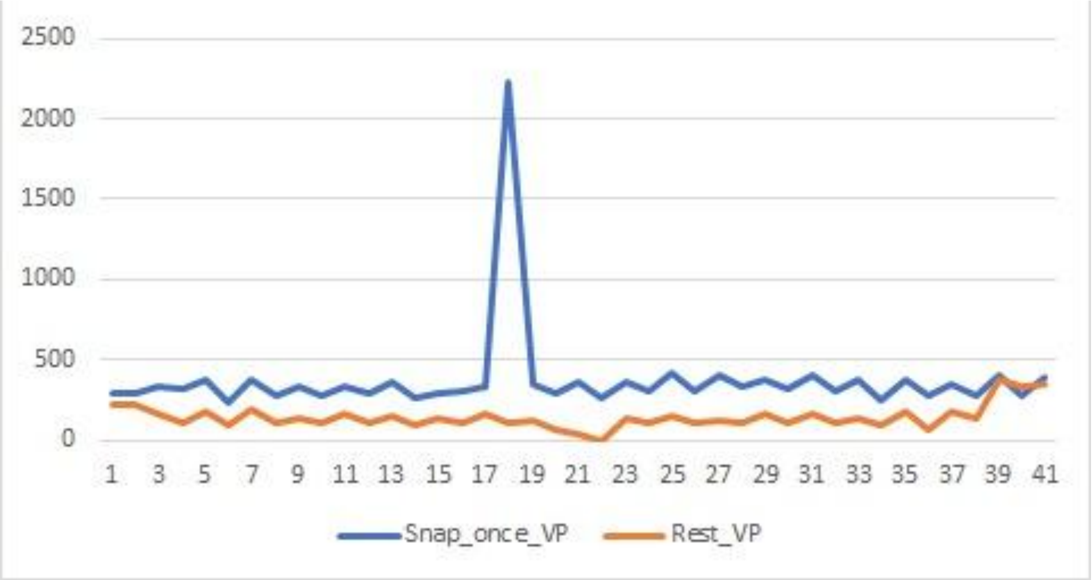
1) Receive sensor data from the ESP32 device
2) Preprocess the Data
3) Run a machine learning model on the data and get predictions
4) Send predictions back to the ESP32 device
5) Store the sensor data and analysis for further usage.

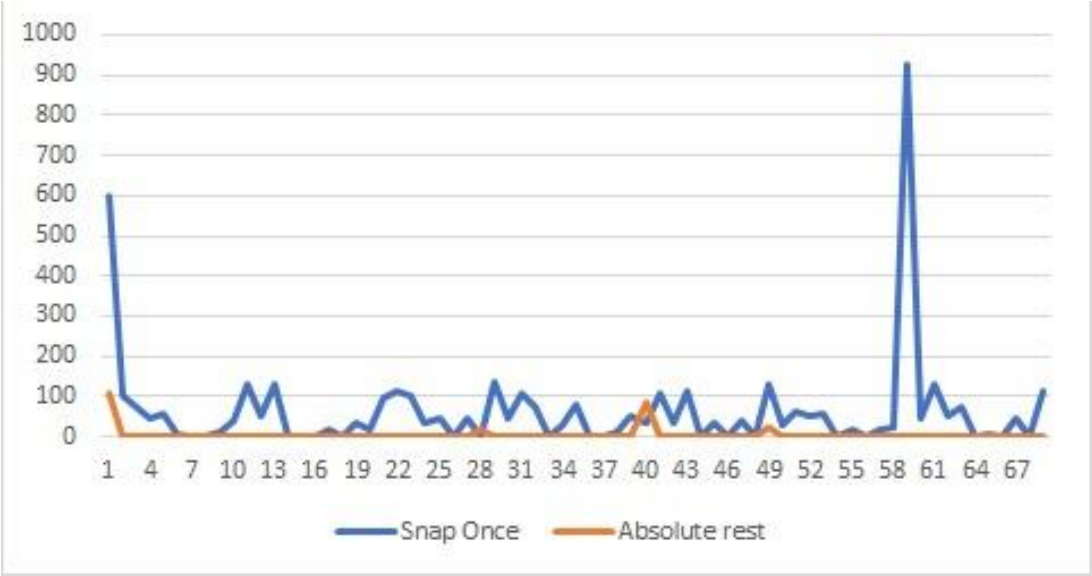
To suit all these purposes we aim to use either Microsoft Azure Cloud Services or Amazon's AWS.

Hardware Development: Results

We achieved a system capable of recording sEMG signals through a miniature user friendly device. The device is easy to operate and can be turned on with a switch. After this, the instructions are displayed on a screen for user to perform an action. The data is recorded and sent over to the host computer in the format of a .csv file that can be utilized for machine learning.

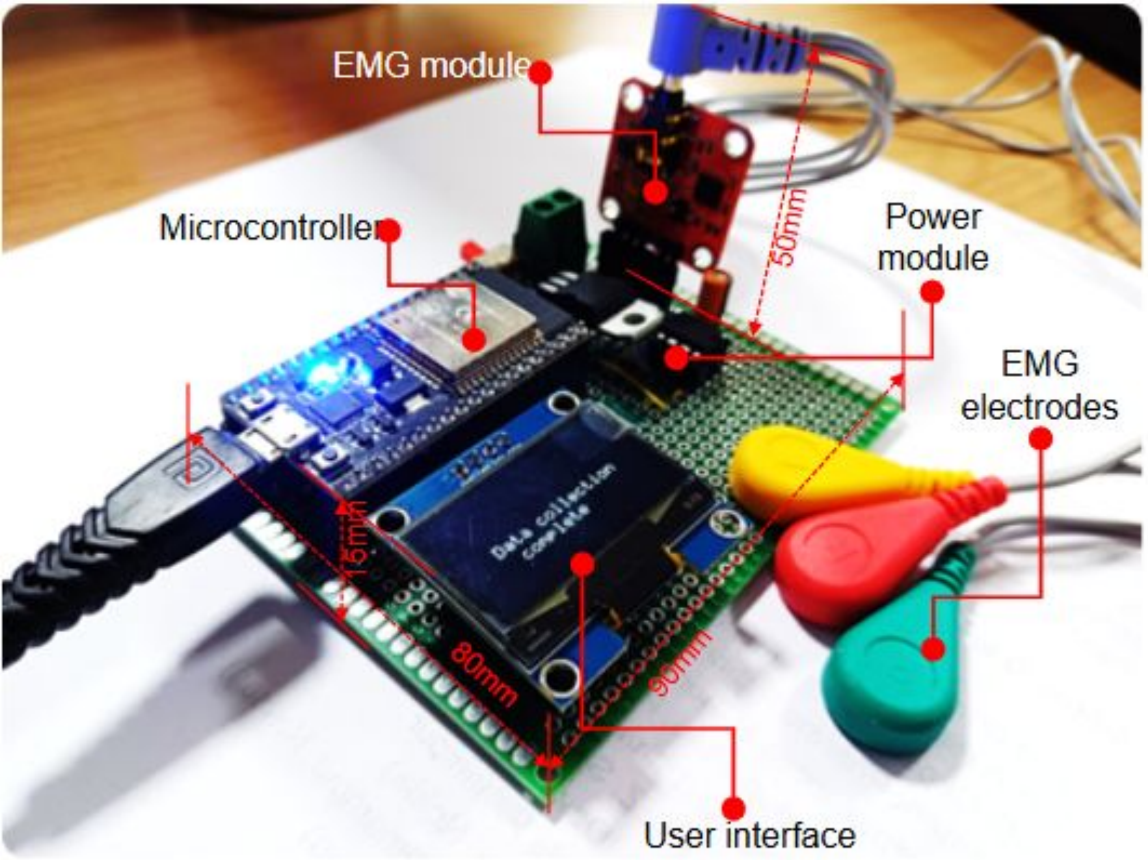
These are the signals obtained from the device:



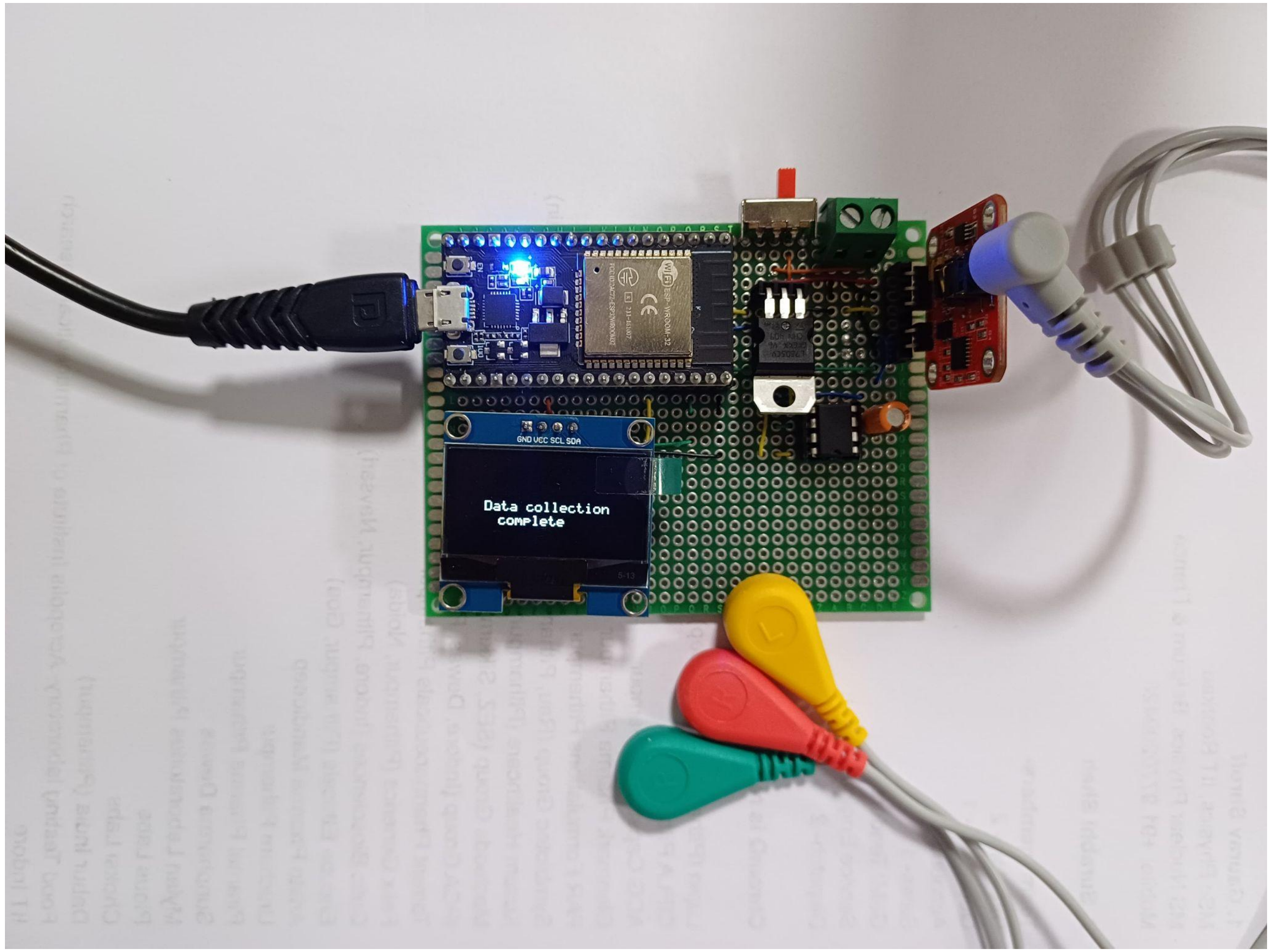


Hardware Development: Results

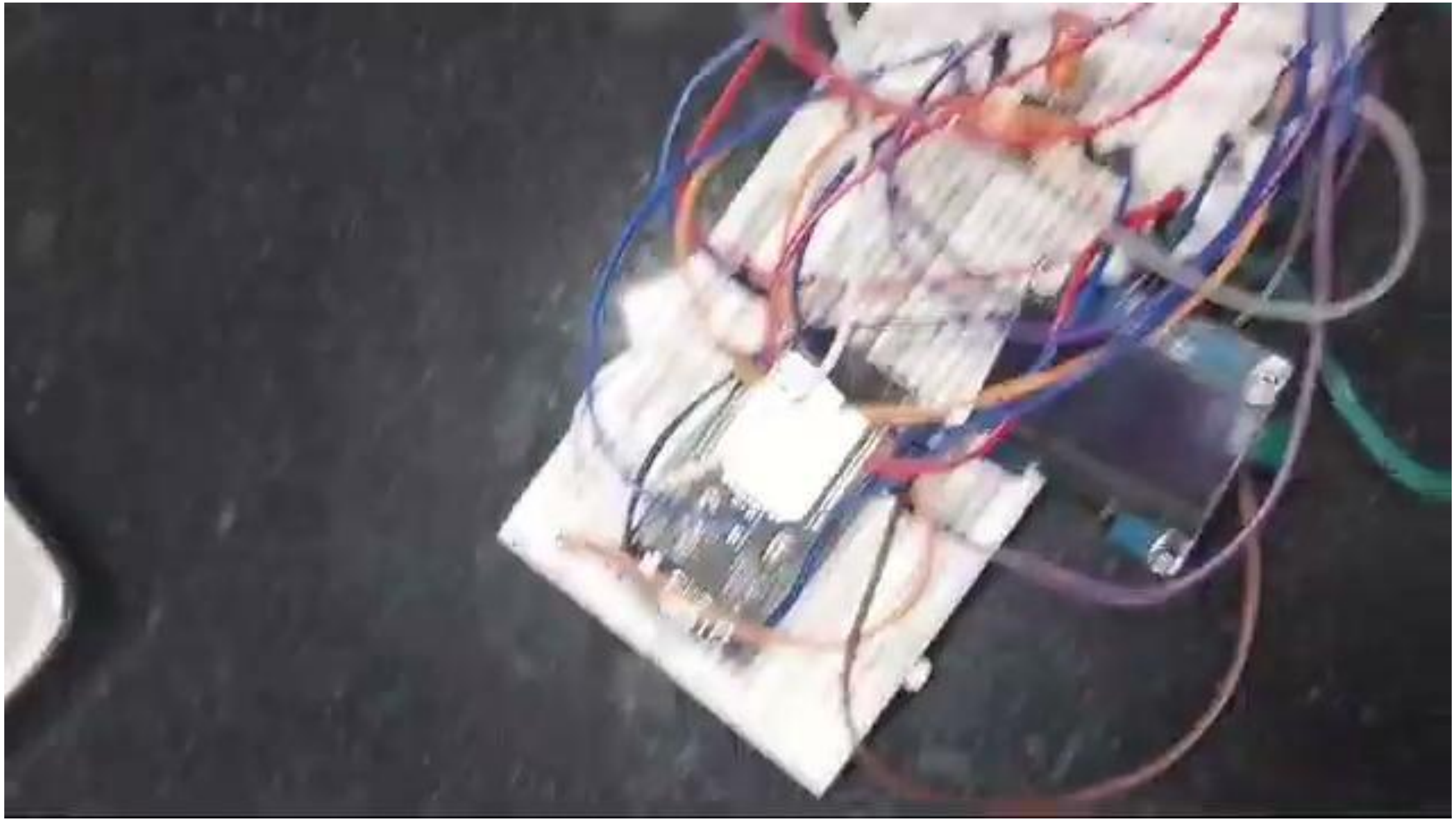
Here is the device prototype



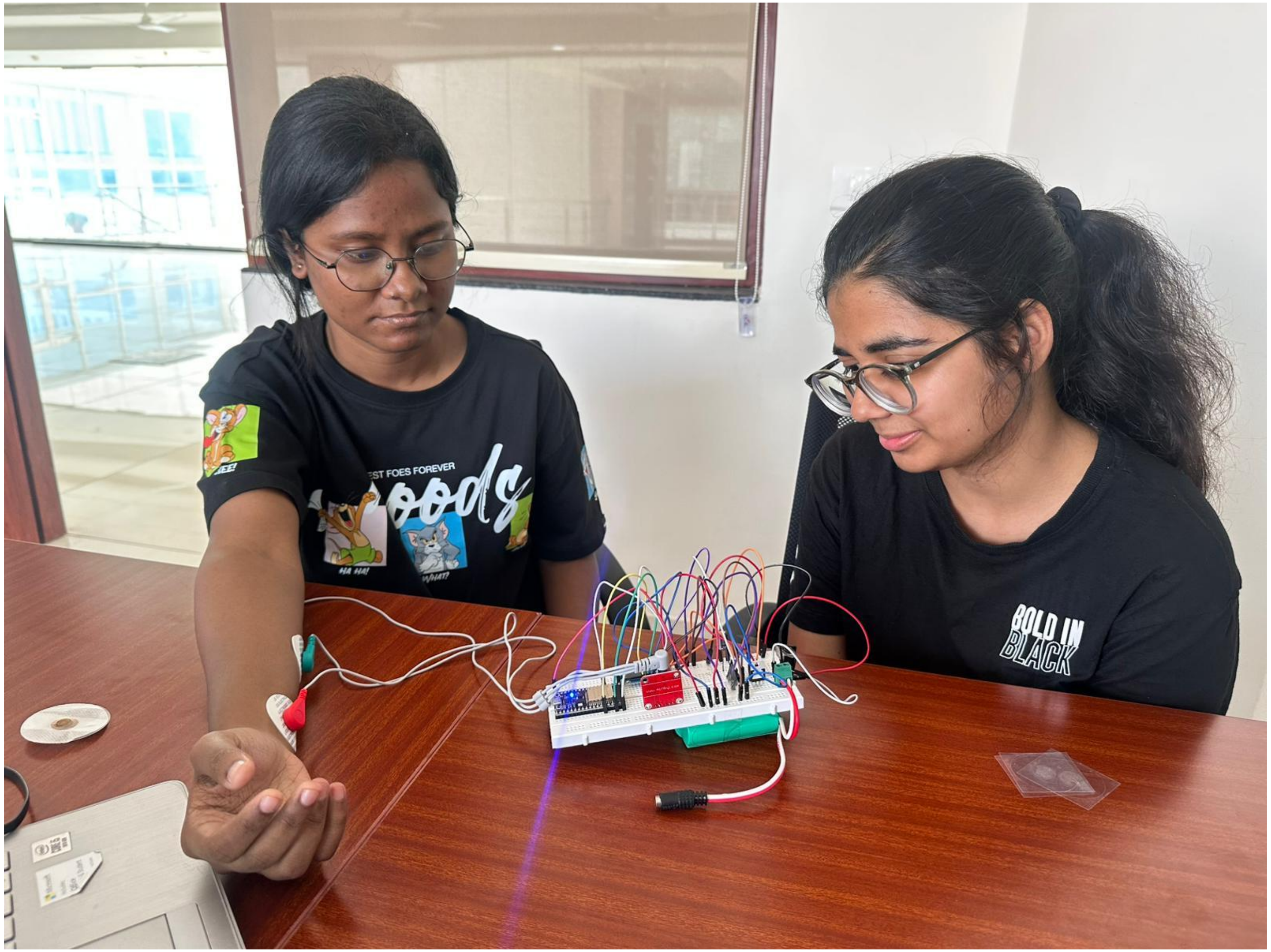
EMG based neuromuscular disorders detection device



Hardware Development: Demonstration Video



Hardware Development: Signal Collection



References

1) Electromyography (EMG) based Classification of Neuromuscular Disorders using Multi-Layer Perceptron I. Elamvazuthi, N.H.X. Duy , Zulfiqar Ali , S.W. Su , M.K.A. Ahamed Khan and S. Parasuraman

1) Techniques of EMG signal analysis: detection, processing, classification and applications M. B. I. Reaz, M. S. Hussain and F. Mohd-Yasin

1) Analysis of Extracted Forearm sEMG Signal Using LDA, QDA, K-NN Classification Algorithms Firas AlOmari and Gunhai Liu

1) Study of signal processing techniques for EMG analysis Manoj Duhan and Chanderpal Sharma

1) Electrodiagnosis in Diseases of Nerve and Muscle, Jun Kimura
2) Anomaly detection of electromyographic signals, Ahsan Ijaz and Jongeun Choi
3) Machine Learning for Detection of Muscular Activity from Surface EMG Signals, Francesco Di Nardo,,Antonio Nocera, Alessandro Cucchiarelli, Sandro Fioretti, and Christian Morbidoni

8) Artificial Muscle Signal Generation using Generative Adversarial Networks , Mahdi EL Mesoudy

9) An artificial EMG generation model based on signal-dependent noise and related application to motion classification Akira Furui, Hideaki Hayashi, Go Nakamura, Takaaki Chin and Toshio Tsuji

Weekly Updates

Week 1

HARDWARE:
Component purchase and comparison phase. Multiple sEMG sensors were compared and the following was selected.
Techtonics EMG Muscle Sensor Module V3.0

Specifications:

Power Supply	Normally ±9V dual power supply, minimum voltage is ±3.5V
Connector	5 (mm)
Audio-style plug	3.5 (mm) jack
Diameter of Electrode Pad	52 (mm)
Cable Length	2 (feet)
Dimension of Module	33.5 x 26 x 12 (mm)
Weight	30gm

Week 2

HARDWARE:

Literature review conducted to learn more about sensor interfacing and data recording.
Following lecture series was followed form a tutorial for the course BPK 409: Wearable Technology and Human Physiology at Simon Fraser University.
The Lab Manual:
https://docs.google.com/document/d/e/2PACX-1vTr1zOyrUedA1yx76olfDe5jn88miCNb3EJcC3INmy8nDmbJ8N5Y0B30EBoOunsWbA2DGOVWpgJzIs9/pub
The video series:

1) https://www.youtube.com/watch?v=F6P9tWrgSZo&t=420s&ab_channel=BPKSFU-Wearables
2) https://youtu.be/aXmisa6QkHQ?si=N_drWwptPqeaxLzH
3) https://youtu.be/7Me-M7gspLo?si=nXXXeooTF82BCiJu

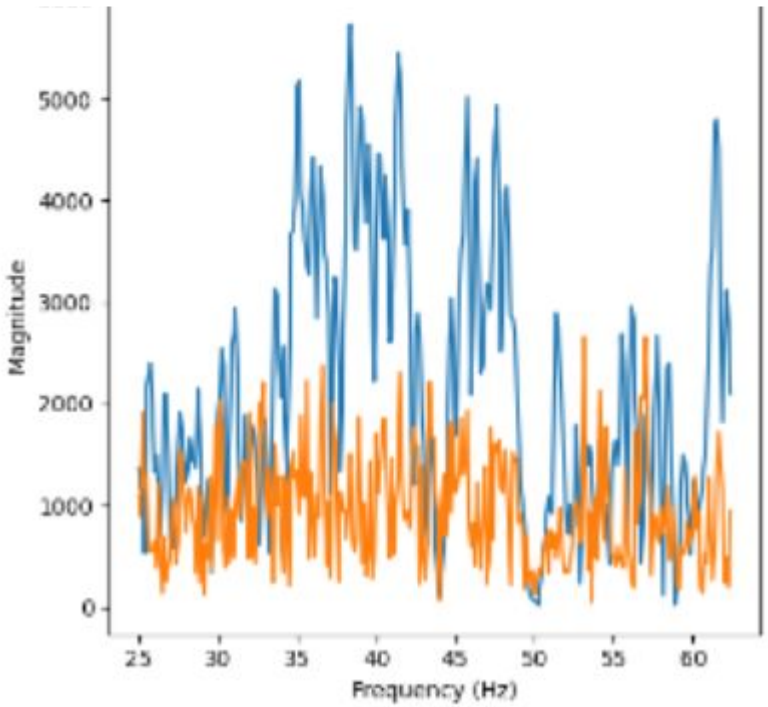
ML:

Literature review conducted to learn more about the data collection and potential sources of noise to include it in signal processing algorithms

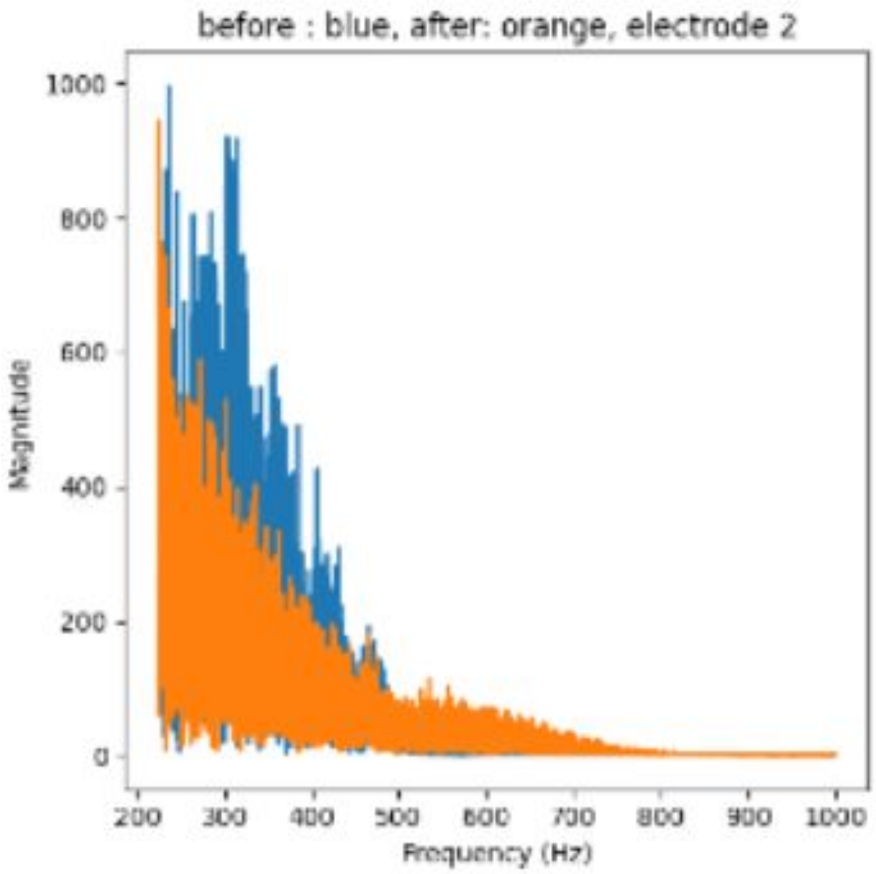
Week 3

Signal Processing algorithms in Python were explored from
https://scientificallysound.org/2016/08/18/python-analysing-emg-signals-part-3/

and their results were seen and compared.
Effect of notch filter:



Effect of butterworth lowpass filter:



Week 3

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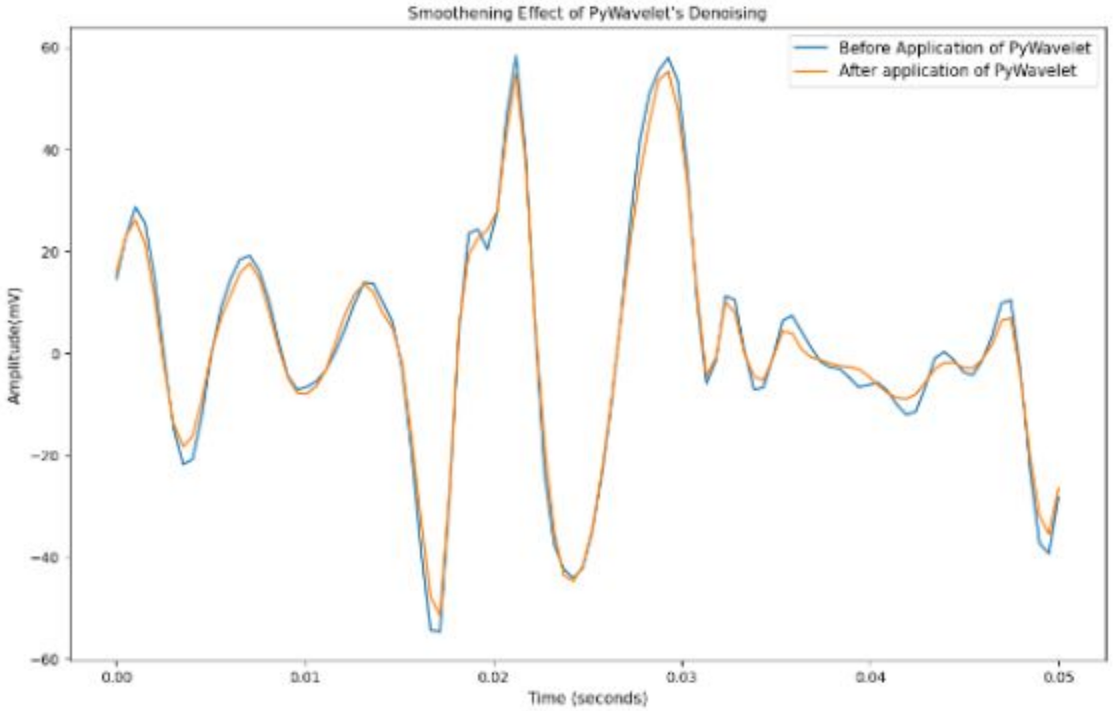

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HARDWARE:

Microcontroller Selection and Data transmission

Several microcontrollers were compared and accounted for. We considered ESP32, ESP8266, Arduino Uno and Arduino Nano. Following is the analysis we obtained:

Microcontroller	Advantages	Disadvantages
Arduino UNO	1) Cost effective 2) Easy Interfacing	1) Slower clock frequency 2) No built in WiFi and Bluetooth capabilities 3) Single Core Processor and hence simultaneous transmission and receiving is not possible
Arduino NANO	1) Compact size 2) Easy interfacing	1) Slower clock frequency 2) No built in WiFi and Bluetooth capabilities 3) Single Core Processor and hence simultaneous transmission and receiving is not possible

Week 4

Microcontroller	Advantages	Disadvantages
ESP8266	1) Built in WiFi Compatibility 2) Dual Core Processor allows simultaneous receiving and transmission	1) No built in Bluetooth capabilities 2) Complex Interfacing
Arduino NANO	1) Built in WiFi and Bluetooth Compatibility 2) Dual Core Processor allows simultaneous receiving and transmission 3) Highest Clock Frequency amongst all the microcontrollers of 240MHz	1) Complex Interfacing

Week 4

Clearly, from all the microcontrollers, ESP32 shows the best set of features, and is suitable for our application. Also the chosen Techtonics sensor is ESP32 compatible hence using it would be suitable for us.

Machine Learning and Data Science:
Literature review conducted about various signal processing which can be incorporated:

1. [Development of an Integrated System of sEMG Signal Acquisition, Processing, and Analysis with AI Techniques (mdpi.com)]
2. [Machine Learning for Detection of Muscular Activity from Surface EMG Signals (mdpi.com)]
3. [[2304.04098] Overview of processing techniques for surface electromyography signals (arxiv.org)]

By integrating AI algorithms, specifically convolutional neural networks (CNNs), with the signal acquisition device, the system achieved higher accuracy in identifying neuromuscular issues. This improvement is due to the system's ability to eliminate redundant information and accurately classify and interpret sEMG signals. Additionally, the development of a complete hardware-software system for sEMG signal acquisition, processing, and analysis represents a significant advancement, allowing for a more seamless and efficient workflow in studying muscle function and neuromuscular control
The system's ability to accurately analyze sEMG signals has practical implications for diagnosing and understanding neuromuscular disorders, potentially guiding treatment plans in clinical settings

Week 4

The study also introduces the Detector of Muscular Activity by Neural Networks (DEMANN), a machine-learning-based method designed to improve the accuracy and reliability of muscle activity detection. The research highlights the importance of accurately assessing muscle-recruitment timing, which is crucial in various fields such as clinical gait analysis and electromyography-driven assistive devices.
The methodology involves utilising sEMG dataset, stratified for signal-to-noise ratio (SNR) and time support, to train a hidden single-layer fully-connected neural network. DEMANN's performance was evaluated on both simulated and real sEMG signals, and it was validated against established algorithms, including the double-threshold statistical algorithm (DT)
The results demonstrated that DEMANN reliably predicted muscle onset and offset events, showing minimal sensitivity to SNR variability. Compared to state-of-the-art algorithms, DEMANN introduced significant improvements in prediction performance.

They delving into various signal processing techniques, including filtering, epoching, and frequency spectral density analysis, which are essential for cleaning and preparing the sEMG data for further analysis.

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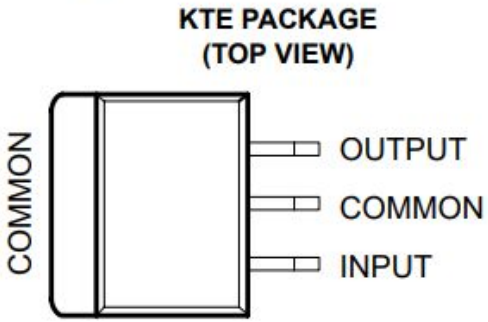
HARDWARE:
Power Supply Circuit formulation and design

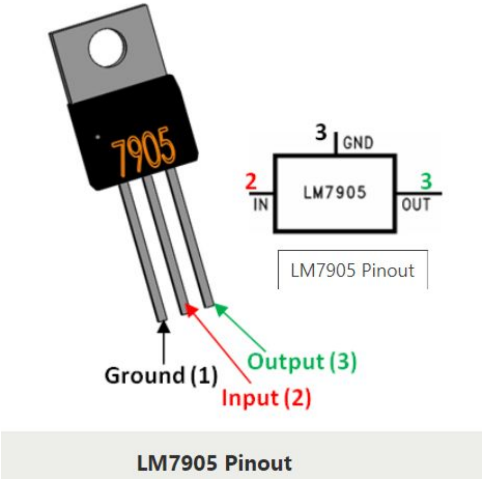
The sensor chosen by us needs a power supply of ±5V, and also needs a separate ground to be given. The chosen microcontroller ESP32 can function at a voltage around 5-9V. Any voltage higher than 9V can destroy the board. And the sensor has a strict requirement of 5V. But the OLED display and other peripherals may need higher voltages, also if components are to be connected in series at any stage, we should have higher voltage.

Also the power supply should be rechargeable, it is best to utilize rechargeable batteries. For this we plan to choose 12V rechargeable Li ion battery which comes with an adapter.

Now, to obtain a potential of +5V we need a voltage controller IC.
For this we can use the LM-7805 IC.

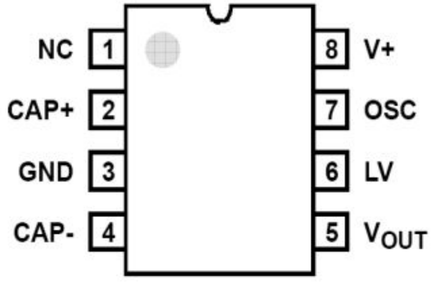


For getting a -5V, we would either need a negative voltage supply circuit. We can either use, LM7905, negative voltage controller IC. For this we can flip the battery terminals, and get a regulated -5V supply.



LM7905 Pinout

Apart from this, we can also use TJ7660, which is a voltage inverter IC. On giving it a supply of +V, we can obtain a -V. This uses a capacitor to achieve this, a basic circuit layout can be.



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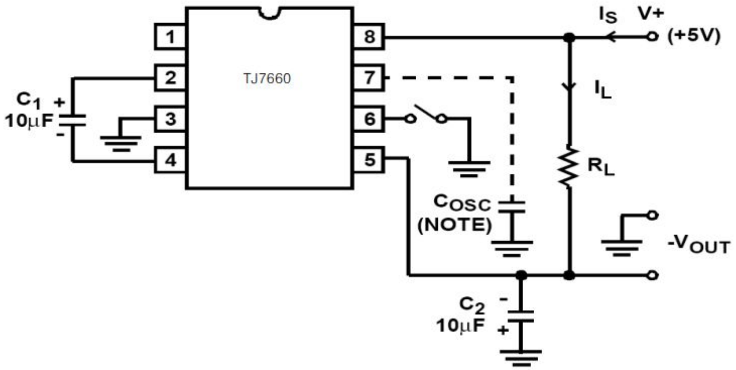
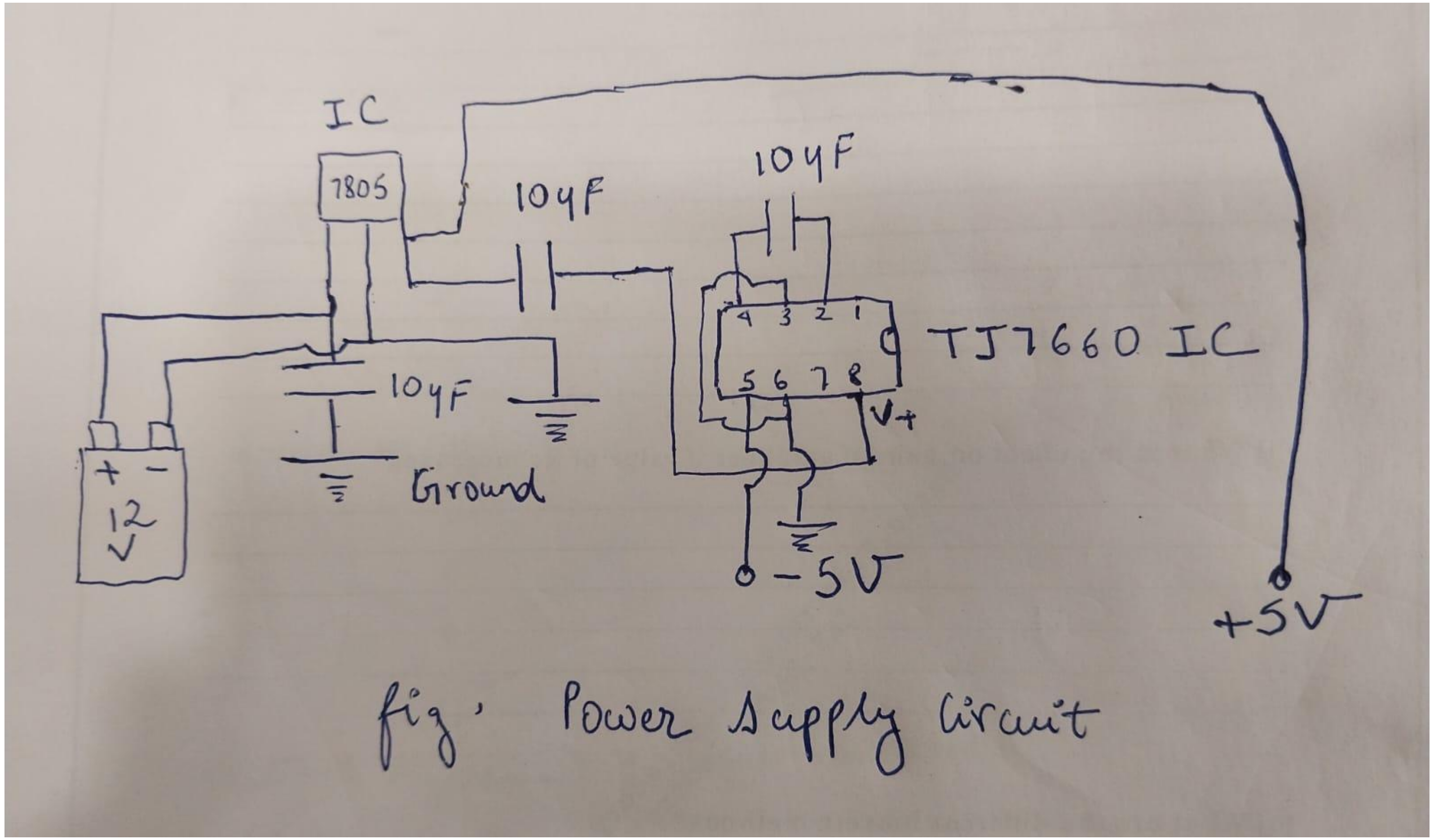


Week 5

The proposed circuit design is:



Week 5

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Machine Learning and Data Science:

Implemented muscle activity detection function into the signals which effectively segrates between baseline noise and actual readings. Parallely did literature review about various algorithms for anomaly detection.

1. GitHub - Jithsaavvy/Explaining-deep-learning-models-for-detecting-anomalies-in-time-series-data-RnD-project: This research work focuses on comparing the existing approaches to explain the decisions of models trained using time-series data and proposing the best-fit method that generates explanations for a deep neural network. The proposed approach is used specifically for explaining LSTM networks for anomaly detection task in time-series data (satellite telemetry data).
2. On Evaluating Black-Box Explainable AI Methods for Enhancing Anomaly Detection in Autonomous Driving Systems (mdpi.com)
3. [2207.11564] A general-purpose method for applying Explainable AI for Anomaly Detection (arxiv.org)
4. 2204.12577 (arxiv.org)

The methodology involves comparing various explainable AI (XAI) techniques to determine the most effective method for generating explanations for LSTM-based anomaly detection models. The study evaluates different configurations of LSTM networks, including simple/vanilla LSTM, encoder-decoder based LSTM, stacked LSTM, and bi-directional LSTM.

Key XAI methods used in this research include SHAP (SHapley Additive exPlanations), LRP (Layer-wise Relevance Propagation), and LIME (Local Interpretable Model-agnostic Explanations)

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Week 5

The study introduces a comprehensive framework to assess black-box XAI methods, specifically SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), by evaluating their performance across six metrics: descriptive accuracy, sparsity, stability, efficiency, robustness, and completeness.

The research highlights the importance of understanding the decision-making processes of AI models, particularly in safety-critical applications like anomaly detection. By applying XAI techniques, the study aims to elucidate the primary features crucial for anomaly classification, thereby enhancing the interpretability of the AI models

This framework's application to anomaly detection in sEMG signals can be highly beneficial. sEMG signals, used to assess muscle activity, often require precise and reliable detection of anomalies to diagnose neuromuscular disorders accurately. By employing XAI techniques, similar to those used in the study, researchers and clinicians can gain better insights into the AI models' decisions, ensuring that the detected anomalies in sEMG signals are well-understood and trustworthy. This can lead to improved diagnostic accuracy and more effective treatment plans for patients with neuromuscular conditions.

Another methodology involves using Integrated Gradients (IG) to reduce attribution errors, which are discrepancies between the model's predictions and the actual causes of anomalies

HARDWARE:

Cloud selection and learning to make IOT Interface

We plan to use either of Microsoft Azure or Amazon's AWS for receiving data from the microcontroller and for running an ML model on its backend.

Here is the analysis we obtained and we find both the services at par with each other.

Criteria	Azure	AWS
Ease of Use	Good integration with Microsoft products; familiar for Windows users.	Steeper learning curve; more flexible for custom setups.
IoT Support	Azure IoT Hub and IoT Central are user-friendly, with quick device management.	AWS IoT Core offers more advanced customization but requires more setup.
Machine Learning	Azure Machine Learning has easy model deployment and integration with IoT.	AWS SageMaker is powerful but can be complex for beginners.
Pricing	Pay-as-you-go model, but pricing can be high for large data processing.	Competitive pricing with cost optimization tools, but services can add up.

Week 6

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Machine Learning and Data Science:
Understanding various metrics, against which model could be validated

Metric	Description	ExplainableAI (XAI)	LSTM	RNN	CNN
F1 Score	Harmonic mean of precision and recall	7.5	9	8	9
Accuracy	% correct of model	7.5	9	8	9
Precision	Proportion of true positive prediction among all positive prediction	7.5	9	8	9
Recall	Proportion of true positive prediction among all positive	7.5	9	8	9
ROC-AUC		7.5	9	8	9
Latency			7	8	7
Scalability			8	7	8

Week 6

The scores provided for various algorithms and explainable AI (XAI) methods are based on general observations and typical performance characteristics in the context of anomaly detection, particularly for sEMG signals. For accuracy, precision, recall, F1 score, and ROC-AUC, deep learning models like LSTM, RNN, and CNN generally perform well due to their ability to learn complex patterns in data. LSTM and CNN often score slightly higher because of their advanced architectures that handle temporal and spatial data effectively. XAI methods like SHAP and LIME do not directly affect these metrics but help in understanding the model's decisions. Their scores reflect their ability to provide accurate explanations that align with the model's predictions.

These scores are illustrative and based on typical performance trends observed in the literature and practical applications.

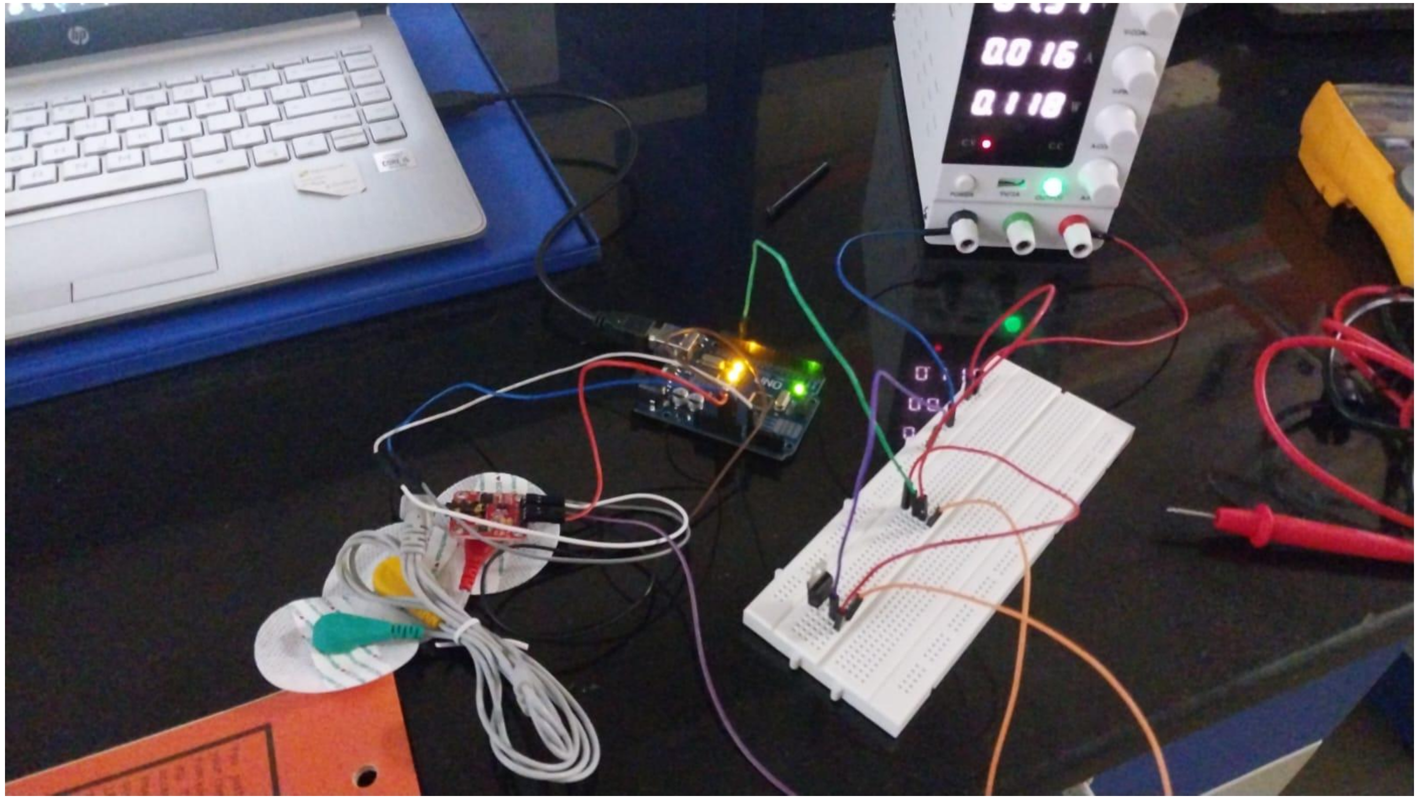
Some references:

1. Lundberg, S. M., & Lee, S.-I. A Unified Approach to Interpreting Model Predictions. Advances in Neural Information Processing Systems
2. Hochreiter, S., & Schmidhuber, J. Long Short-Term Memory. Neural Computation

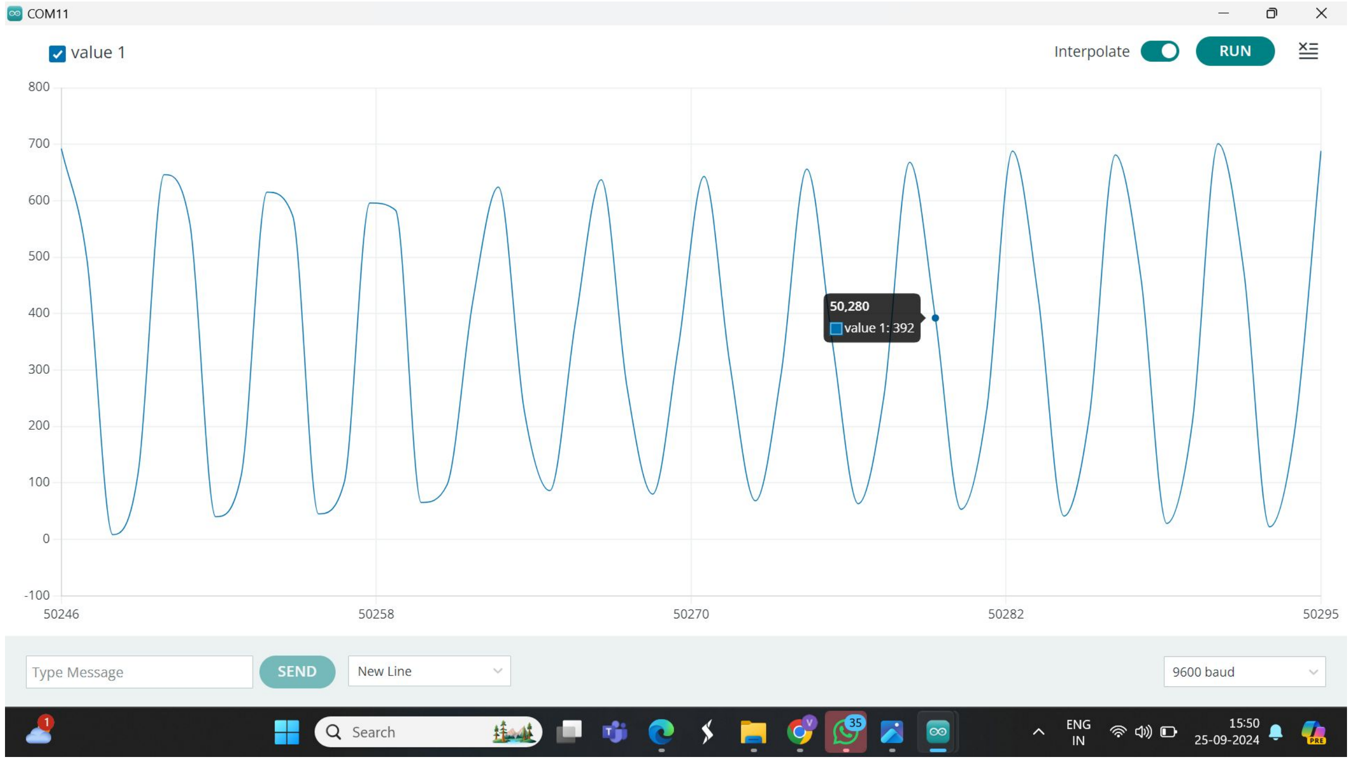
Week 7

HARDWARE:
Basic Circuit assembly

We gathered various circuit components and tried to get an output from the sensor. Here is the circuit:



HARDWARE:
This is the output we obtained on an initial level. This output is not corresponding to any muscle movement as of now and was sent through data transmission cable to the laptop.



Week 7

Machine Learning and Data Science:

Made compatible python scripts for signal processing, which was robust.
Exploring more viable options and implementation on VAEs

Week 8

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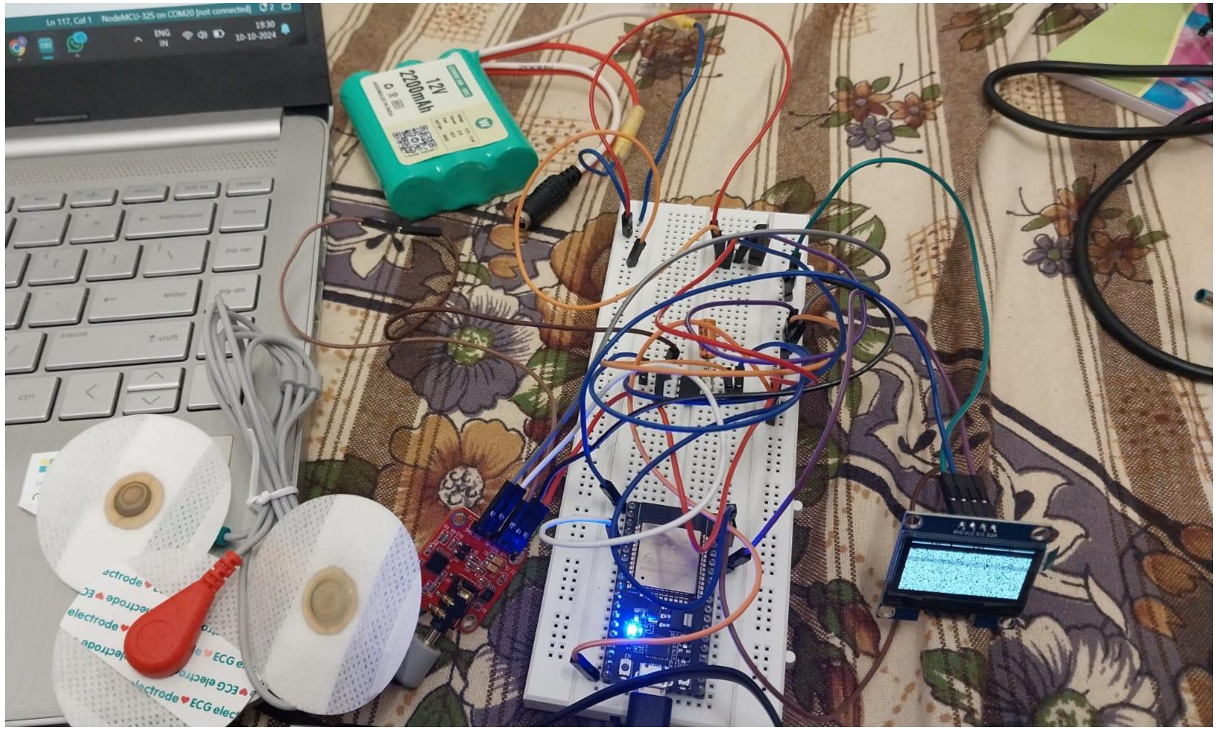
HARDWARE:

First Prototype of Standalone Device complete

A complete device that can take input through sensor, is completely battery operated and makes independent decisions without help of computer was built. Not yet linked with an ML algorithm, but it can display the signal and its parameters on the connected OLED display.



Week 8

Machine Learning and Data Science:

Extensive review and implementation of algorithms along with extensive debugging.

Some of the challenges faced while implementing CNN and VAE models were related to the quality of the data. To enhance data quality, I made several changes to the signal processing techniques, which consistently resulted in a sufficient SNR greater than 25. Additionally, I introduced a threshold SNR value, ensuring that any signals not meeting this threshold were excluded from model training. This approach was necessary because training is computationally intensive, and the database is set to be expanded from the existing ones.

Also the motivation to do so was, overfitting is a common problem with these complex models, especially when the training dataset is small. Overfitting is when the model learns the noise in the training data rather than the underlying patterns, resulting in poor generalization on new data.

Also did hyperparameter tuning, to get optimal result, which is yet to achieve.

Week 9

Hardware:

Initial level of data collection had begun and the next work was to start saving the data collected till the cloud access was given.

Usually, all the data than an ML model requires is to be made available is .csv format, hence an algorithm had to be put up in microcontroller to collect data samples for 8 seconds first and then save that data into a .csv file.

Initial Instructions were setup on OLED display first.

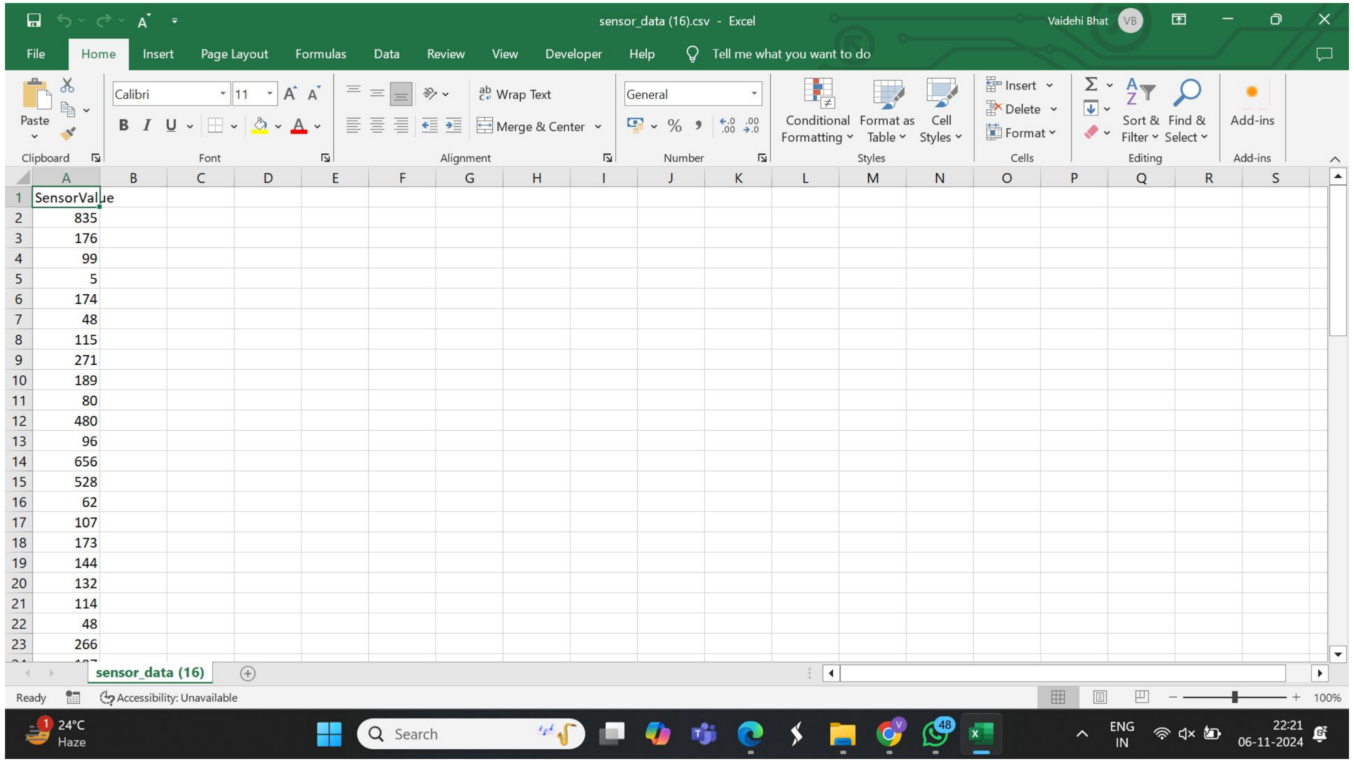
The instructions were:

"Welcome to sEMG Monitoring Session"
"Place your hand at 90 Degrees angle on a flat surface."
"Get Ready to SNAP your fingers in 3..2..1"

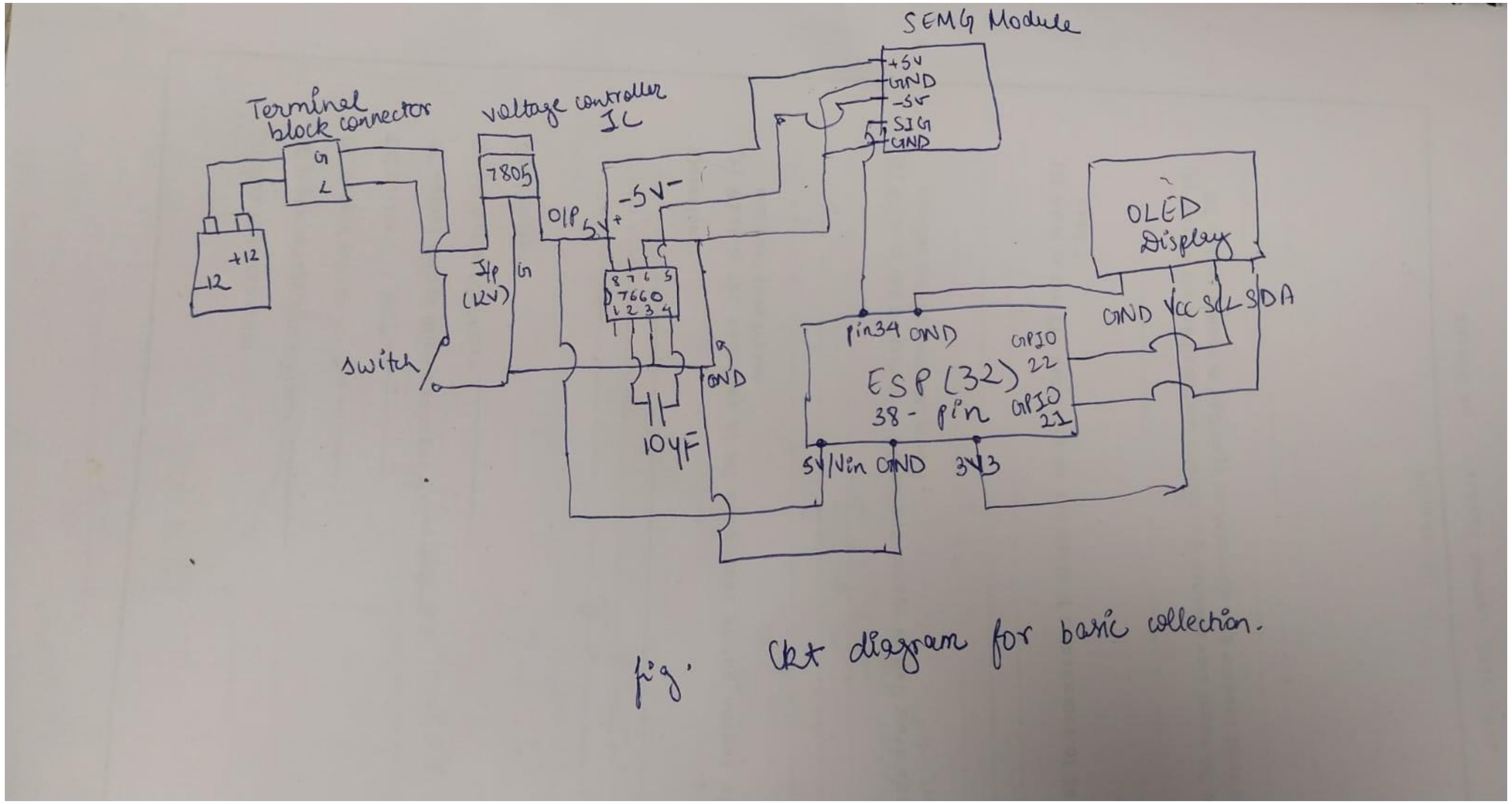
Then a code to add countdown was added which triggers the onset of data collection, collects data for 8 seconds and then stops.

Hardware:

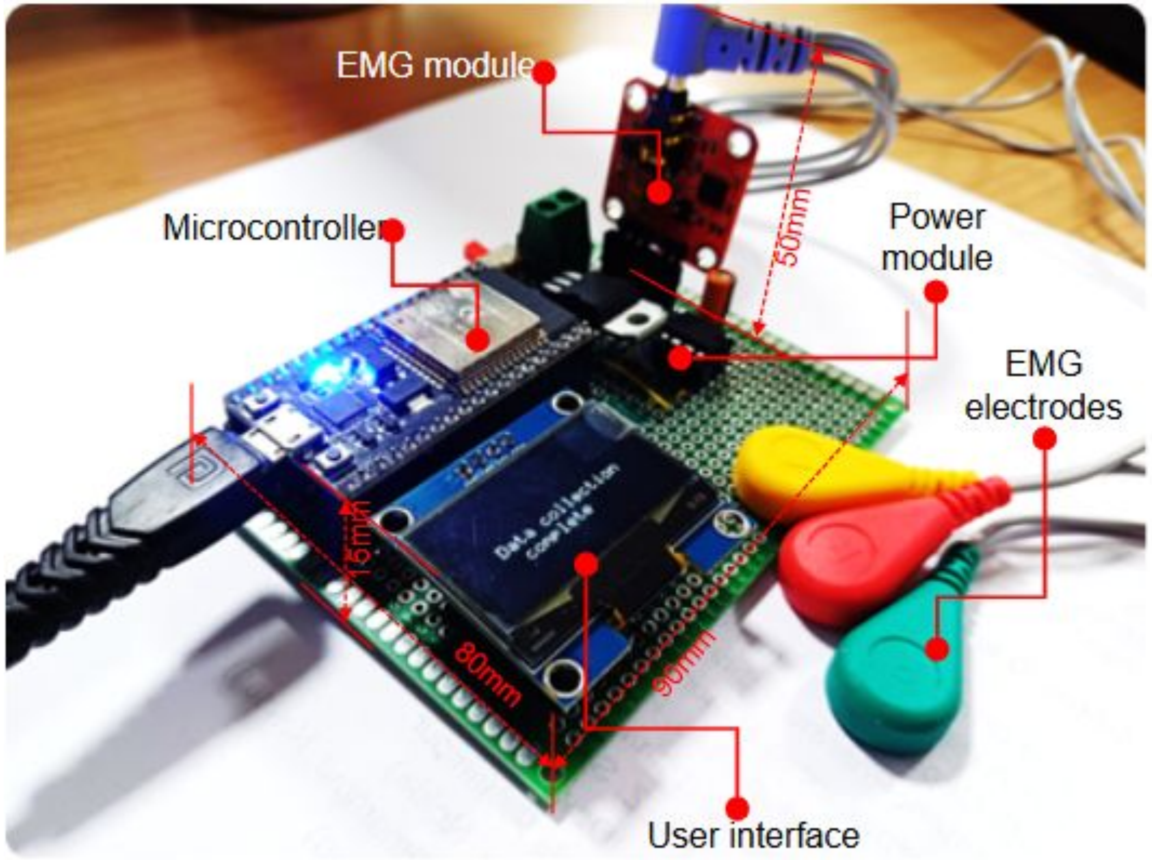
The data now collected had to be converted into a .csv file and to be sent over to a computer till cloud access was given. Hence the microcontroller code was made, which after data collection would convert it into the .csv file and send it wirelessly to the computer from where I can enter a URL and directly download the file.



Hardware:
The components were soldered according to the following schematic on a perf board.



Hardware:

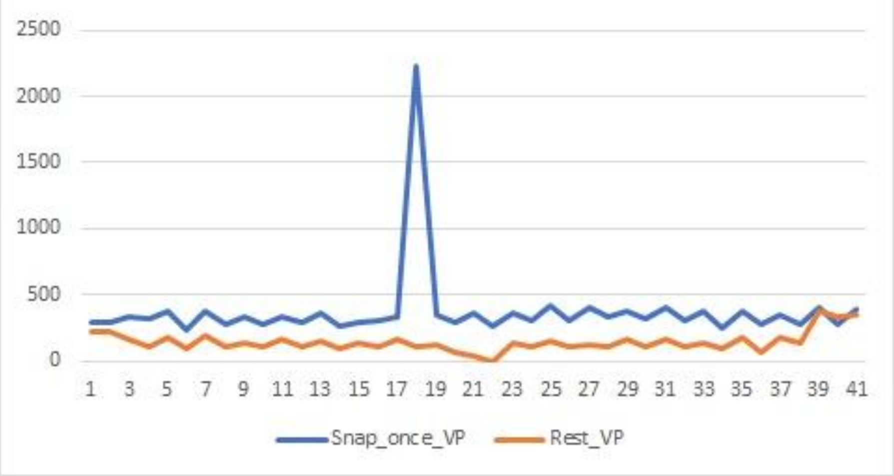


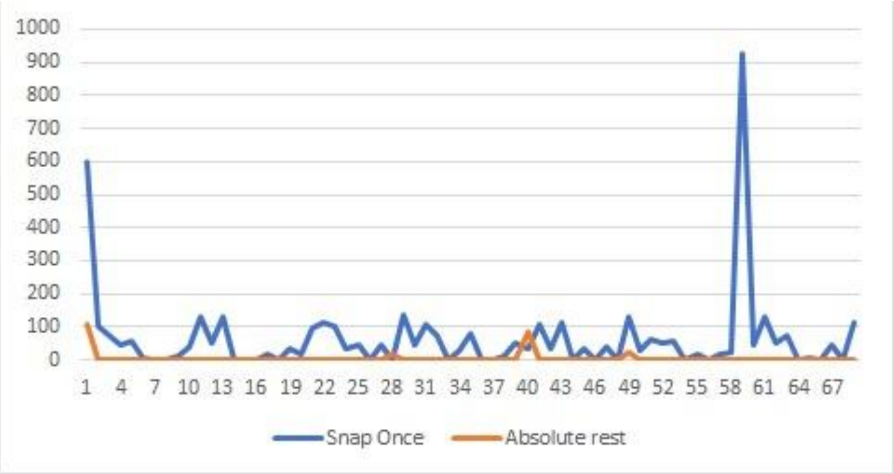
EMG based neuromuscular disorders detection device

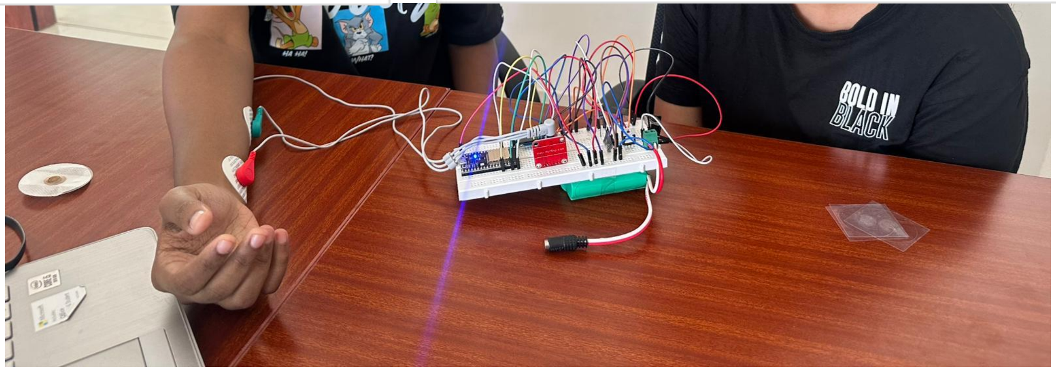
Week 12

Hardware:

Data collection was started and trials were made on experiment subjects. We were able to successfully capture muscle characteristics.

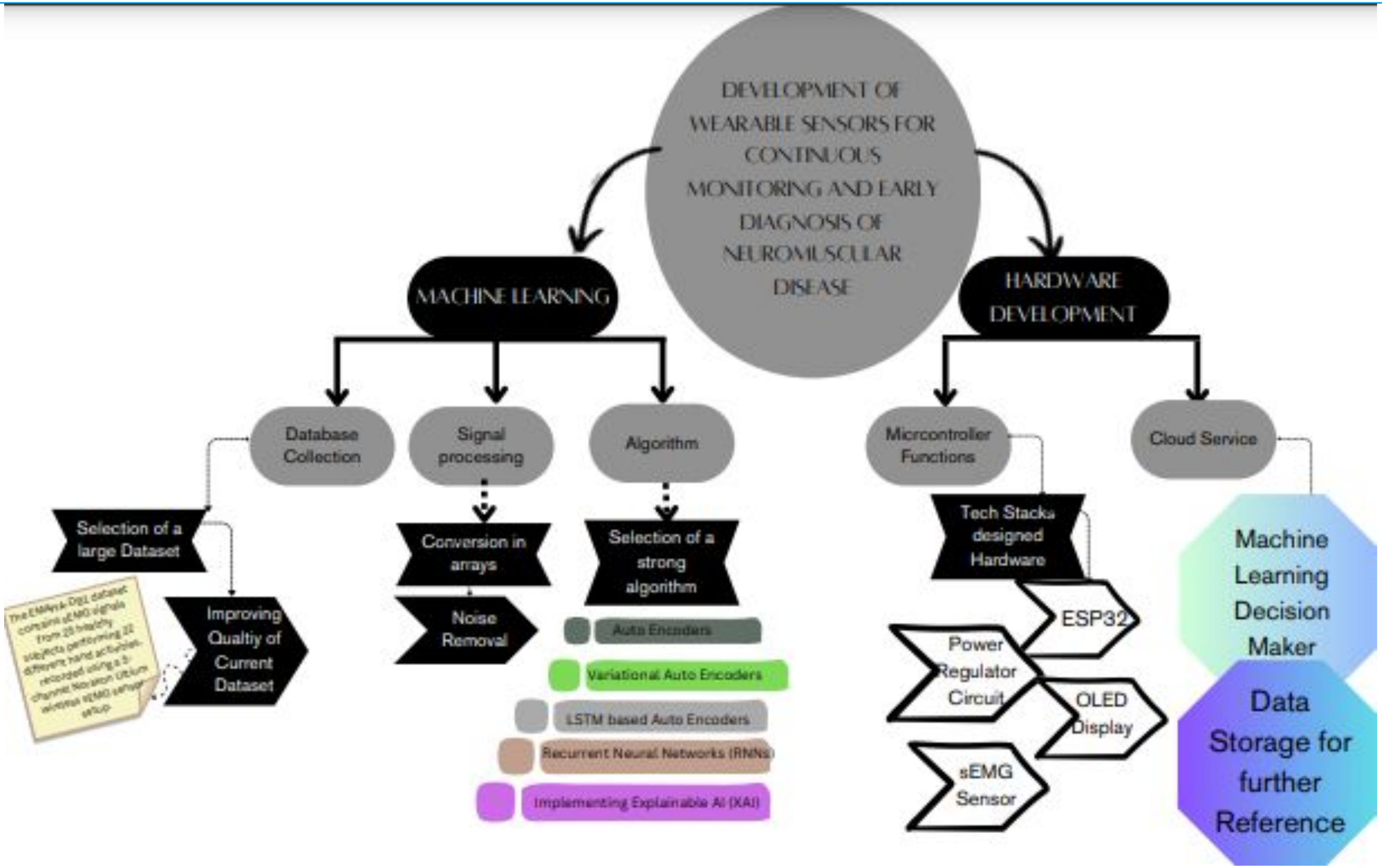






Solution-at-a-Glance

Solution Overview



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Thank you!