CENTER FOR DIGITAL HEALTHCARE

SIDDHI2024

Summer Internship for Data-Driven Healthcare Innovations

Enhancing Diagnostic Capabilities with Machine Learning for Neuromuscular Disorders

Content

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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
- …
- Week 8 Updates

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

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Project Report

Team

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Introduction and Motivation

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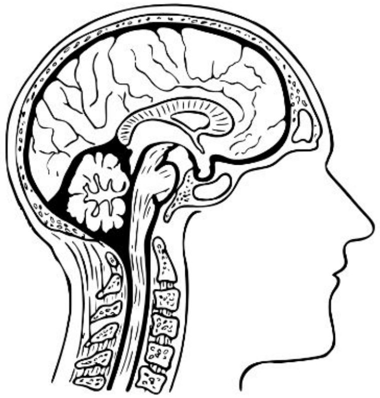
Neuromuscular Disorders in India

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



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

Understanding the issue!

Definition

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.

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

As there is no way to reverse neuromuscular disorder effects, 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.

The task is to create a user friendly monitoring system that can be easily purchased by households, and intermittently they can use it to monitor their health, and spot early signs of neuromuscular disorders via analysis of the electrical activity of their muscles. This has to be done by incorporating knowledge of EMG signals and their analysis methods through thorough literature review, followed by building robust algorithms that can separate normal data from diseased and putting it all up on an interface that can be accessed easily by the user.

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

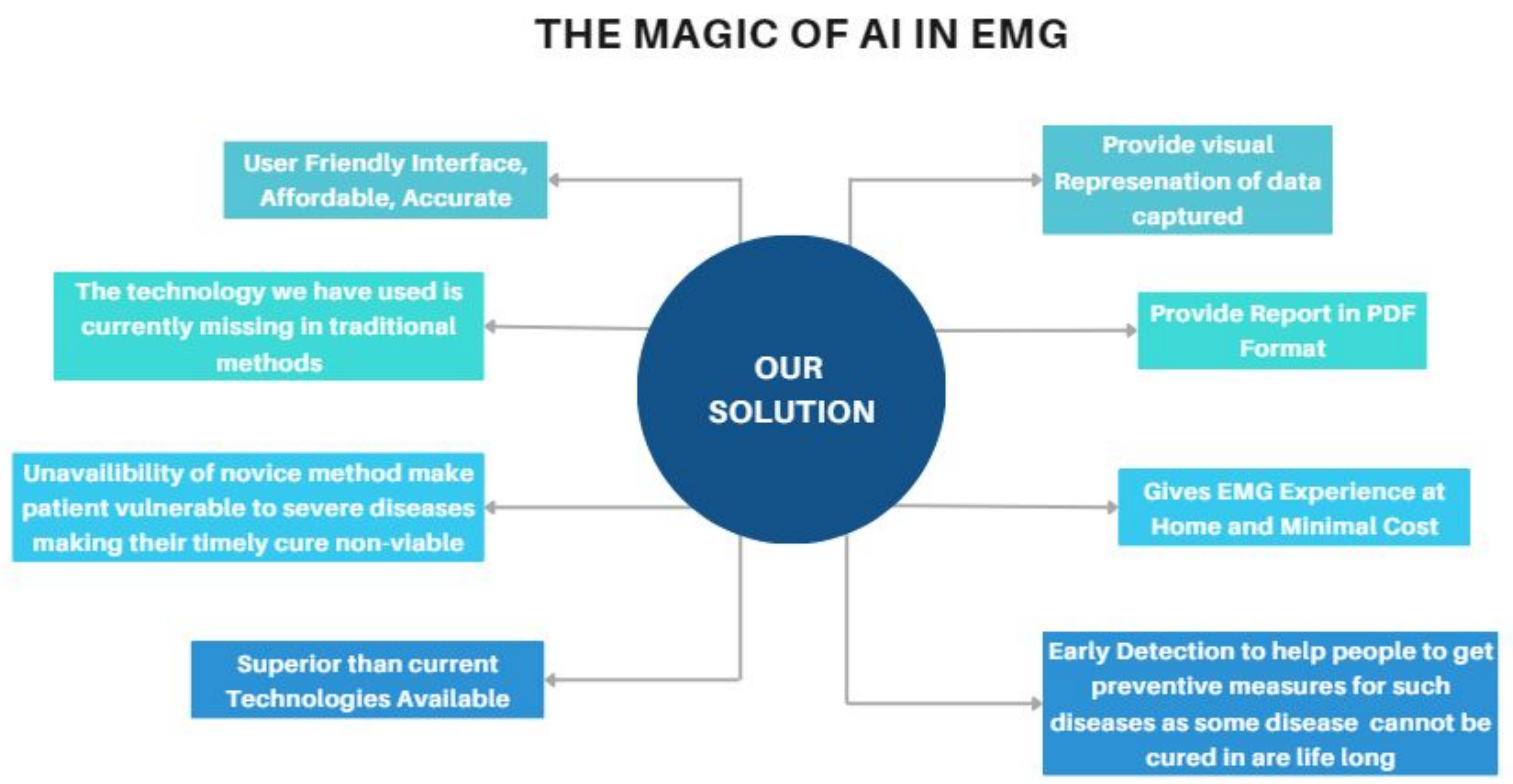
Our solution prioritizes user-friendliness, portability, and remote diagnostics. Upon receiving raw EMG signal data from the surface sensors , providing a non invasive and easy to use method , it processes the signal and gives out a processed EMG wave visualisation for consultation to medical practitioners through the application

Further the machine learning algorithm will predict whether the EMG data is indicative of certain possibilities of Neuromuscular diseases 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.
- 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.

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

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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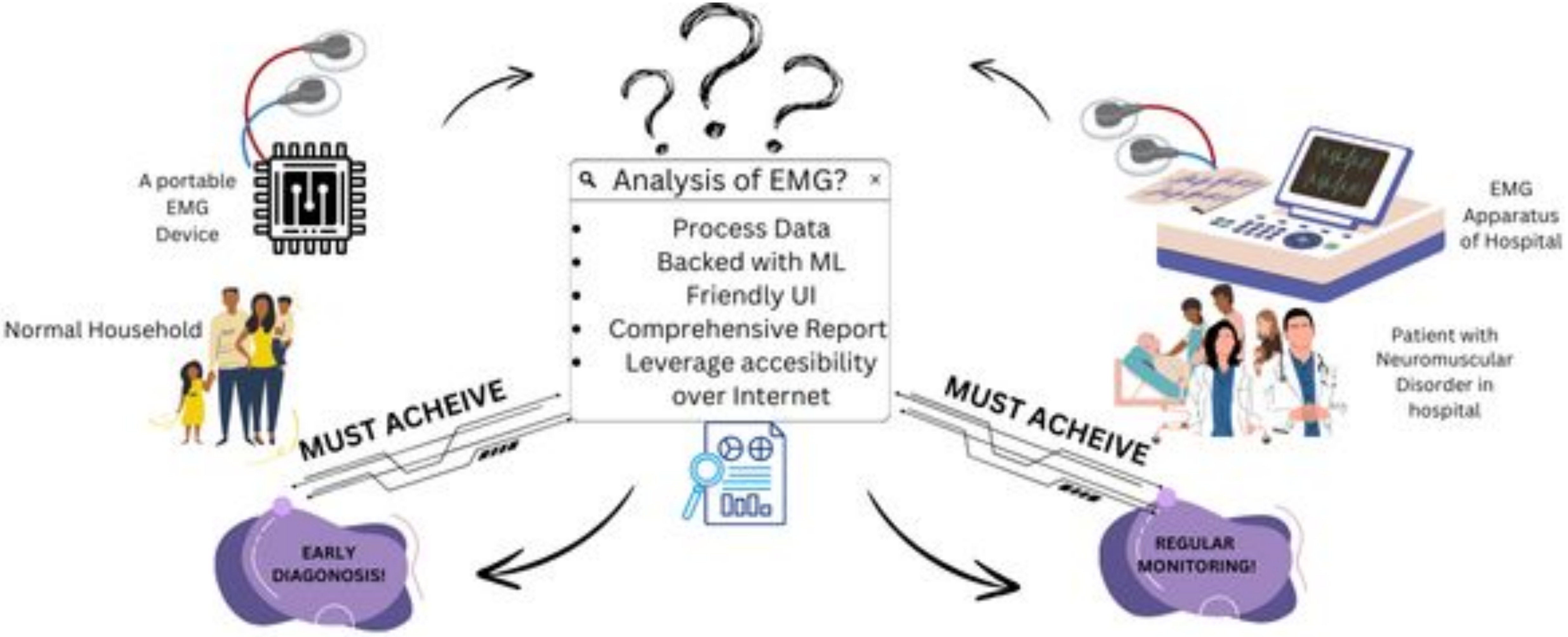
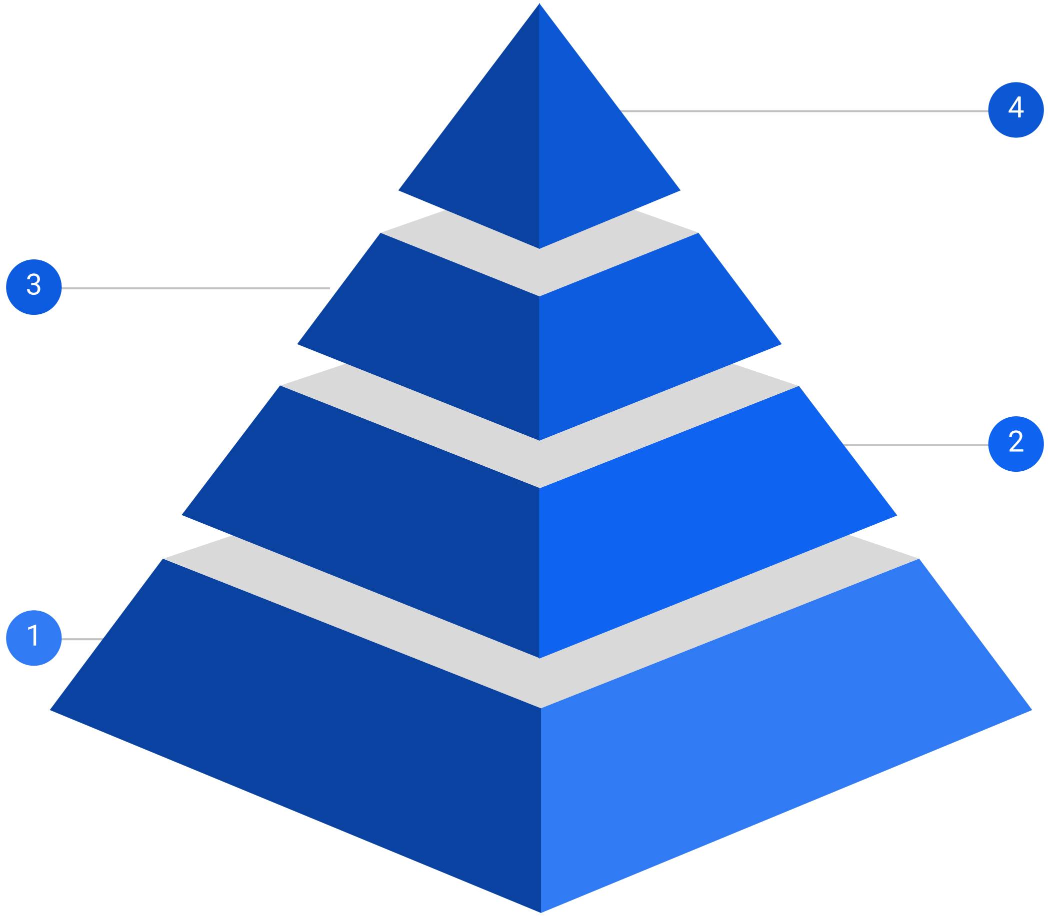


Project Tasks

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

- Project Tasks
  - Data Science and Machine Learning
    - Data Acquisition and Data Management
    - Signal Processing
    - Feature Extraction
    - Model Building and Fine Tuning
  - Web/App Development
    - Choosing an outline/template
    - Front End UI design for patient access
    - Back End integration with Signal Processing and Machine Learning
    - Patient database linkup with history feature

Data Science and Machine Learning: Methodology



Model Building and Fine Tuning

Using various models and fine tuning it to our extracted feature dataset to improve the performance in detecting the outliers

Feature Extraction

Extracted essential features which are significant of muscular activities to detect any anomalies in the patient emg signal.

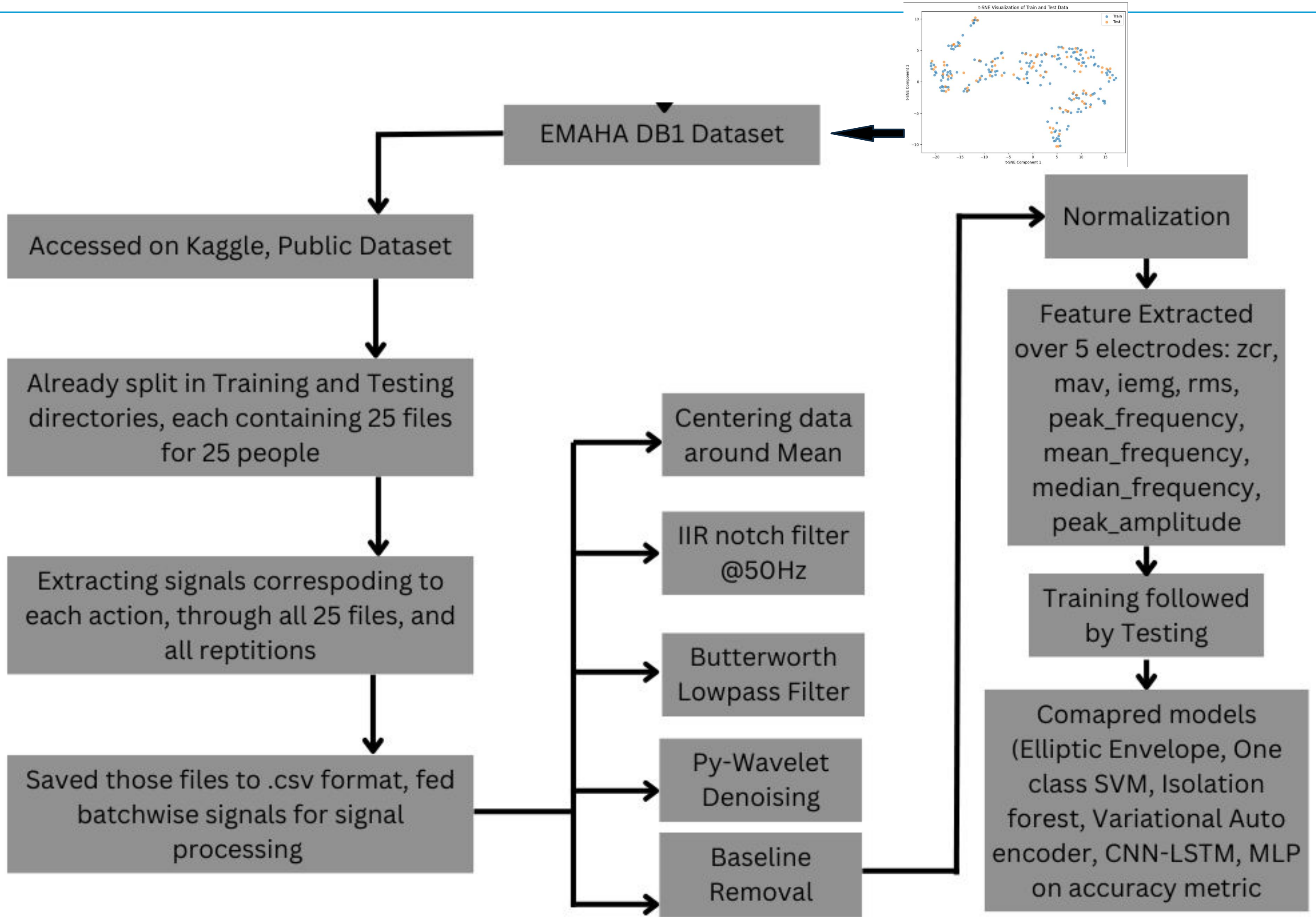
Signal Processing

Used different techniques for signal processing to remove noise and smoothen the signal, while preserving essential information

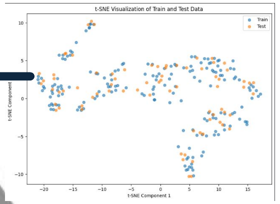
Data Acquisition and Management

For our research, we utilized the Electromyography Analysis of Hand Activities - DataBase 1 (EMAHA-DB1), to study of surface electromyography (sEMG) signals gathered during different daily activities..

Methodology: Model Selection



Methodology: Validation and Refinement



EMAHA DB1 Dataset

Training all models on accuracy as metric

Primary Testing Metric

PhysioNet's Myopathy+ Neuropathy signal

ISSUE: Not specific to action or muscle

Custom Test Functions: Anomaly Inducers

- Increases ZCR
- Decreases ZCR
- Increases amplitude of MUAP
- Decreases amplitude of MUAP
- Create dips in Amplitude
- Create dips in frequency spectrum

Benefits:
1) Indicators of actual neuromuscular disorders based on literature review
2) Action Specific, Muscle specific, suitable for our data

Ranges and definitions of functions backed by literature review and analyzing the distribution of data

Filter out models based on these testing parameters

Final model to backend

Data Science and Machine Learning: Results

After careful consideration of all the models in the picture, we went ahead with on One Class Support Vector Machine,

One Class Classification (OCC) with support vector machines(SVM) aims to differentiate samples of one particular class by learning from single class samples during training. It is one of the most commonly used approaches to solve Anomaly Detection (AD), a subfield of machine learning that deals with identifying anomalous cases which the model has never seen before.

Follow the table to see its performance alongside the other models across various test metrics:
Table

Data Science and Machine Learning: Results

MODEL_NAME	Principle	Accuracy	Confusion Matrix
One Class SVM	Anomaly detection, trained on normal data only	93.30%	[[0 0] [5 70]]
			Confidences/Result:
Elliptic Envelope	Anomaly detection, trained on normal data only	97.34%	[[0 0] [2 73]]
			Confidences/Results:
Multi Layer Perceptron	Trained on 250 Normal and 15 abnormal signals	52.50%	precision recall f1-score support 0.0 0.13 0.50 0.21 10 1.0 0.88 0.53 0.66 70 accuracy 0.53 80 macro avg 0.51 0.51 0.43 80 weighted avg 0.79 0.53 0.60 80
			array([[5, 5], [33, 37]])
CNN-LSTM	Trained on 250 Normal and 15 abnormal signals	100%	array([[9, 1], [0, 70]])

Data Science and Machine Learning: Results

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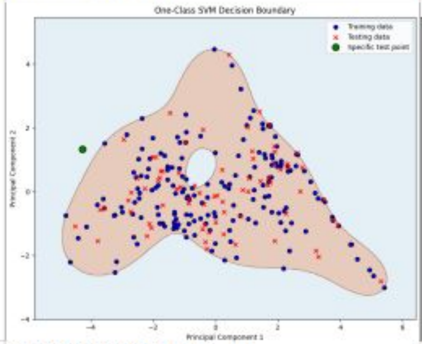
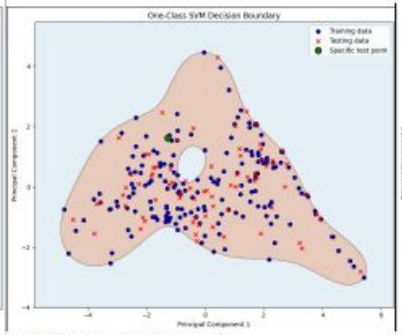
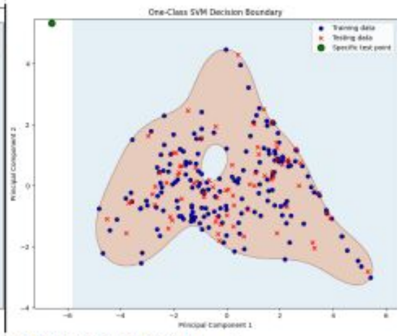
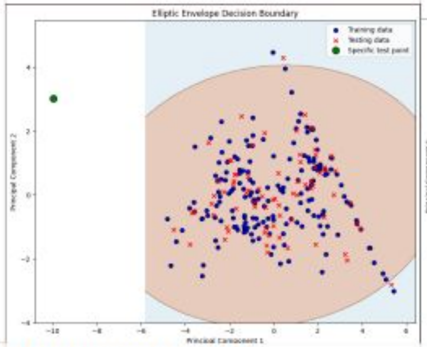
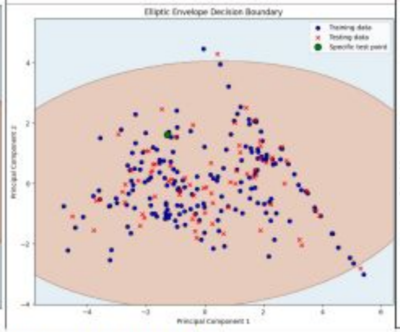
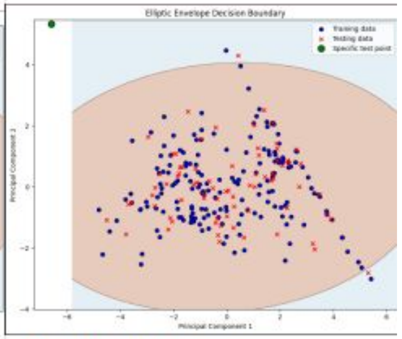
MODEL_NAME	Increased_Amplitude	Random Dips	Increased ZCR
One Class SVM			
	-0.0320801856375644/ Passed	0.00693936750212004/Failed	-0.296167893125982/Passed
Elliptic Envelope			
	-18.84154585625435/Passed	10.815658410413882/Failed	-22.038538874275908/Passed
Multi Layer Perceptron	Failed	Passed	Failed
CNN-LSTM	Failed	Failed	Failed

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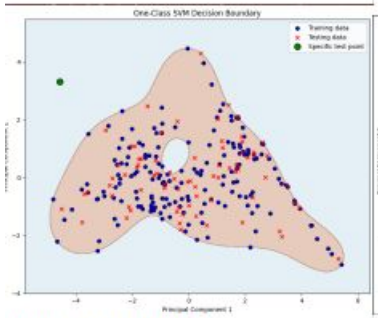
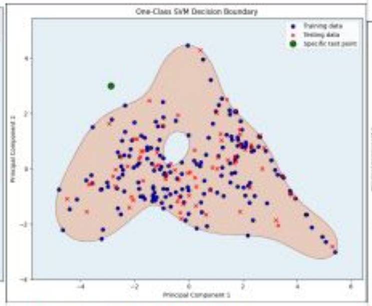
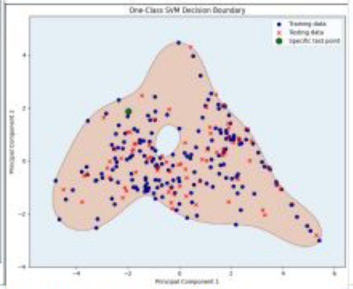
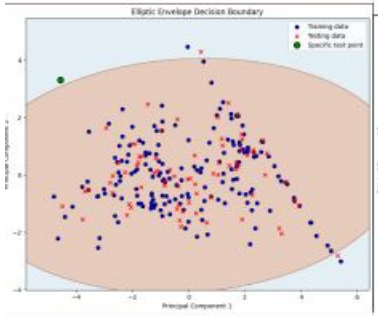
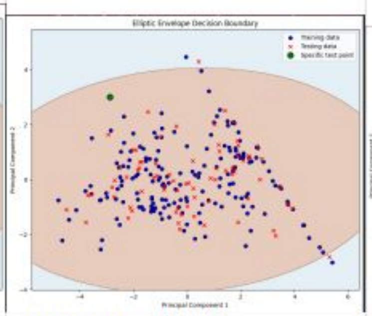
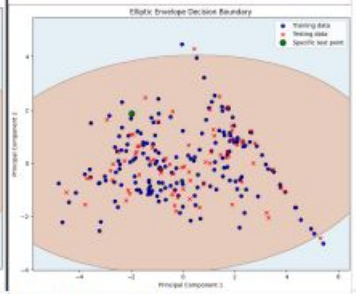
Data Science and Machine Learning: Results

MODEL_NAME	Decreased ZCR	Frequency Laps	Reduced_MUAP	Accuracy(over 10 actions)
One Class SVM				94.67%, 96%, 98.67%, 96%, 98.67%, 89.33%, 92%, 88%, 96%, 88%
	-0.171541431148752/Passed	-0.052284337021127864/Passed	0.011793485845486229/Failed	Average Accuracy: 93.74%
Elliptic Envelope				100%, 97.34%, 98.67%, 100%, 98.67%, 96%, 100%, 97.34%, 100%, 98.67%
	-1.28838294483602/Passed	3.6108071180854804/Failed	9.467734650211217/Failed	Average Accuracy: 98.669%
Multi Layer Perceptron	Failed	Failed	Failed	
CNN-LSTM	Failed	Failed	Failed	

Data Science and Machine Learning: Results

One Class SVM had lesser accuracy than Elliptic Envelope and CNN_LSTM, but then the accuracy as a parameter isn't the only method, this is because as the training was carried out on a data that contained healthy signals, accuracy is itself isn't a parameter to be tested. The custom test functions defined, 6 of them, OC_SVM passed 4 out of 6 checks, which was better than any other model in hand. Hence we go ahead with OC_SVM providing an **average accuracy of 93.74%**.

Now here are the boundaries sketched by one class SVM for each action, anything within these boundaries is considered normal by the model.

Data Science and Machine Learning: Results

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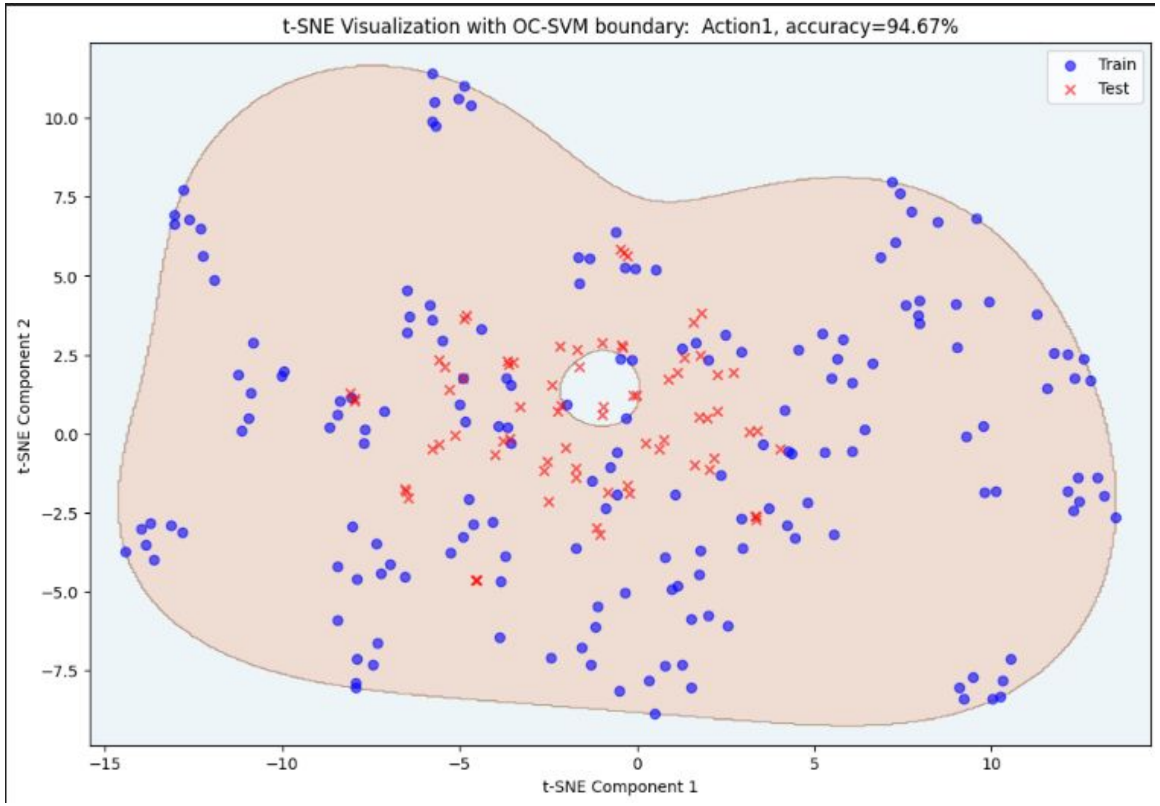

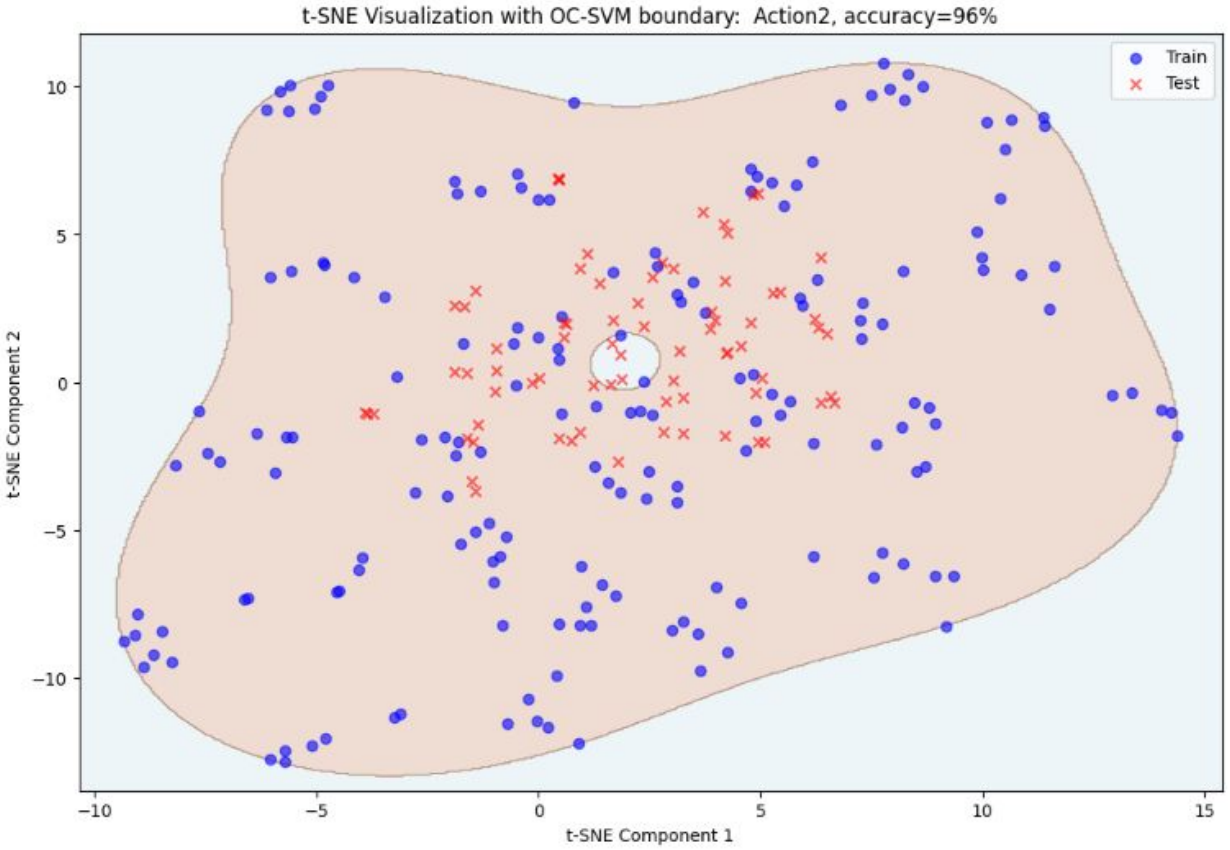

Boundaries sketched by One class SVM for action 1 and action 2

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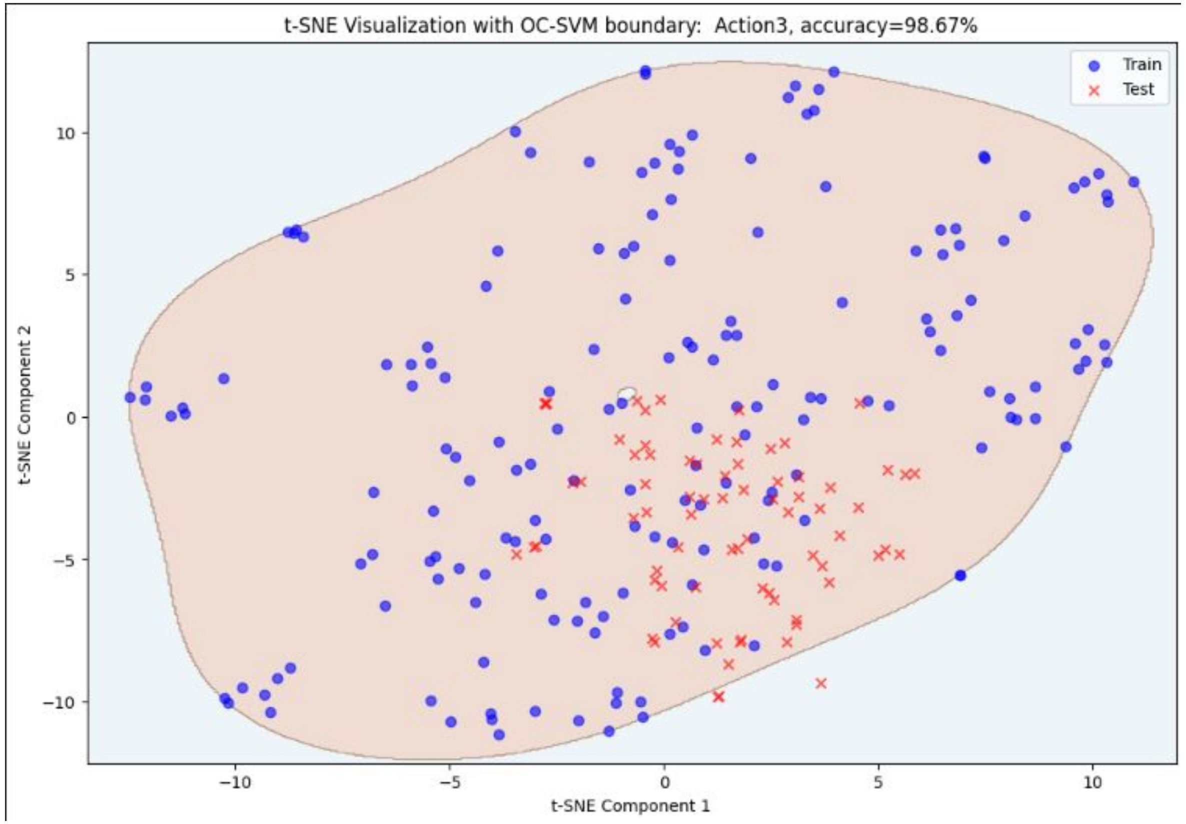
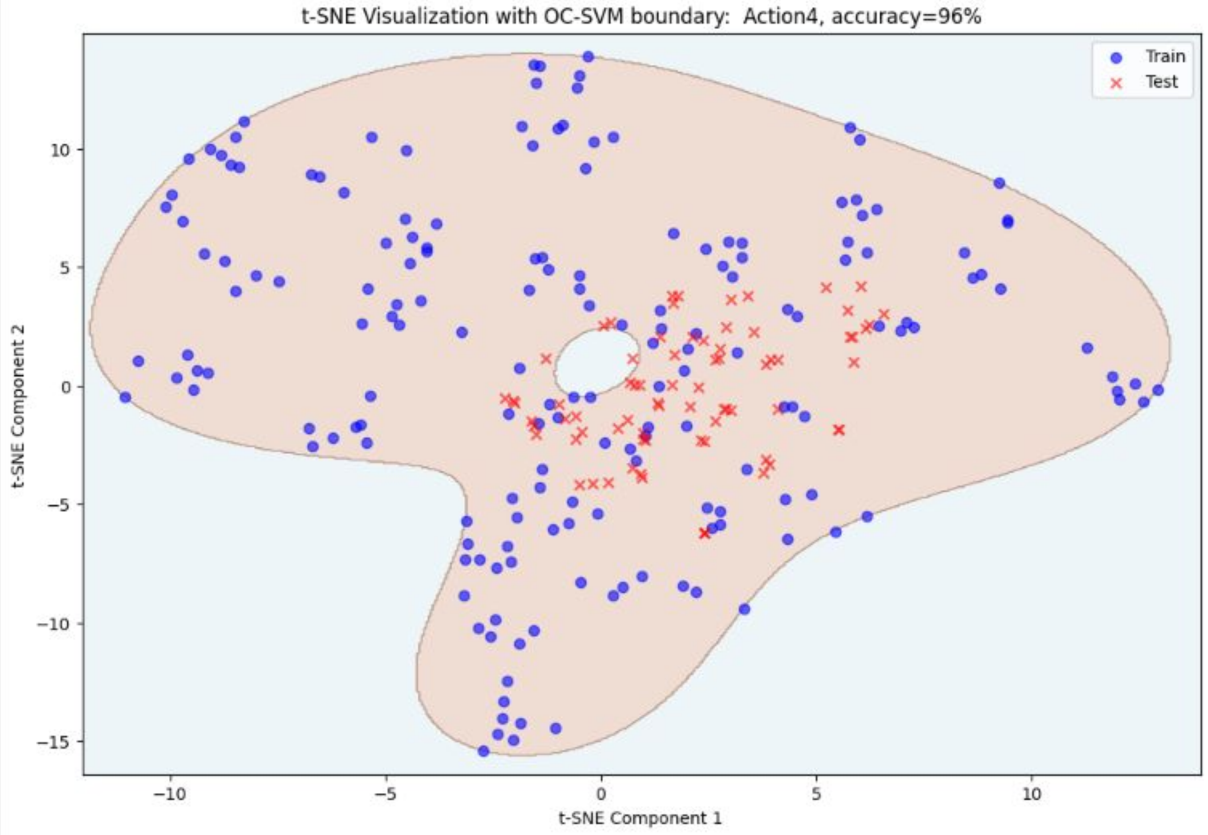
Data Science and Machine Learning: Results





Boundaries sketched by One class SVM for action 3 and action 4

Data Science and Machine Learning: Results

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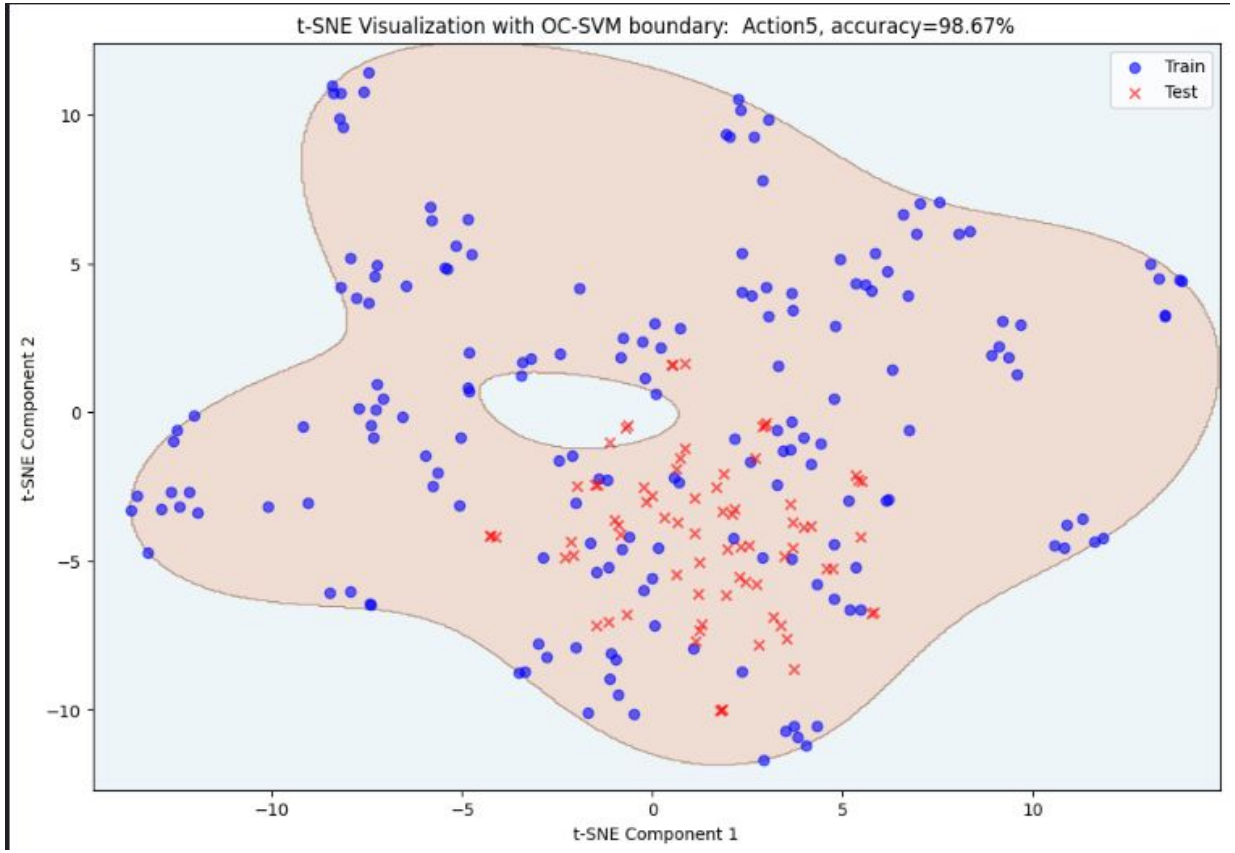
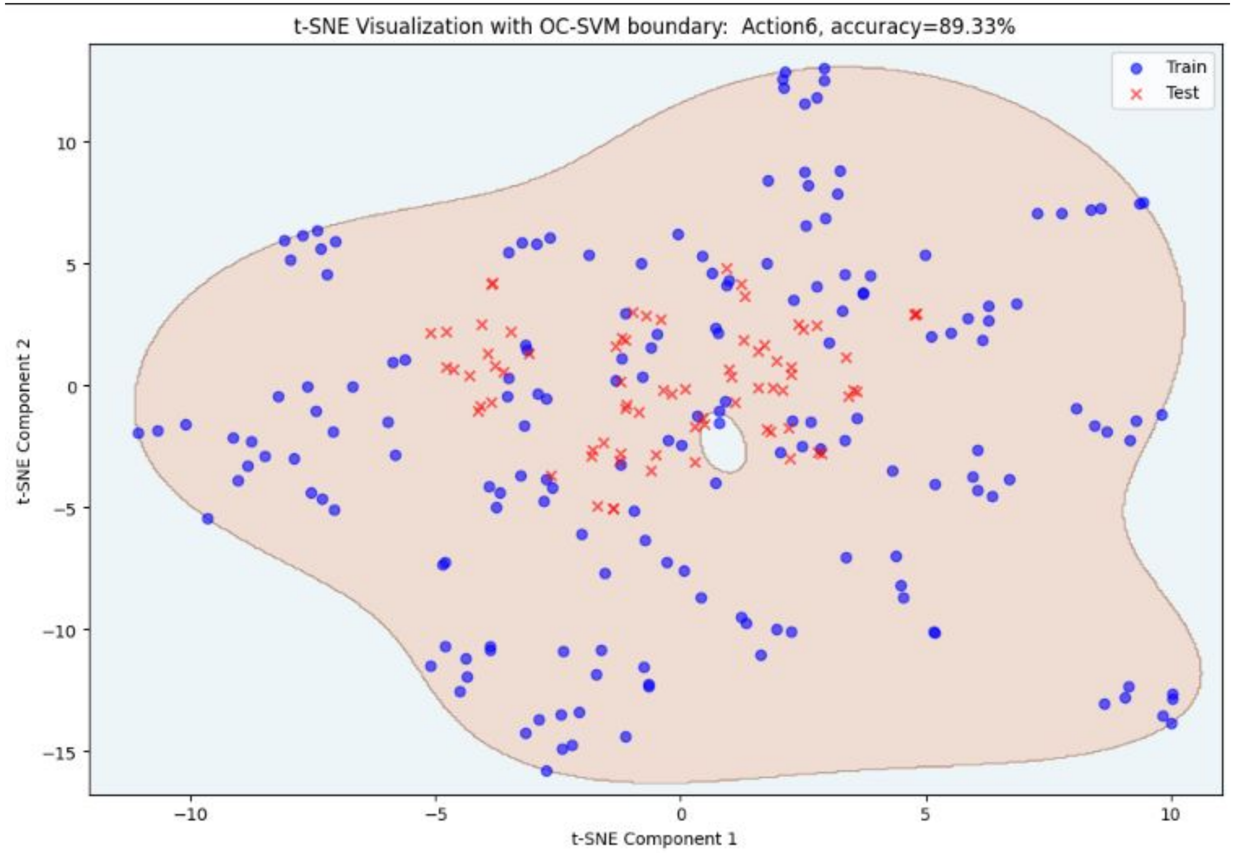
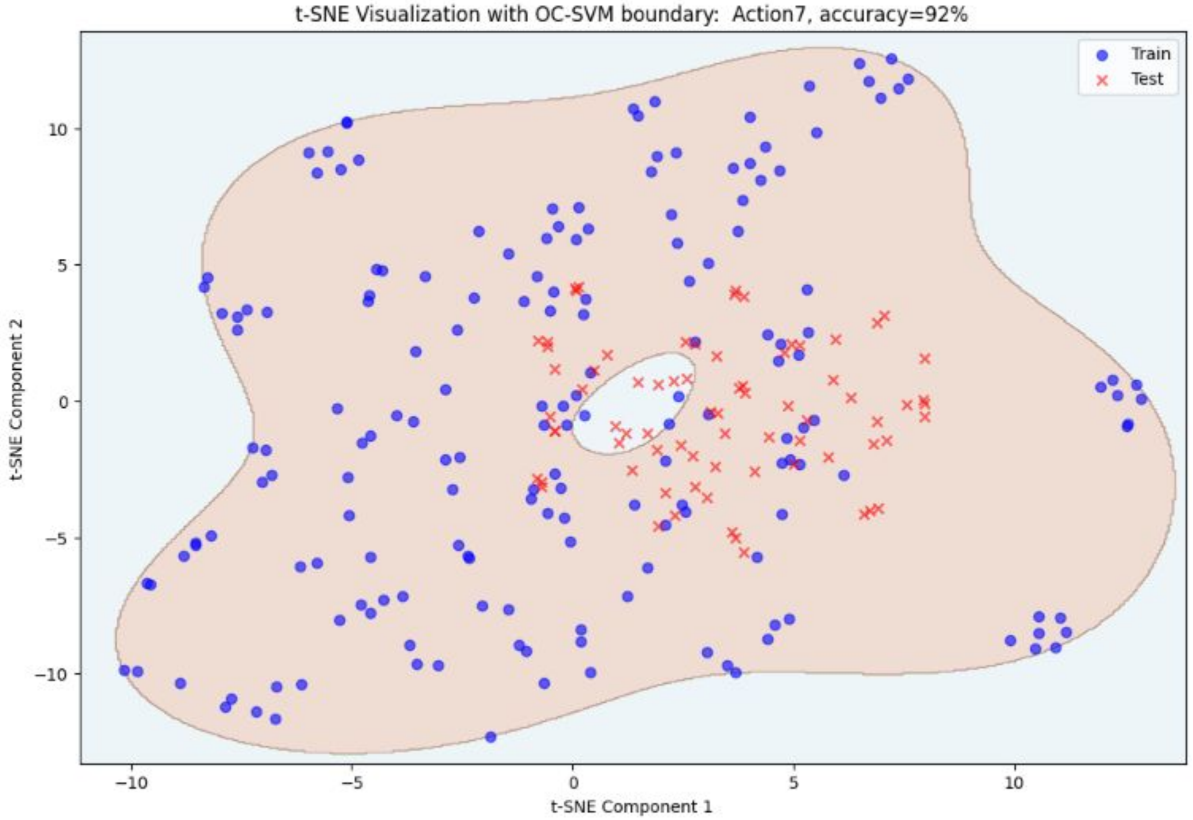
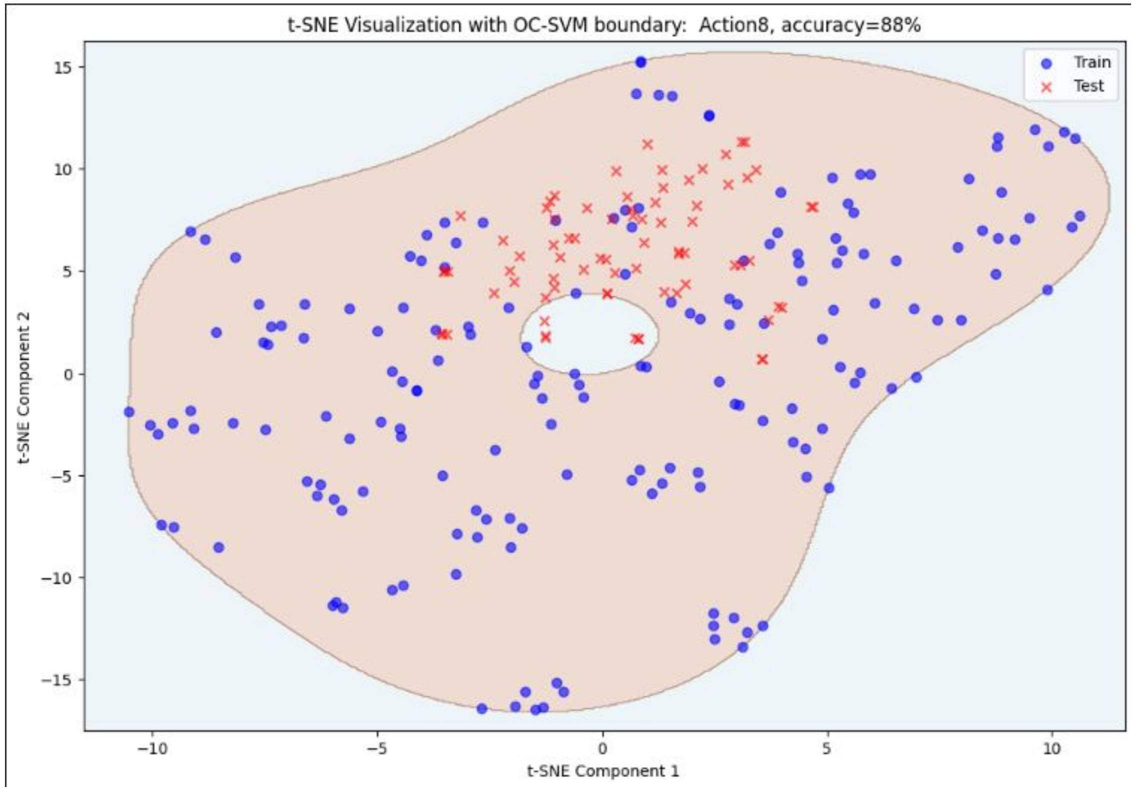




Boundaries sketched by One class SVM for action 5 and action 6

Data Science and Machine Learning: Results





Boundaries sketched by One class SVM for action 7 and action 8

Data Science and Machine Learning: Results

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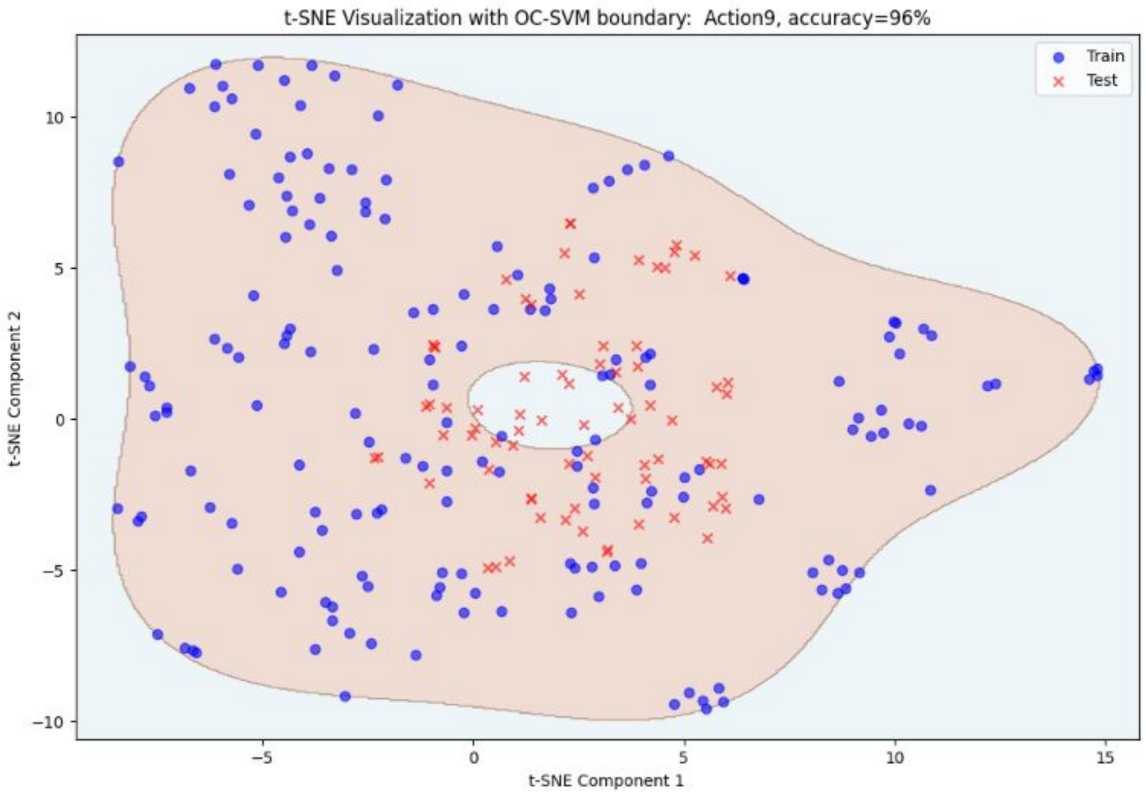

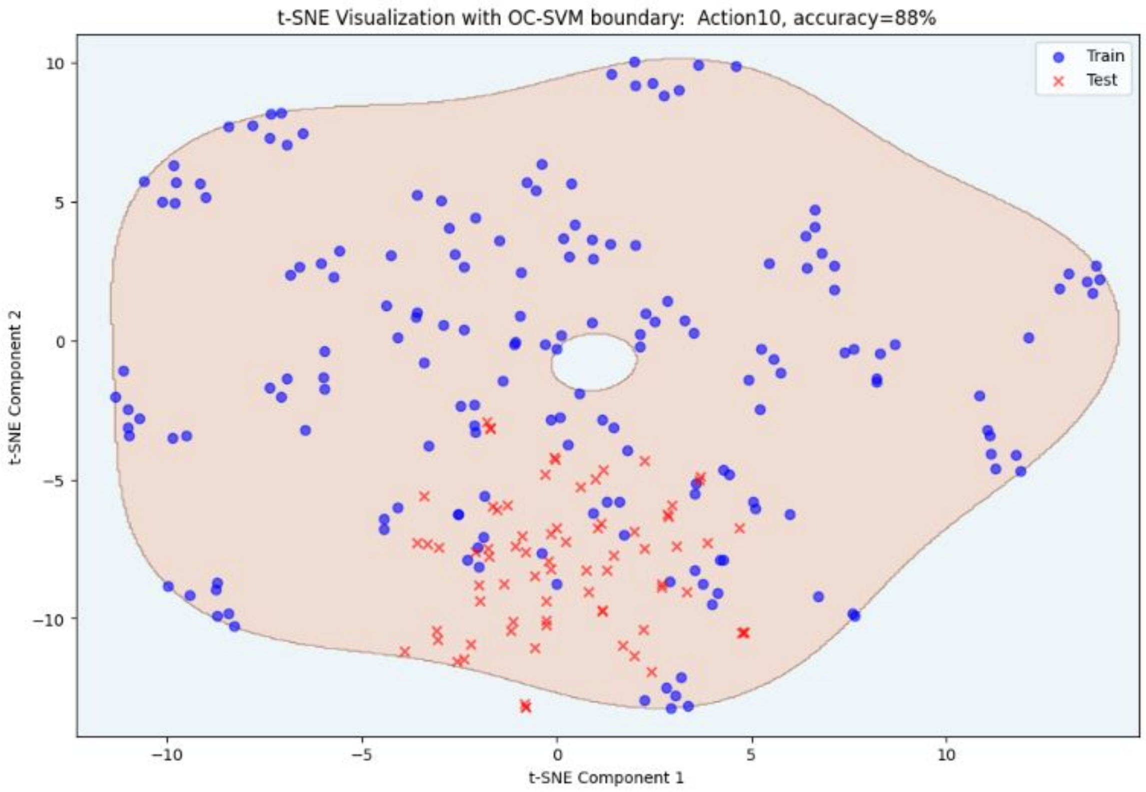

Boundaries sketched by One class SVM for action 9 and action 10

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Web/ App Development: Methodology

Back End Integration with Signal Processing and Machine Learning

Implement robust backend systems that leverage signal processing and machine learning algorithms to analyze patient data, providing insights and supporting advanced diagnostic capabilities.

Choosing an Outline/Template for the Website

Select a website outline or template that prioritizes clear navigation, a responsive design, and accessibility features to ensure a seamless user experience for patients.

Giving a visual and an intuitive visualization about the patient's report

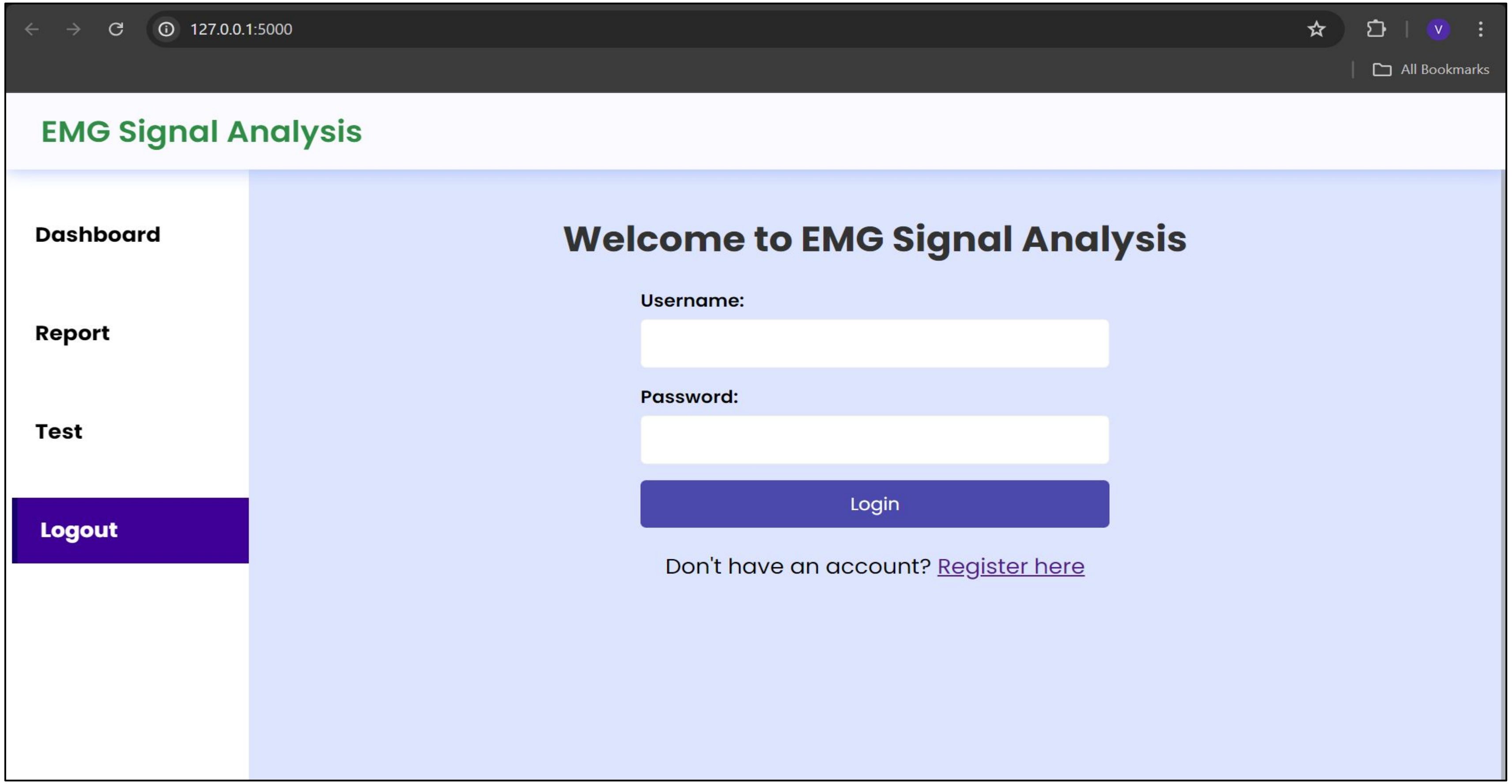
To show the results generated by the model at the backend and present it to the user giving them an opportunity to download the report in the form of PDF document providing final result of the model prediction

Linking a Database Management System to store patient's record

Develop a user-friendly interface that allows patients to easily access their medical records, through a secure and intuitive platform

Web/App Development: Results

Login page to maintain record of users



Web/App Development: Results

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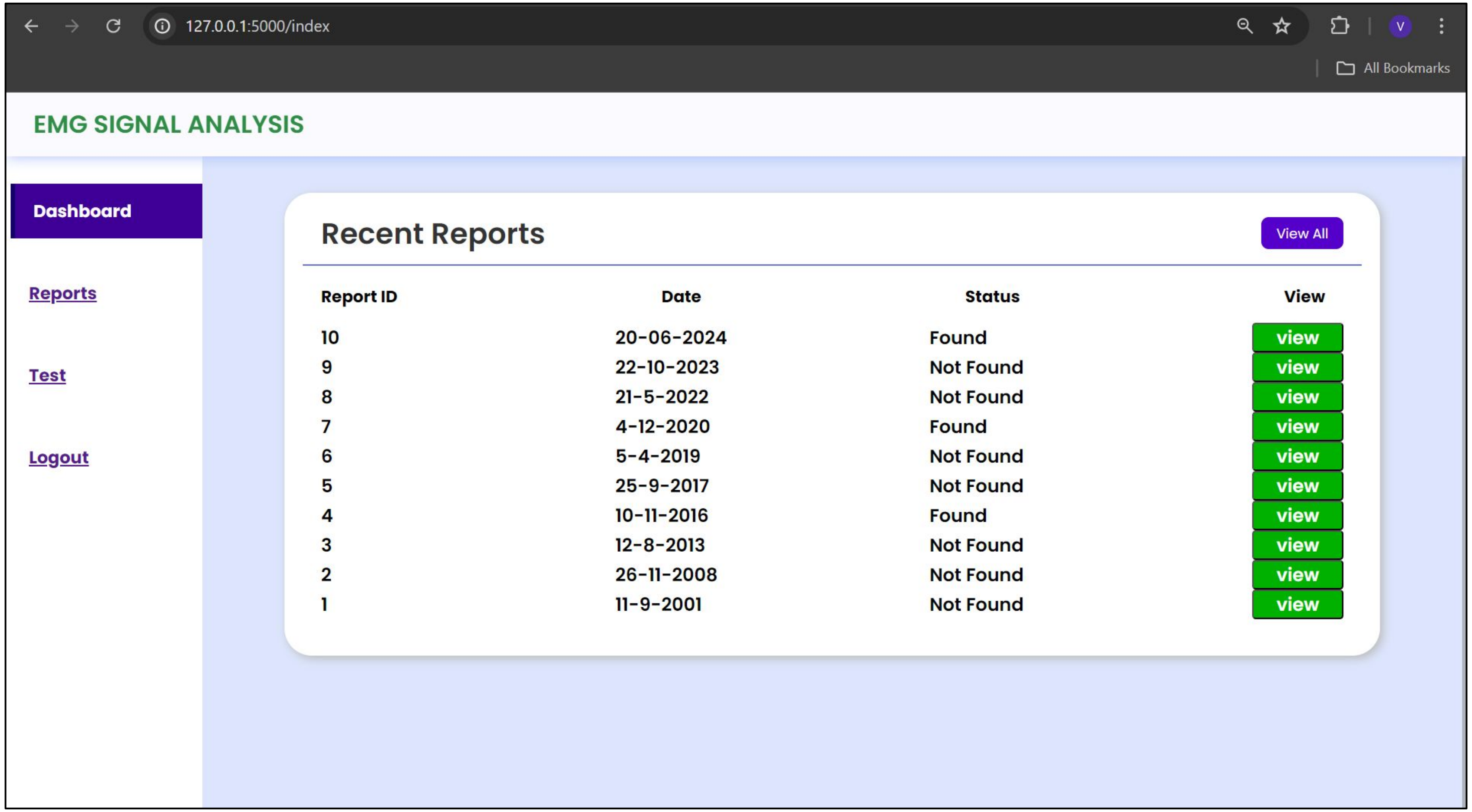
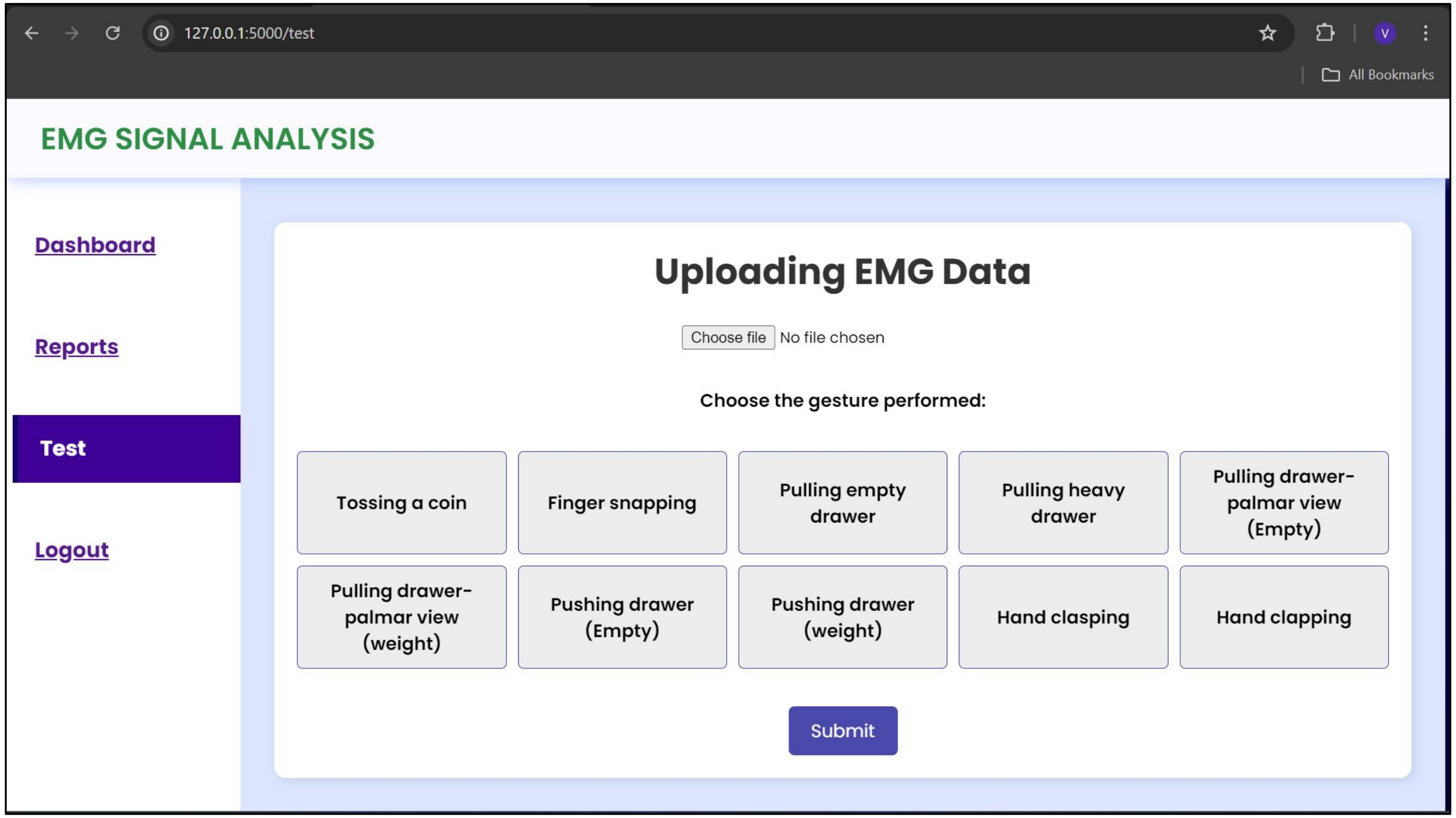
Dashboard to show last 10 Report of the user



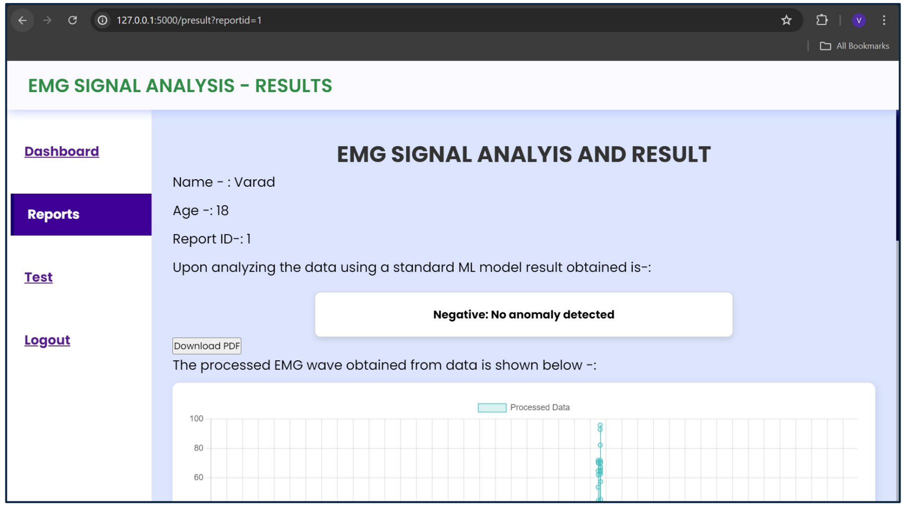
Web/App Development: Results (will be filled later)

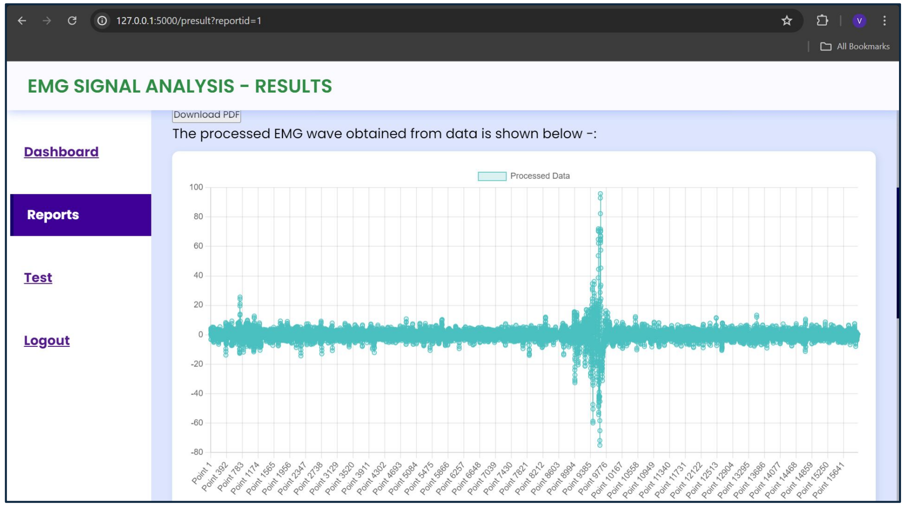
Test Page with uploading csv feature and gesture selection

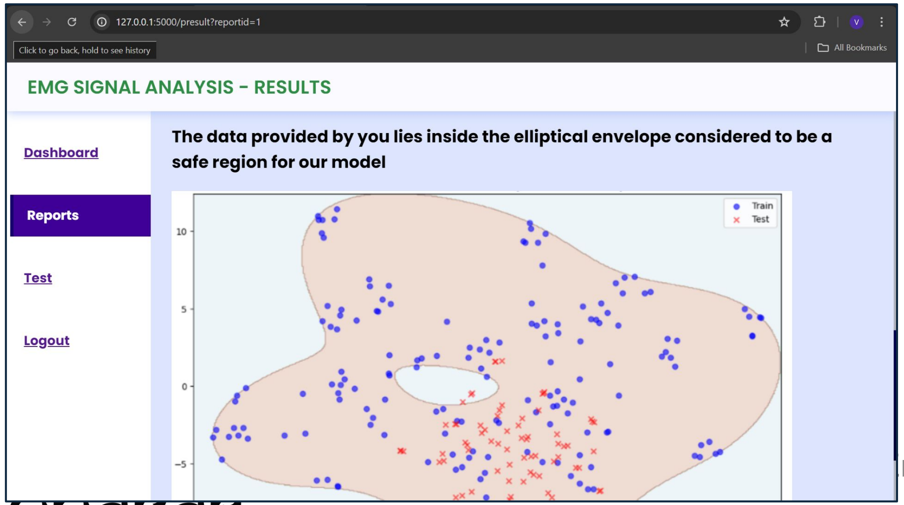


Web/App Development: Results

Processed EMG wave from sensor data and ML model abnormality detection

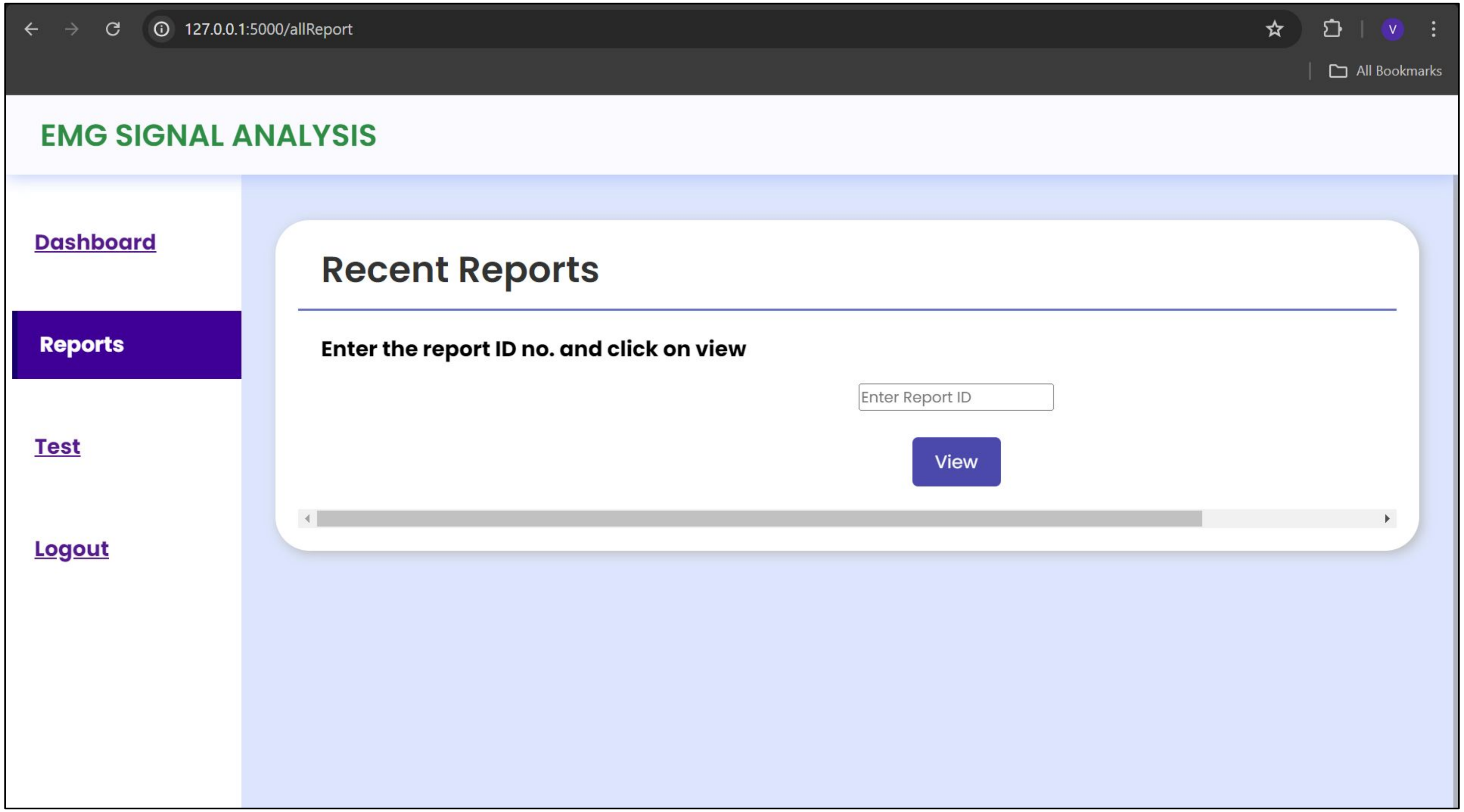






Web/App Development: Results

Feature to view previous reports (Manual Search)



Web/App Development: Results (will be filled later)

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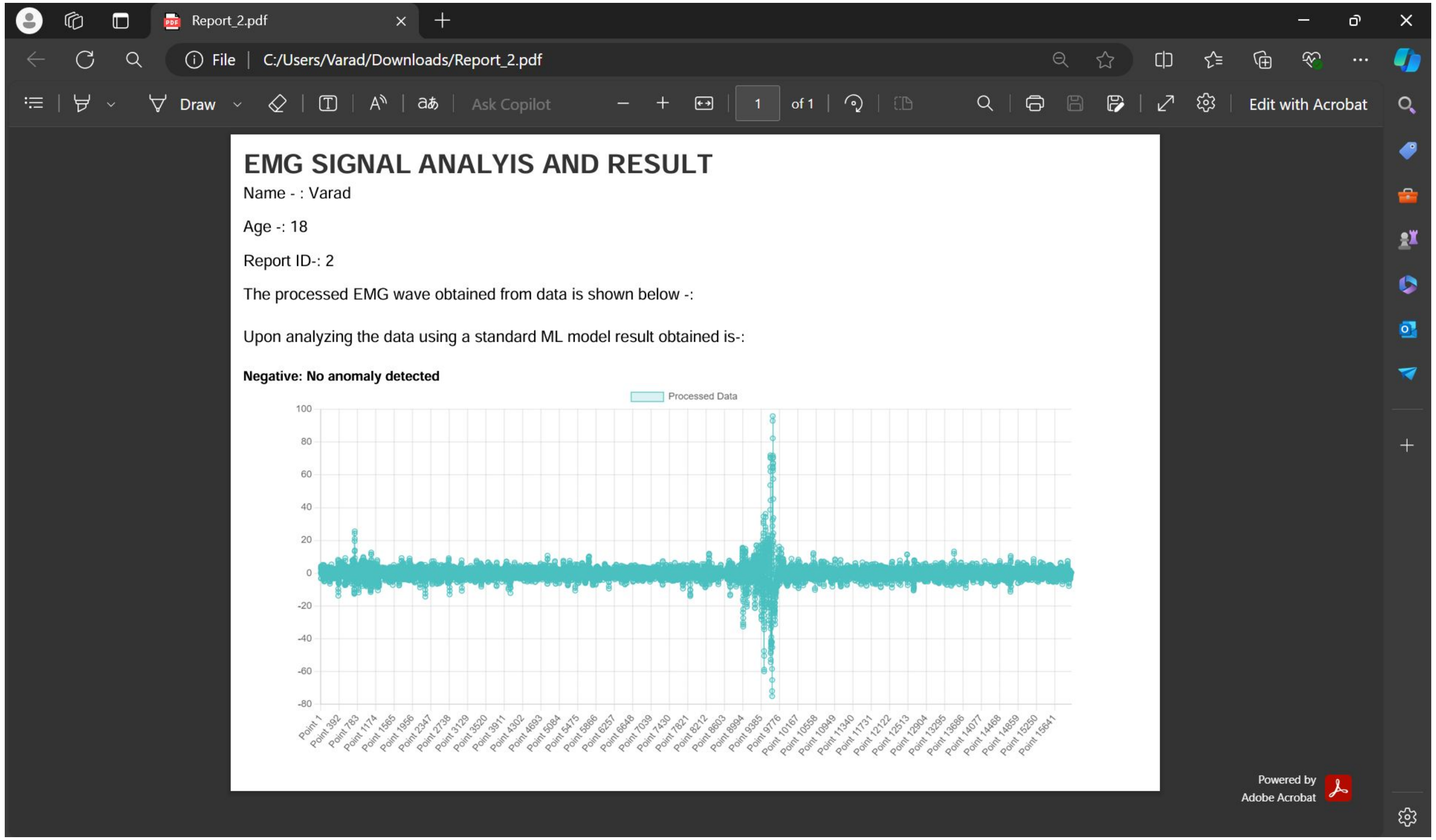
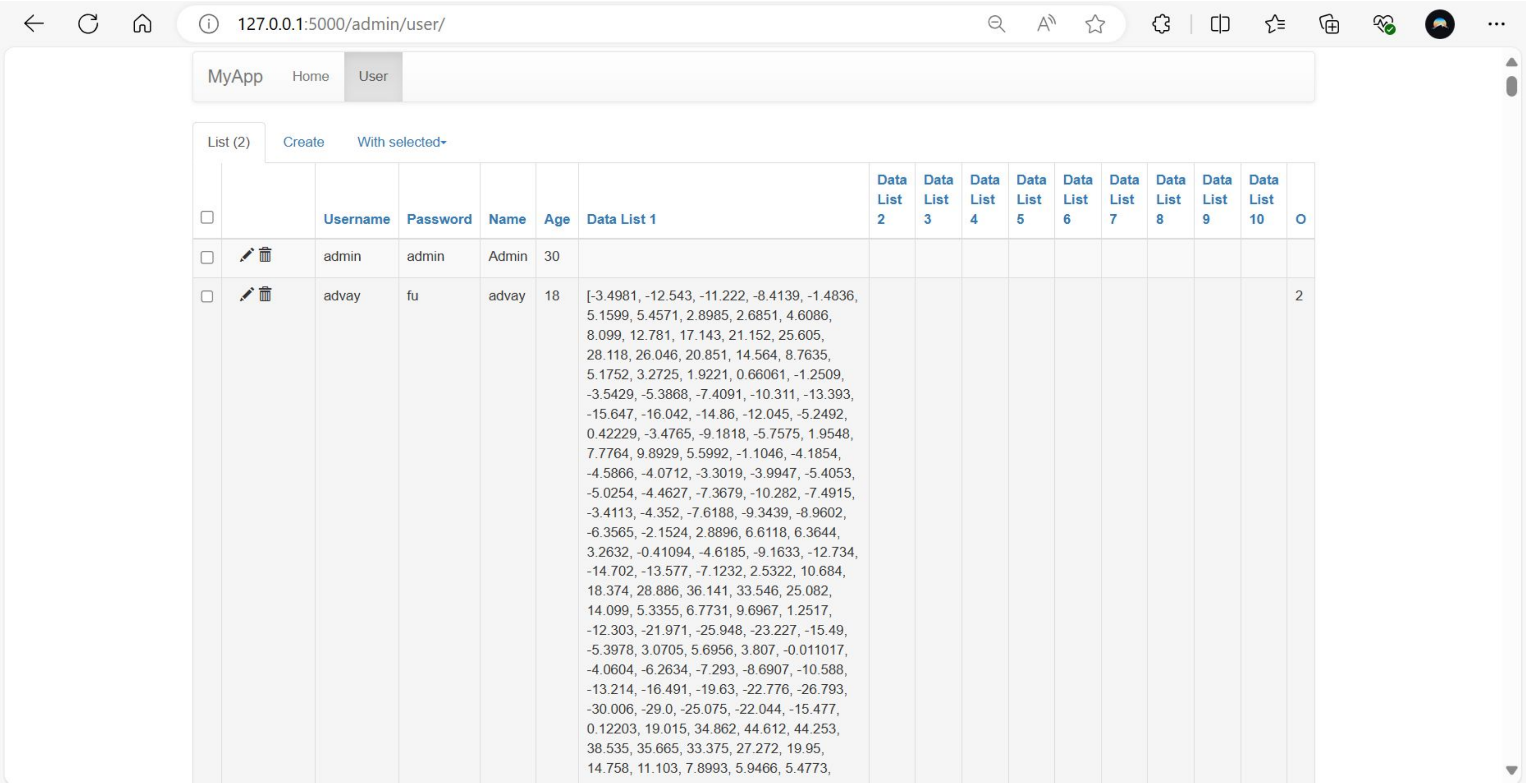
Report Download in PDF file



Web/App Development: Results (will be filled later)

Admin access to data of patient



		Username	Password	Name	Age	Data List 1	Data List 2	Data List 3	Data List 4	Data List 5	Data List 6	Data List 7	Data List 8	Data List 9	Data List 10	O
		admin	admin	Admin	30											
		advay	fu	advay	18	[-3.4981, -12.543, -11.222, -8.4139, -1.4836, 5.1599, 5.4571, 2.8985, 2.6851, 4.6086, 8.099, 12.781, 17.143, 21.152, 25.605, 28.118, 26.046, 20.851, 14.564, 8.7635, 5.1752, 3.2725, 1.9221, 0.66061, -1.2509, -3.5429, -5.3868, -7.4091, -10.311, -13.393, -15.647, -16.042, -14.86, -12.045, -5.2492, 0.42229, -3.4765, -9.1818, -5.7575, 1.9548, 7.7764, 9.8929, 5.5992, -1.1046, -4.1854, -4.5866, -4.0712, -3.3019, -3.9947, -5.4053, -5.0254, -4.4627, -7.3679, -10.282, -7.4915, -3.4113, -4.352, -7.6188, -9.3439, -8.9602, -6.3565, -2.1524, 2.8896, 6.6118, 6.3644, 3.2632, -0.41094, -4.6185, -9.1633, -12.734, -14.702, -13.577, -7.1232, 2.5322, 10.684, 18.374, 28.886, 36.141, 33.546, 25.082, 14.099, 5.3355, 6.7731, 9.6967, 1.2517, -12.303, -21.971, -25.948, -23.227, -15.49, -5.3978, 3.0705, 5.6956, 3.807, -0.011017, -4.0604, -6.2634, -7.293, -8.6907, -10.588, -13.214, -16.491, -19.63, -22.776, -26.793, -30.006, -29.0, -25.075, -22.044, -15.477, 0.12203, 19.015, 34.862, 44.612, 44.253, 38.535, 35.665, 33.375, 27.272, 19.95, 14.758, 11.103, 7.8993, 5.9466, 5.4773,										2

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Demonstration Video

https://www.kaggle.com/code/vaidehibhat/filtering-models

https://colab.research.google.com/drive/1rbQg-4KgRAA0W8O4eYDlRb8G2-jsoCAW#scrollTo=GwRsRoXDFxID

https://drive.google.com/file/d/1MVHWCYsCc68VP8tzk_m-H_vnH7gnQvM-/view?usp=sharing

References

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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

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

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

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

5) Electrodiagnosis in Diseases of Nerve and Muscle, Jun Kimura
6) Anomaly detection of electromyographic signals, Ahsan Ijaz and Jongeun Choi
7) 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

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Literature Review of the following:

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

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

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

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

5) Electrodiagnosis in Diseases of Nerve and Muscle, Jun Kimura

Worked on building a pipeline that can do data loading and noise removal. Data loading refers to get data from .mat files into something that is well labelled, bifurcated, and can be understood by the model.
Here’s how an unprocessed data piece looks like:

```
          0         1         2         3         4         5         6  \
0 -0.983609 -2.787212 -4.641816 -4.496123 -3.184739 -1.451605 -0.453968
1  2.385031  3.684812  5.520929  6.009290  5.744475  5.855770  5.783593
2  0.168942  0.468134  0.876308  0.872670  0.686430  0.794585  0.900127
3 -5.831843 -3.332388  0.255209  4.255660  6.555284  4.488868  0.375133
4  7.765452  6.676410  5.431494  4.420876  3.645989  2.955160  2.432257

          7         8         9  ...   3191990   3191991   3191992   3191993  \
0 -2.257468 -4.614902 -3.987850  ...  1.751224  1.593317 -0.218387 -2.216589
1  4.895363  3.587906  2.167830  ...  1.918487  3.227761  3.514390  2.656576
2  0.587735  0.231043  0.179022  ...  0.273790  0.287932  0.284756  0.282285
3 -2.103453 -3.268494 -4.165915  ... -2.647059 -1.683142 -0.482043 -0.400286
4  2.140569  2.053895  2.156312  ...  0.125277  0.128148  0.130609  0.132603

    3191994   3191995   3191996   3191997   3191998   3191999
0 -3.684677 -3.740223 -2.860212 -1.898651 -1.176295 -1.118542
1  1.218045 -0.202013 -1.000839 -0.567873  0.388351  0.976889
2  0.283228  0.290109  0.300517  0.309099  0.313716  0.312406
3 -0.872657 -0.990518 -0.938677 -0.977120 -1.042310 -1.104695
4  0.134120  0.135144  0.135673  0.135720  0.135279  0.134346
```

Week 2

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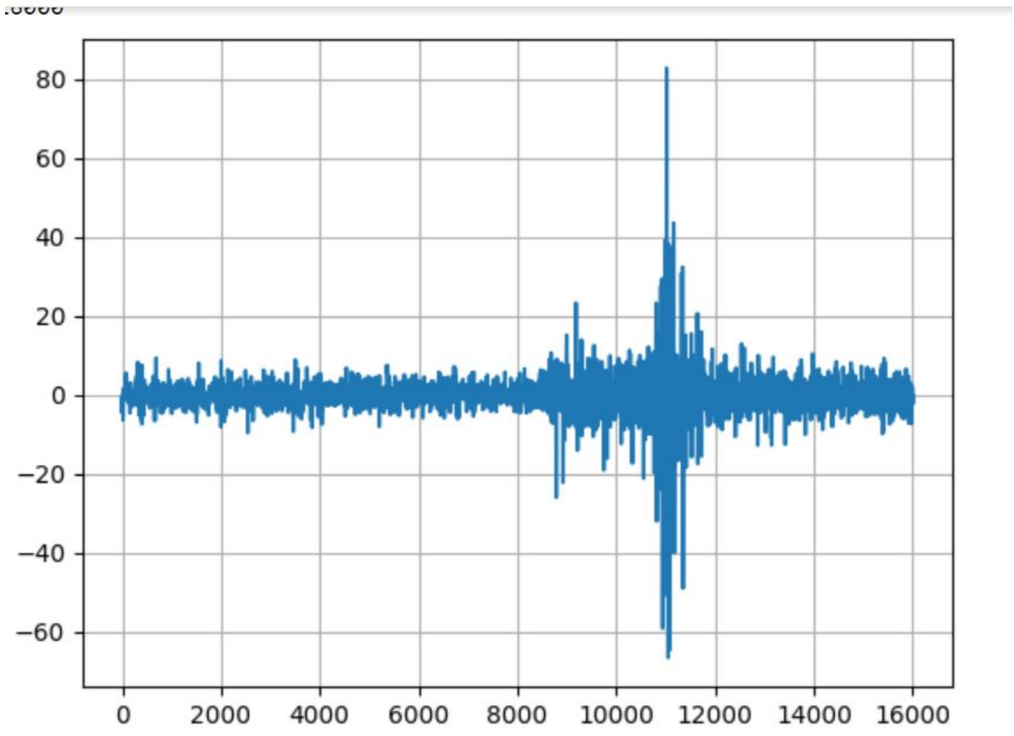
After loading it, we visualize an emg signal corresponding to a movement:



Week 2

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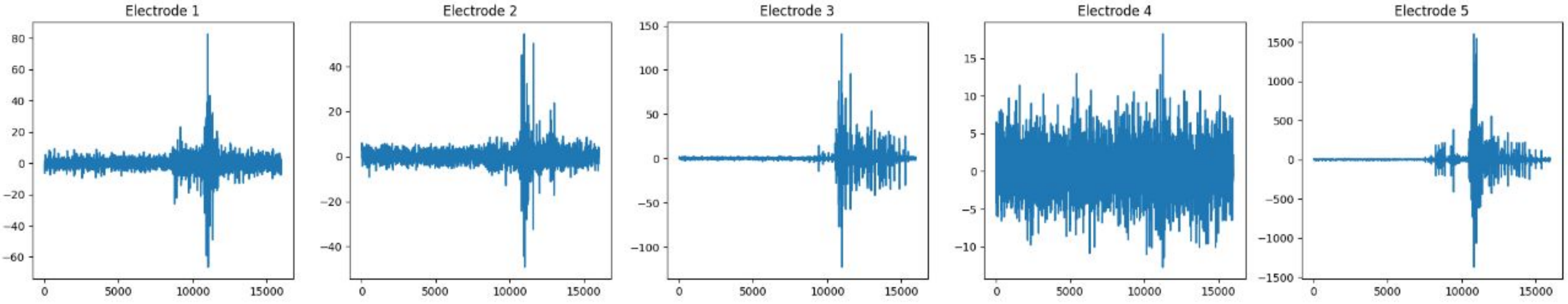
Here's a visualization of data collected from all the 5 electrodes, for 1 particular activity



Week 2

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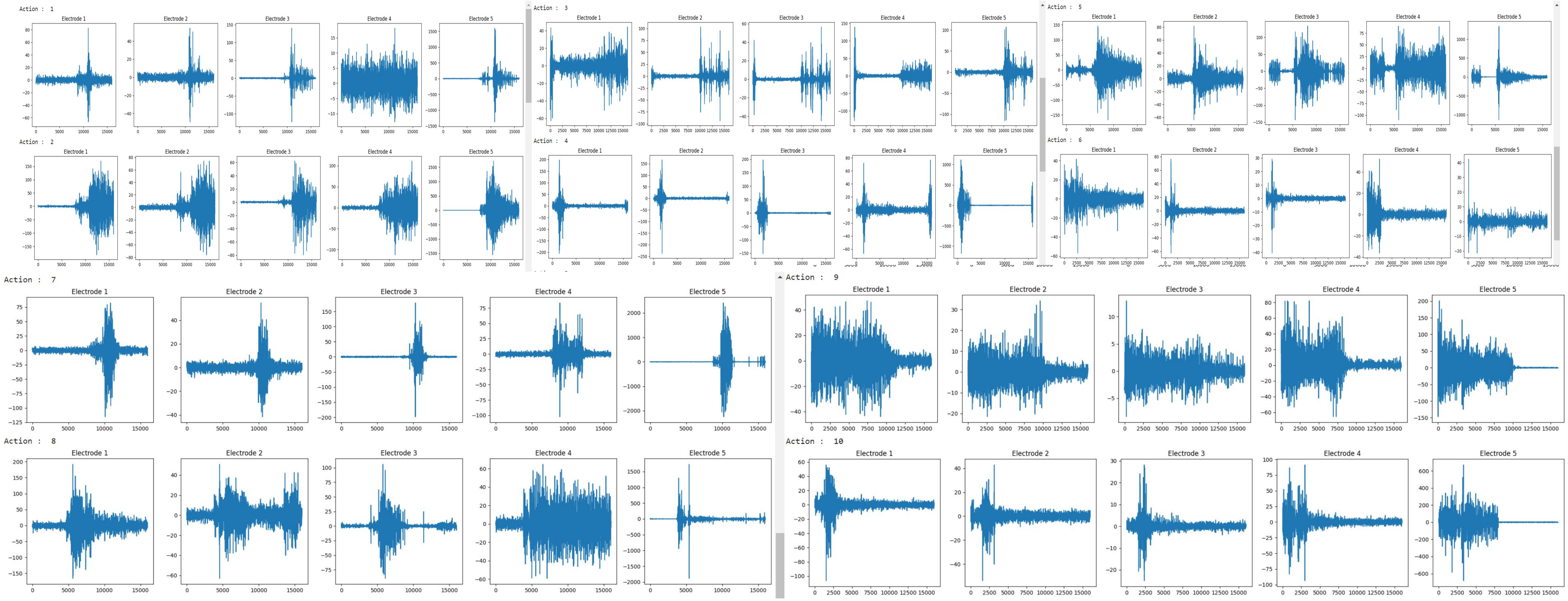
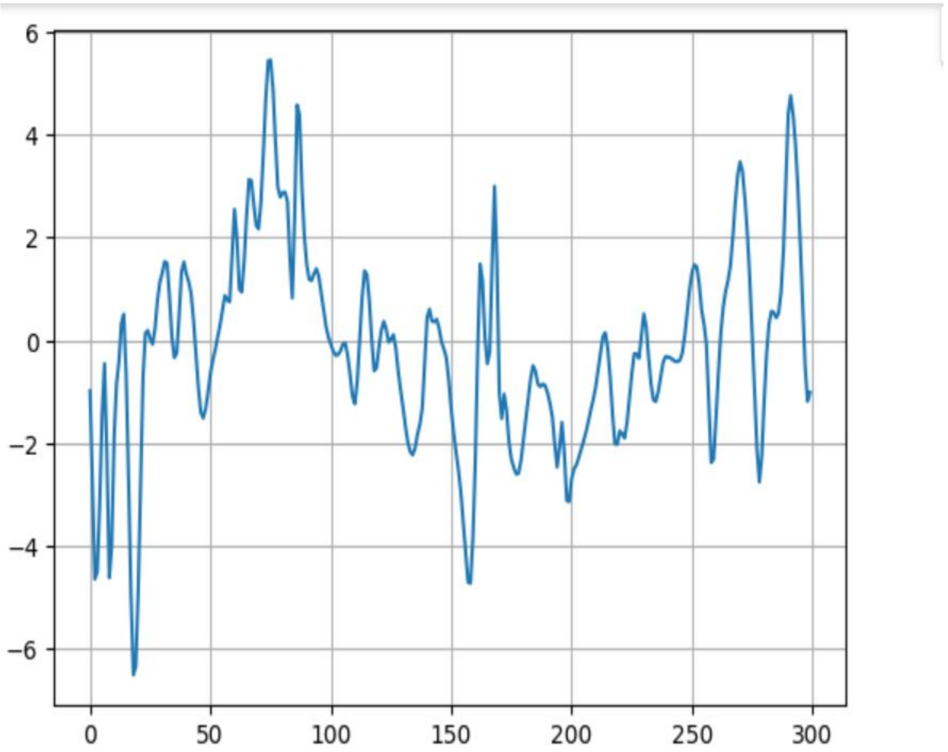
Here’s data collected from all 5 electrodes of 10 different activities performed

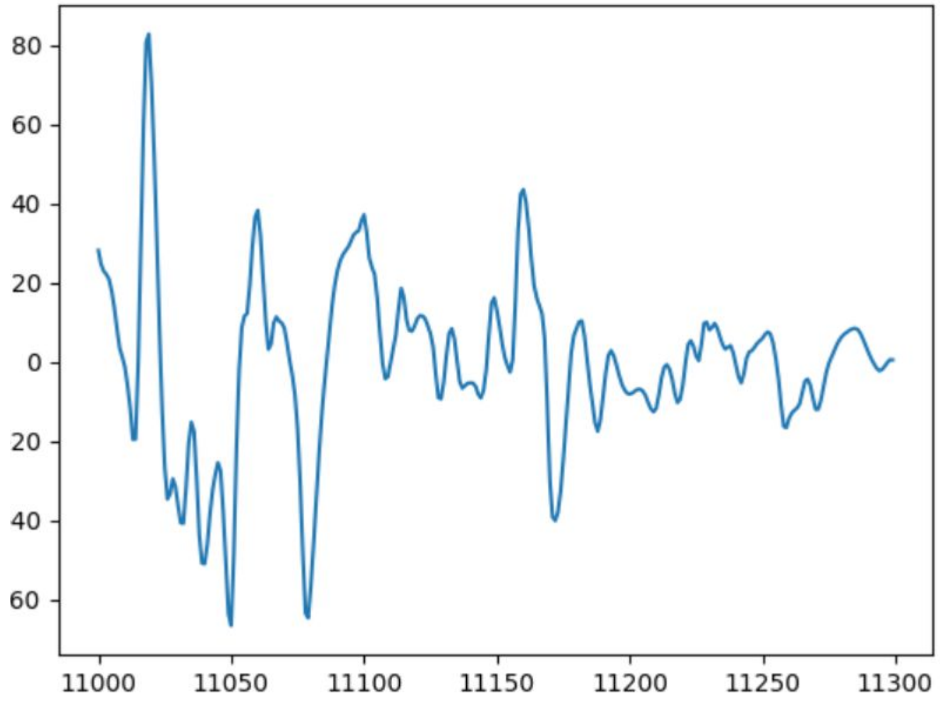


Week 2

Here are zoomed in portions of signal corresponding to one activity from one electrode.

First one is of rest period, second is when person was performing movement.





Week 2

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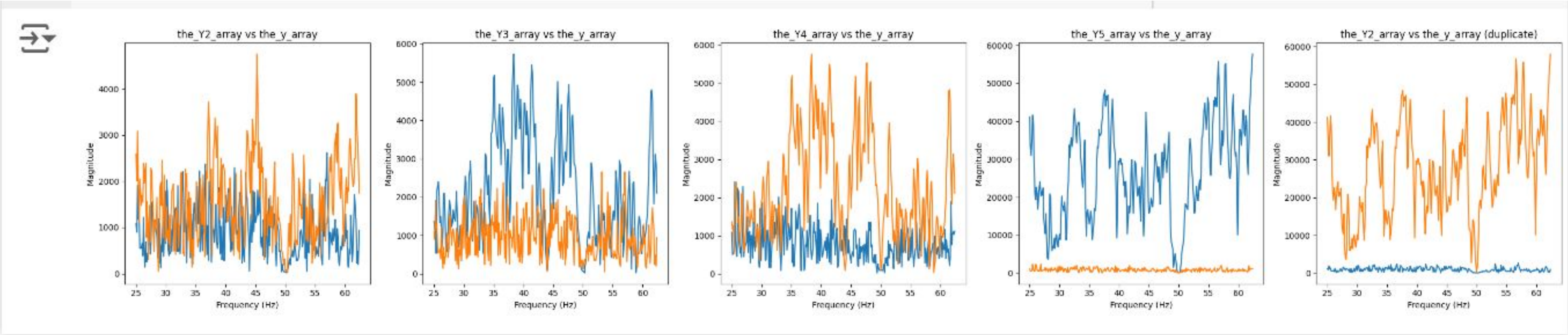
Results on the signal's frequency spectrum (Fourier Transform) after applying iir notch filter at 50 Hz. The blue signal represent modified signal, orange on is initial signal.



Week 2

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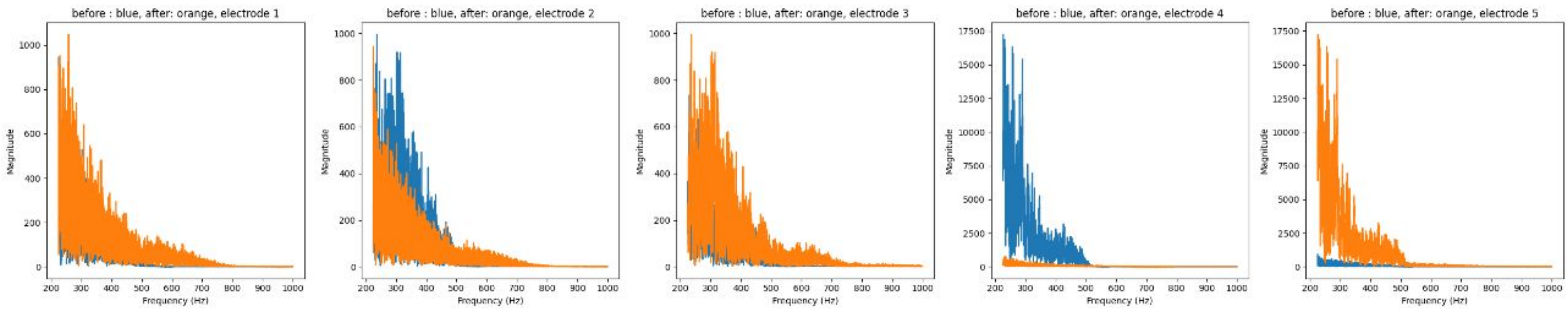
Results on signal's frequency spectrum(Fourier Transform) after applying butterworth lowpass filter with cutoff at 500Hz, new signal is orange, initial signal was blue.



Week 3

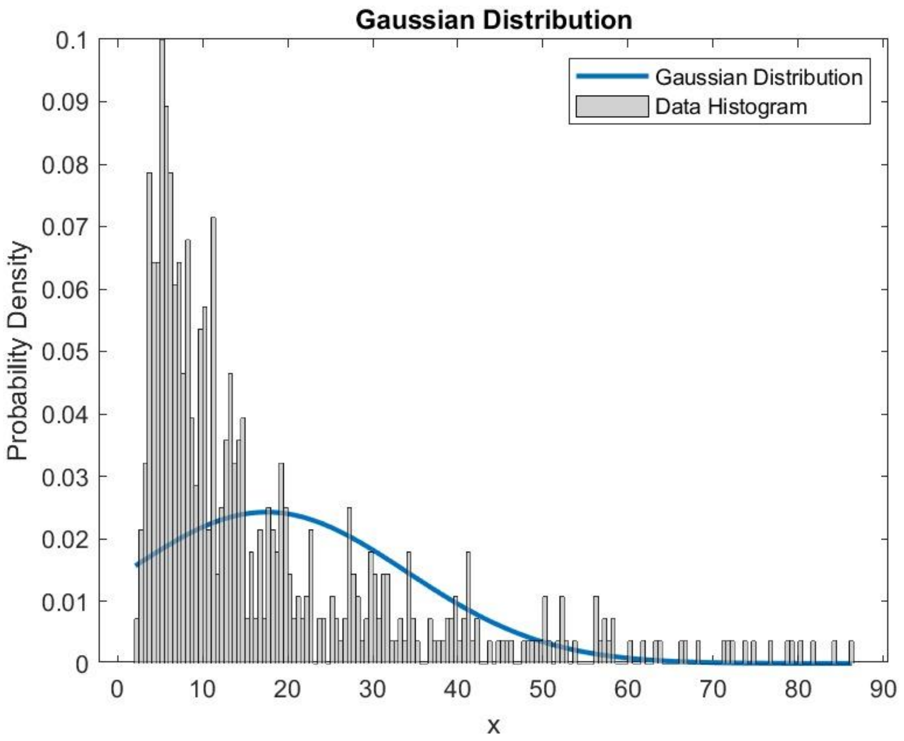
The sEMG database received was expanded and completed by incorporating all the 25 patient samples (Total 2500 samples of data). This sEMG data (unprocessed) was then analysed on various parameters across time domain, frequency domain and time-frequency domain. These parameters describe the state of muscle in terms of its activity and responsiveness.

Parameters:

Mean Absolute Value ('mav')	: Signifies muscle activation. Helps to differentiate between healthy and diseased muscle
Root Mean Square ('rms')	: Measure of signal amplitude. Helps in assessing muscle strength and detecting abnormal muscle activity
Zero-Crossing Rate ('zcr')	: Number of times signal crosses zero axis. High zcr common in neuromuscular disorders
Waveform length ('wavel')	: Measure complexity of signal. Changed in waveform length reflect variations in control and coordination
Mean Frequency ('mf)	: Average frequency of signal. Shift in mf reflects muscle fatigue and neuromuscular disorders
Median Frequency ('medf')	: Divides the power spectrum into two equal parts. Sensitive to muscle fiber composition and indicates muscle fatigue
Max Power ('maxp')	: Peak power in the frequency spectrum. High values may indicate abnormal muscle contractions.
Frequency Band Analysis ('freq')	: Identifies dominant frequency components; abnormal bands can signal neuromuscular impairments.
Integrated EMG ('iemg_trap')	: Total muscle activity over time. High values suggest abnormal muscle activity or overuse injuries.

Week 3

A histogram was plotted corresponding to these parameters. Preliminary analysis suggests that the distribution of most of the parameters can be approximated to a gaussian distribution also taking into account that most of the physiological parameters tend to follow gaussian distribution. This attribute has to be verified through various test to concrete the findings.



Electrodiagnosis in Diseases of Nerve and Muscle: Principles and Practice is a popular handbook for electrodiagnostic engineers and scientists worldwide, written by Prof. Jun Kimura, Father of Electrodiagnostic Neurology. After carefully going through some selected chapters from this book, we identified some of these features as they are known to contribute into diagnosis of neuromuscular diseases. Find the relevant text from the book in upcoming slides.

and increases diagnostic sensitivity.

Physiologic properties that characterize an MUP include duration, amplitude, area, phases, turns, number of satellites, and degree of waveform variability.[31,190] Additional measures of interest include spike duration, thickness[143] and size index[189] using special computer algorithms. Quantitative studies customarily analyze at least 20 different units to compare the mean with reference values. An alternative method relies on identifying extreme values, which fall outside the normal range.[191] This outlier technique helps identify abnormalities limited to a few motor unit potentials that escape detection in the assessment solely based on mean values.

Currently available quantitative techniques

Automated Methods

Different investigators have explored the possibility of automatically analyzing the MUP.[160,168] Such a system converts the recorded potentials to a digital equivalent for computer analysis. The usual measurements include duration, amplitude, polarity, number of phases, and integrated area under the waveform. One of the inherent

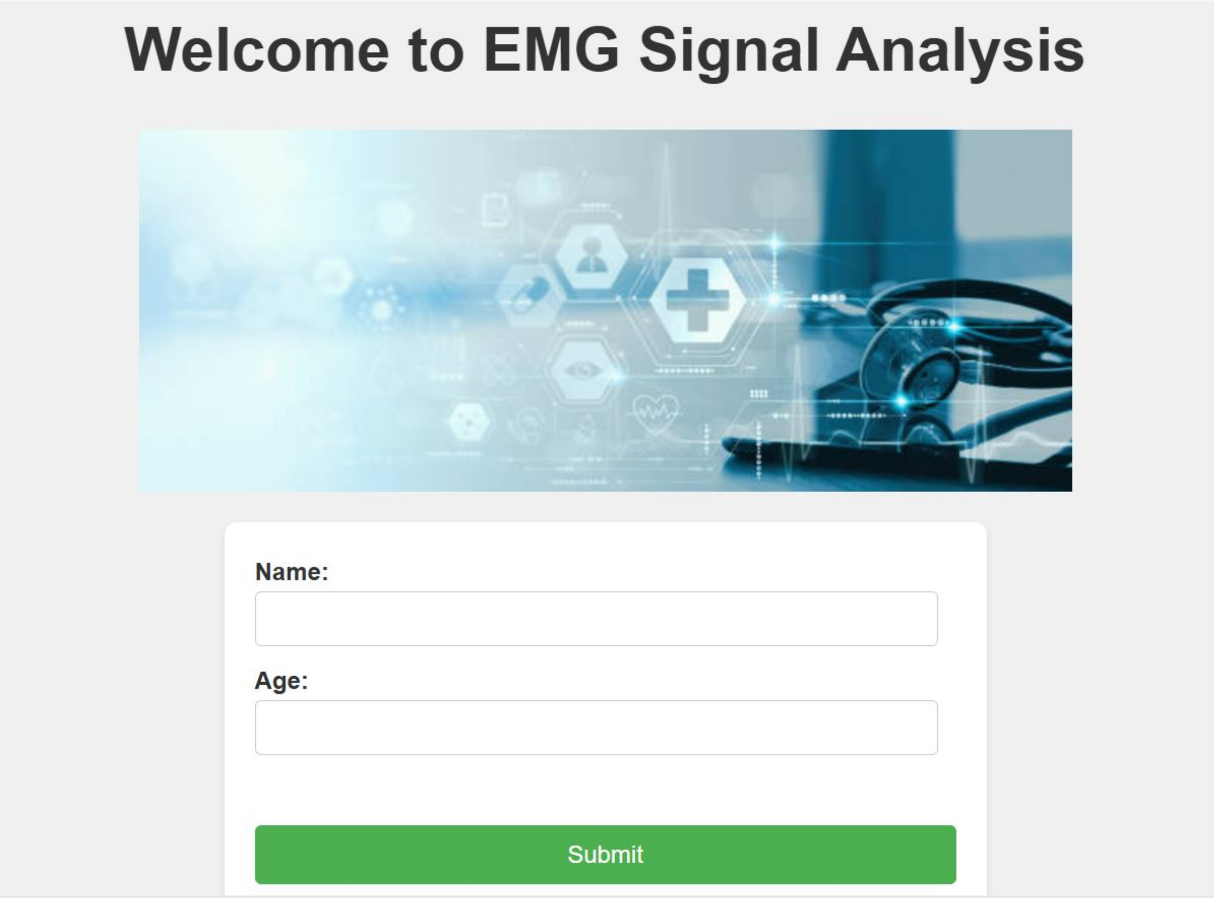
The waveform of any action potential comprises many sine waves of different frequencies. Thus, a frequency spectrum provides another objective means of characterizing an MUP. This type of analysis reveals an inverse relationship between the MUP duration and the amount of high-frequency components. Several investigators have studied frequency spectra, or a histogram of

activities against frequency, in normal and diseased muscles.[37,132] The highest peak seen during maximal contraction falls between 100 and 200 Hz in normal subjects. This peak shifts to a higher frequency in subjects with myopathy and to a lower frequency in subjects with anterior horn cell lesions. The clear difference seen in

cal study, further reduces intertrial variability and improves diagnostic sensitivity.[161] As discussed earlier, the normal ranges depend on many factors other than simply the characteristics of the motor unit itself. Hence, each laboratory should ideally construct its own table of normal values. A close scrutiny of the technique that duplicates the

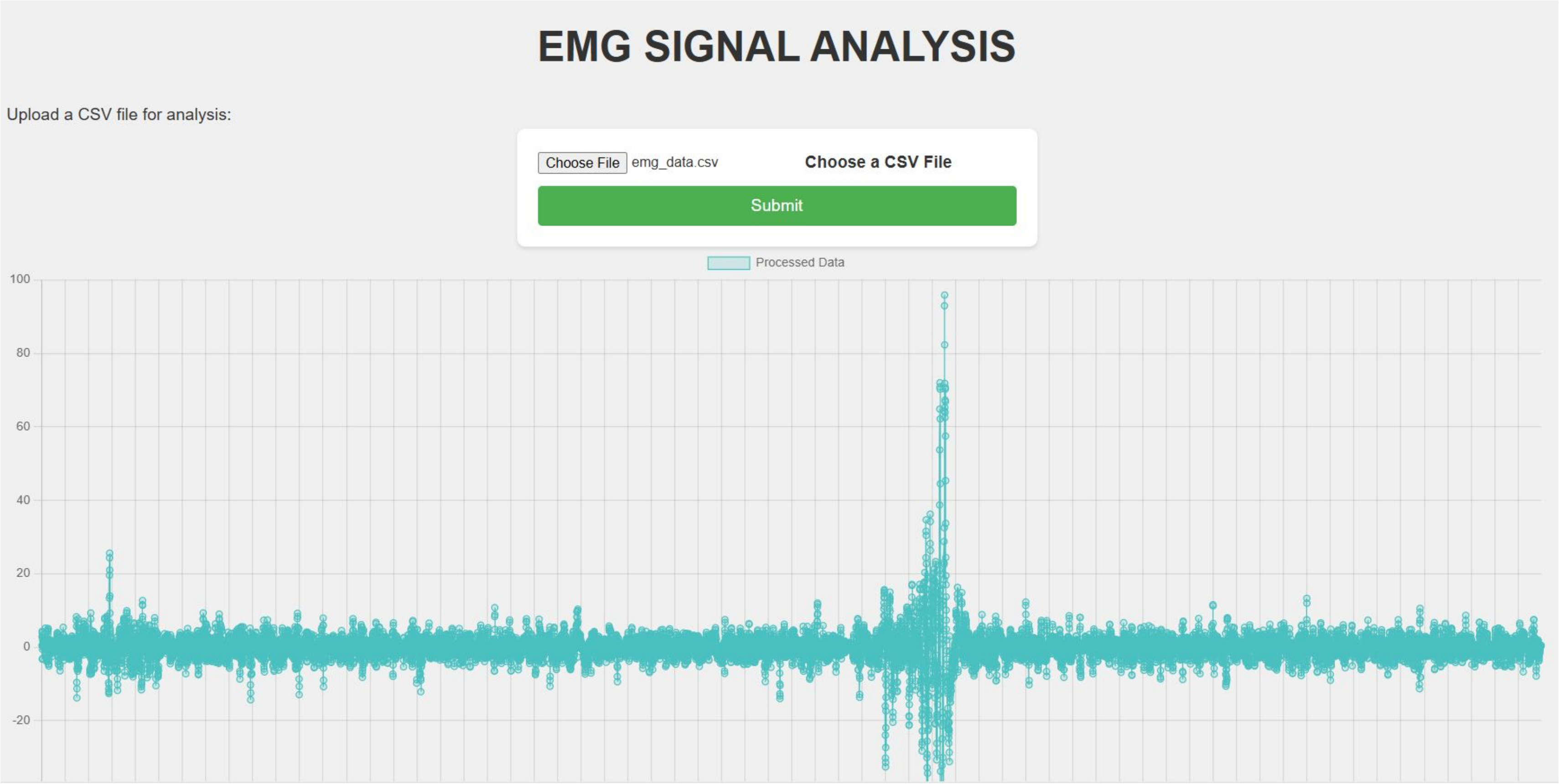
Week 3

Working on the frontend part of the App and deciding upon basic layout and functionalities of the App and preparing basic templates



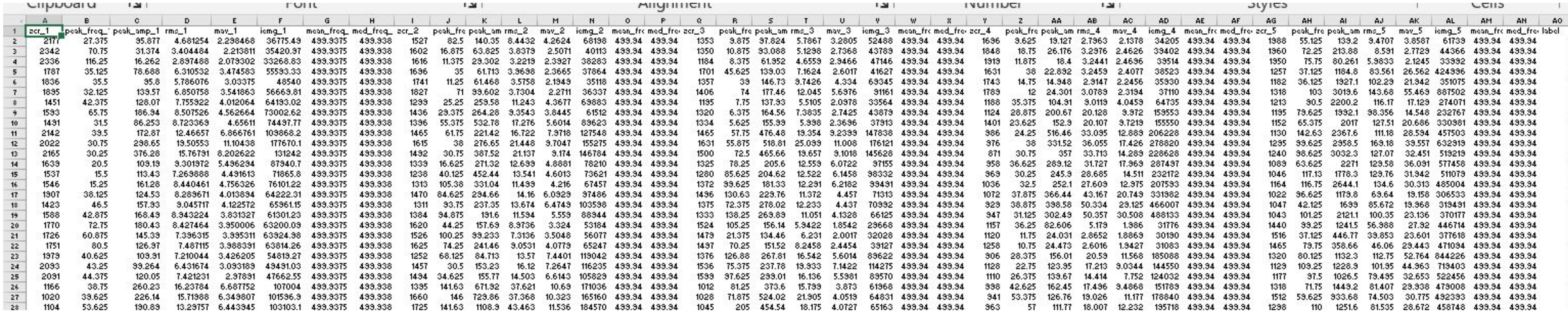
Week 3

Preparing the backend for the Signal preprocessing part and successfully showing processed EMG signal through uploaded sensor value data through App



Week 4

After features were reviewed, the challenge began by getting the features extracted segment wise for each activity performed, combining the data of all the 25 individuals through all the 5 electrodes, together at a place, with proper labellings for the model to make sense of the data. Here's how it looked like,



	zcr_1	peak_freq_	peak_amp_1	rms_1	mav_1	iemg_1	mean_freq_	med_freq_	zcr_2	peak_fre
2	2177	27.375	95.877	4.681254	2.298468	36775.49	499.9375	499.938	1527	82.5
3	2342	70.75	31.374	3.404484	2.213811	35420.97	499.9375	499.938	1602	16.875
4	2336	116.25	16.262	2.897488	2.079302	33268.83	499.9375	499.938	1616	11.375
5	1787	35.125	78.688	6.310532	3.474583	55593.33	499.9375	499.938	1696	35
6	1836	35.5	95.8	5.786076	3.03375	48540	499.9375	499.938	1741	11.25
7	1895	32.125	139.57	6.850758	3.541863	56669.81	499.9375	499.938	1827	71
8	1451	42.375	128.07	7.755922	4.012064	64193.02	499.9375	499.938	1299	25.25
9	1593	65.75	186.94	8.507526	4.562664	73002.62	499.9375	499.938	1436	29.375
10	1491	31.5	86.253	8.723369	4.65611	74497.77	499.9375	499.938	1396	55.375
11	2142	39.5	172.87	12.46657	6.866761	109868.2	499.9375	499.938	1465	61.75
12	2022	30.75	298.65	19.50553	11.10438	177670.1	499.9375	499.938	1615	38
13	2165	30.25	376.28	15.76791	8.202622	131242	499.9375	499.938	1492	30.75
14	1639	20.5	109.19	9.301972	5.496294	87940.7	499.9375	499.938	1339	16.625
15	1537	15.5	113.43	7.269888	4.491613	71865.8	499.9375	499.938	1238	40.125
16	1546	15.25	161.28	8.440461	4.756326	76101.22	499.9375	499.938	1313	105.38
17	1907	38.125	124.53	8.289671	4.013894	64222.31	499.9375	499.938	1470	84.625
18	1423	46.5	157.93	9.045717	4.122572	65961.15	499.9375	499.938	1311	93.75
19	1588	42.875	168.49	8.943224	3.831327	61301.23	499.9375	499.938	1384	94.875
20	1770	72.75	180.43	8.427464	3.950006	63200.09	499.9375	499.938	1620	44.25
21	1726	60.875	145.39	7.396315	3.995311	63924.98	499.9375	499.938	1526	100.25
22	1751	80.5	126.97	7.487115	3.988391	63814.26	499.9375	499.938	1625	74.25
23	1979	40.625	109.91	7.210044	3.426205	54819.27	499.9375	499.938	1252	68.125
24	2093	43.25	99.264	6.431674	3.093189	49491.03	499.9375	499.938	1457	30.5
25	2091	44.375	120.05	7.421231	2.97891	47662.55	499.9375	499.938	1494	34.625
26	1166	38.75	260.23	16.23784	6.687752	107004	499.9375	499.938	1395	141.63
27	1020	39.625	226.14	15.71988	6.349807	101596.9	499.9375	499.938	1660	146
28	1104	53.625	190.89	13.29757	6.443945	103103.1	499.9375	499.938	1725	141.63

	peak_am	rms_2	mav_2	iemg_2	mean_fre	med_fre	zcr_3	peak_fre	peak_am	rms_3
2	140.35	8.4432	4.2624	68198	499.94	499.94	1353	9.875	97.824	5.7867
3	63.825	3.8379	2.5071	40113	499.94	499.94	1350	10.875	93.088	5.1298
4	29.302	3.2219	2.3927	38283	499.94	499.94	1184	8.375	61.952	4.6559
5	61.713	3.9698	2.3665	37864	499.94	499.94	1701	45.625	139.03	7.1624
6	61.468	3.5758	2.1949	35118	499.94	499.94	1357	39	146.73	9.7426
7	99.602	3.7304	2.2711	36337	499.94	499.94	1406	74	177.46	12.045
8	259.58	11.243	4.3677	69883	499.94	499.94	1195	7.75	137.93	5.5105
9	264.28	9.3543	3.8445	61512	499.94	499.94	1320	6.375	164.56	7.3835
10	532.78	17.276	5.6014	89623	499.94	499.94	1334	5.625	155.99	5.998
11	221.42	16.722	7.9718	127548	499.94	499.94	1465	57.75	476.48	19.354
12	276.65	21.448	9.7047	155275	499.94	499.94	1631	55.875	518.81	25.099
13	387.52	21.137	9.174	146784	499.94	499.94	1500	72.5	465.66	19.657
14	271.32	12.699	4.8881	78210	499.94	499.94	1325	78.25	205.6	12.559
15	452.44	13.541	4.6013	73621	499.94	499.94	1280	85.625	204.62	12.522
16	331.04	11.499	4.216	67457	499.94	499.94	1372	99.625	181.33	12.291
17	294.66	14.16	6.0929	97486	499.94	499.94	1496	130.63	229.76	11.372
18	237.35	13.674	6.4749	103598	499.94	499.94	1375	72.375	278.02	12.233
19	191.6	11.594	5.559	88944	499.94	499.94	1333	138.25	269.89	11.051
20	157.69	8.9736	3.324	53184	499.94	499.94	1524	105.25	156.14	5.9422
21	99.233	7.3136	3.5048	56077	499.94	499.94	1479	21.375	134.46	6.231
22	241.46	9.0531	4.0779	65247	499.94	499.94	1497	70.25	151.52	8.2458
23	84.713	13.57	7.4401	119042	499.94	499.94	1376	126.88	267.81	16.542
24	153.23	16.12	7.2647	116235	499.94	499.94	1536	75.375	237.78	19.933
25	155.77	14.503	6.6143	105829	499.94	499.94	1599	97.625	299.01	16.136
26	671.92	37.621	10.69	171036	499.94	499.94	1012	81.25	373.6	15.799
27	729.86	37.368	10.323	165160	499.94	499.94	1028	71.875	524.02	21.905
28	1108.9	43.463	11.536	184570	499.94	499.94	1045	205	454.54	18.175

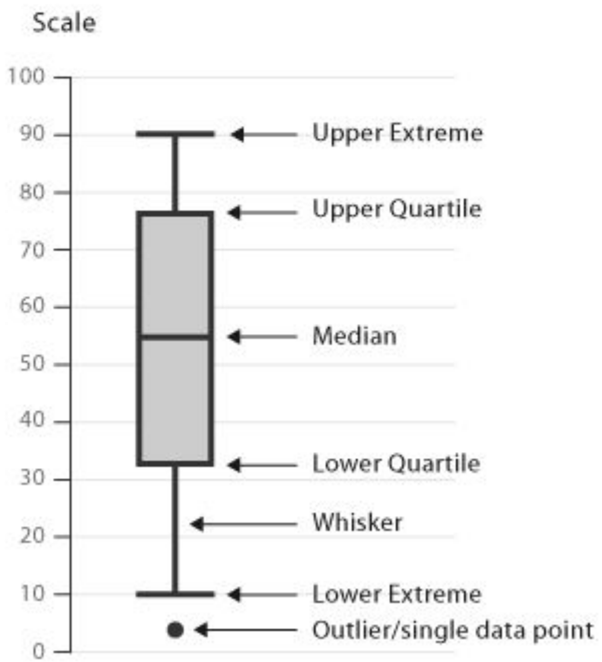
	mav_3	iemg_3	mean_fre	med_fre	zcr_4	peak_fre	peak_am	rms_4	mav_4	iemg_4
2	3.2805	52488	499.94	499.94	1696	9.625	19.127	2.7963	2.1378	34205
3	2.7368	43789	499.94	499.94	1848	18.75	26.176	3.2976	2.4626	39402
4	2.9466	47146	499.94	499.94	1919	11.875	18.4	3.2441	2.4696	39514
5	2.6017	41627	499.94	499.94	1631	38	22.892	3.2459	2.4077	38523
6	4.334	69345	499.94	499.94	1743	14.75	14.948	2.9147	2.2456	35930
7	5.6976	91161	499.94	499.94	1789	12	24.301	3.0789	2.3194	37110
8	2.0978	33564	499.94	499.94	1188	35.375	104.91	9.0119	4.0459	64735
9	2.7425	43879	499.94	499.94	1124	28.875	200.67	20.128	9.972	159553
10	2.3696	37913	499.94	499.94	1401	23.625	152.9	20.107	9.7219	155550
11	9.2399	147838	499.94	499.94	986	24.25	516.46	33.095	12.889	206228
12	11.008	176121	499.94	499.94	976	38	331.52	36.055	17.426	278820
13	9.1018	145628	499.94	499.94	871	30.75	357	33.713	14.289	228628
14	6.0722	97155	499.94	499.94	958	36.625	289.12	31.727	17.969	287497
15	6.1458	98332	499.94	499.94	969	30.25	245.9	28.685	14.511	232172
16	6.2182	99491	499.94	499.94	1036	32.5	252.1	27.609	12.975	207593
17	4.457	71313	499.94	499.94	1072	37.875	366.44	43.167	20.749	331982
18	4.437	70992	499.94	499.94	929	38.875	398.58	50.334	29.125	466007
19	4.1328	66125	499.94	499.94	947	31.125	302.49	50.357	30.508	488133
20	1.8542	29668	499.94	499.94	1157	36.25	82.606	5.179	1.986	31776
21	2.0017	32028	499.94	499.94	1120	11.75	24.031	2.8652	1.8869	30190
22	2.4454	39127	499.94	499.94	1258	10.75	24.473	2.6016	1.9427	31083
23	5.6014	89622	499.94	499.94	906	28.375	156.01	20.59	11.568	185088
24	7.1422	114275	499.94	499.94	1128	22.75	123.95	17.213	9.0344	144550
25	5.5981	89570	499.94	499.94	1110	26.375	139.67	14.414	7.752	124032
26	3.873	61968	499.94	499.94	998	42.625	162.45	17.496	9.4868	151789
27	4.0519	64831	499.94	499.94	941	53.375	126.76	19.026	11.177	178840
28	4.0727	65163	499.94	499.94	963	57	111.77	18.007	12.232	195718

	mean_fre	med_fre	zcr_5	peak_fre	peak_am	rms_5	mav_5	iemg_5	mean_fre	med_fre	label
2	499.94	499.94	1988	55.125	139.2	9.4707	3.8587	61739	499.94	499.94	1
3	499.94	499.94	1960	72.25	213.88	8.591	2.7729	44366	499.94	499.94	1
4	499.94	499.94	1950	75.75	80.261	5.9833	2.1245	33992	499.94	499.94	1
5	499.94	499.94	1257	37.125	1184.8	83.561	26.562	424996	499.94	499.94	1
6	499.94	499.94	1182	36.125	1927.1	102.29	21.942	351075	499.94	499.94	1
7	499.94	499.94	1318	103	3019.6	143.68	55.469	887502	499.94	499.94	1
8	499.94	499.94	1213	90.5	2200.2	116.17	17.129	274071	499.94	499.94	1
9	499.94	499.94	1195	79.625	1992.1	98.356	14.548	232767	499.94	499.94	1
10	499.94	499.94	1152	65.375	2017	127.51	20.686	330981	499.94	499.94	1
11	499.94	499.94	1130	142.63	2367.6	111.18	28.594	457503	499.94	499.94	1
12	499.94	499.94	1295	99.625	2958.5	169.18	39.557	632919	499.94	499.94	1
13	499.94	499.94	1240	98.625	3032.3	127.07	32.451	519219	499.94	499.94	1
14	499.94	499.94	1089	63.625	2271	129.58	36.091	577458	499.94	499.94	1
15	499.94	499.94	1046	117.13	1778.3	129.76	31.942	511079	499.94	499.94	1
16	499.94	499.94	1164	116.75	2644.1	134.6	30.313	485004	499.94	499.94	1
17	499.94	499.94	1022	96.625	1179.8	69.64	19.158	306533	499.94	499.94	1
18	499.94	499.94	1047	42.125	1699	85.672	19.968	319491	499.94	499.94	1
19	499.94	499.94	1043	101.25	2121.1	100.35	23.136	370177	499.94	499.94	1
20	499.94	499.94	1440	99.25	1241.5	56.988	27.92	446714	499.94	499.94	1
21	499.94	499.94	1516	37.125	446.77	39.853	23.601	377618	499.94	499.94	1
22	499.94	499.94	1465	79.75	358.66	46.06	29.443	471094	499.94	499.94	1
23	499.94	499.94	1320	80.125	1132.3	112.75	52.764	844226	499.94	499.94	1
24	499.94	499.94	1129	109.25	1228.9	101.95	44.963	719403	499.94	499.94	1
25	499.94	499.94	1177	97.5	1026.5	79.495	32.653	522456	499.94	499.94	1
26	499.94	499.94	1318	71.75	1449.2	81.407	29.938	479008	499.94	499.94	1
27	499.94	499.94	1512	59.625	933.68	74.503	30.775	492393	499.94	499.94	1
28	499.94	499.94	1298	110	1251.6	81.535	28.672	458748	499.94	499.94	1

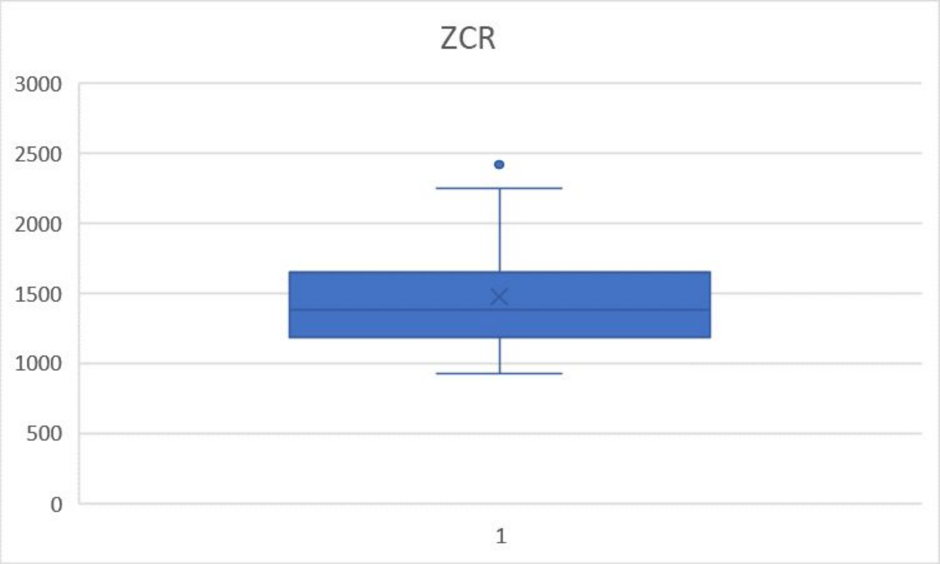
Week 4

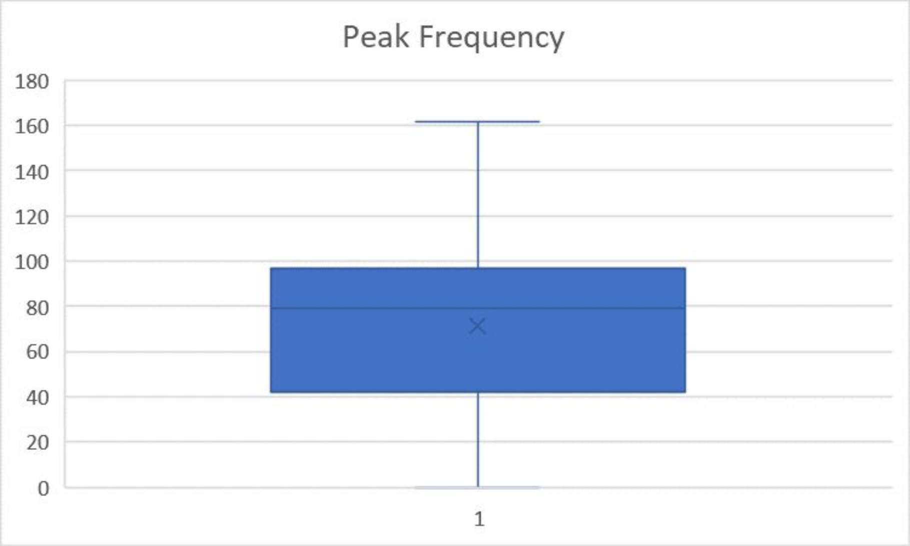
Here, we plot the box and whisker plots of the data, showing the ranges and variation in the data. A little about Box and Whisker plot,

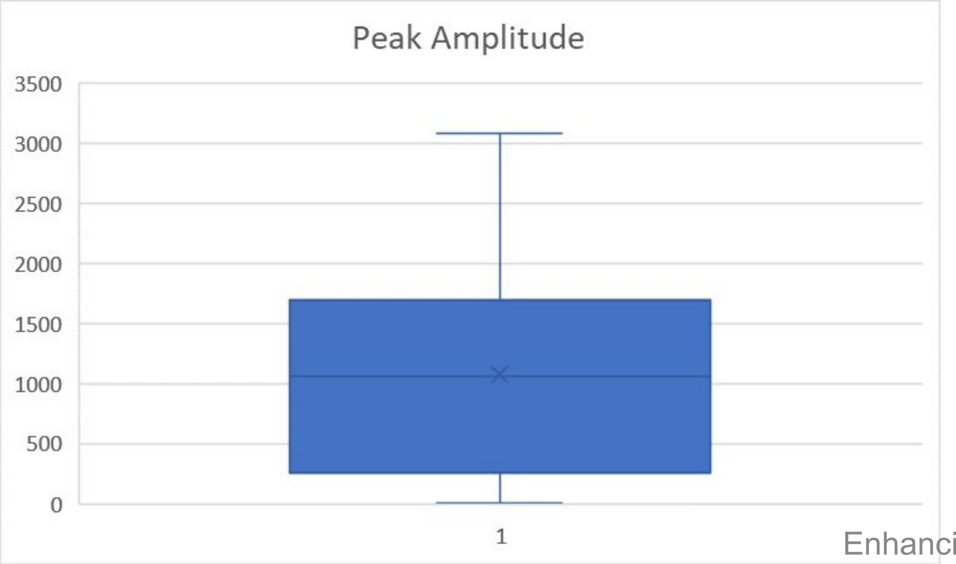
The lines extending parallel from the boxes are known as the "whiskers", which are used to indicate variability outside the upper and lower quartiles. Outliers are sometimes plotted as individual dots that are in-line with whiskers.

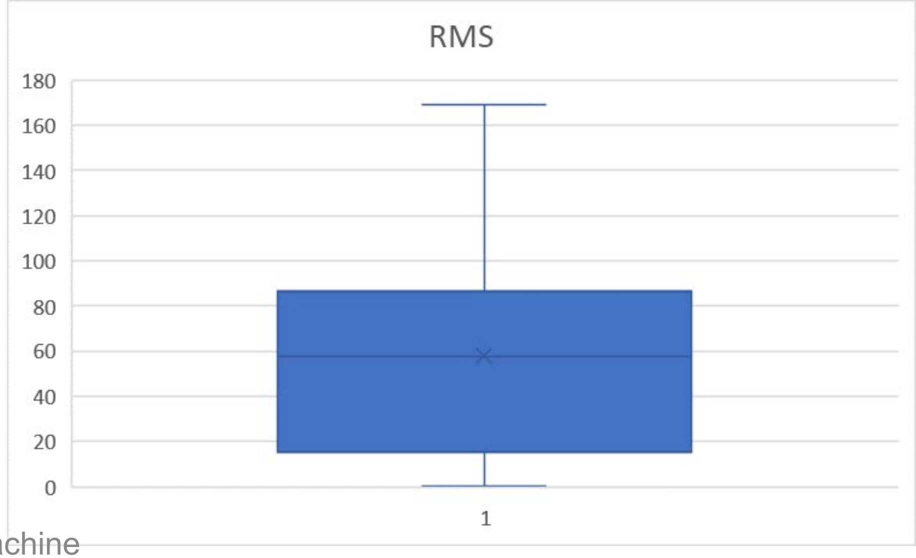


Week 4

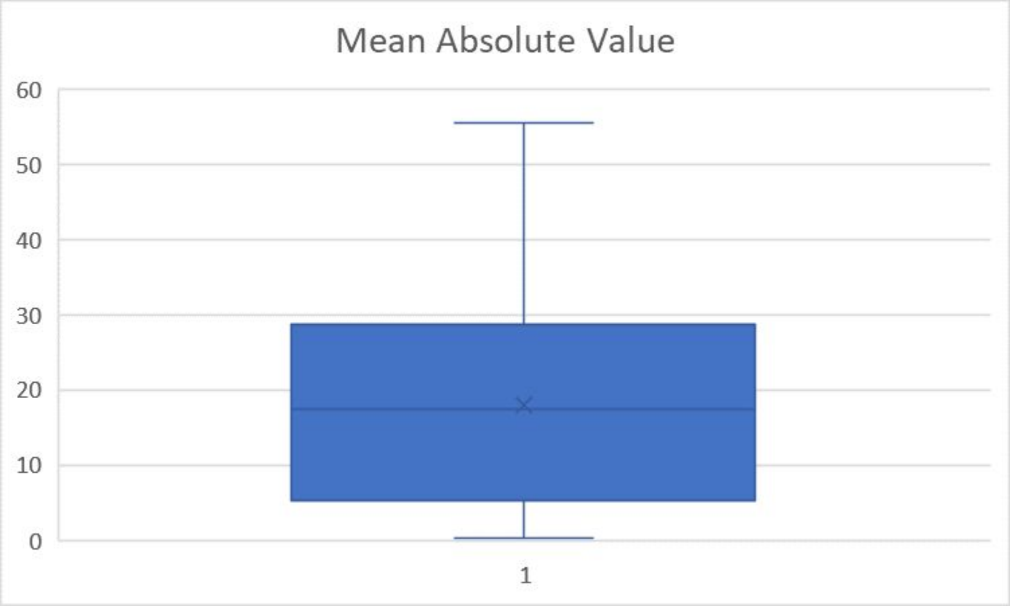

ZCR
3000
2500
2000
1500
1000
500
0
1

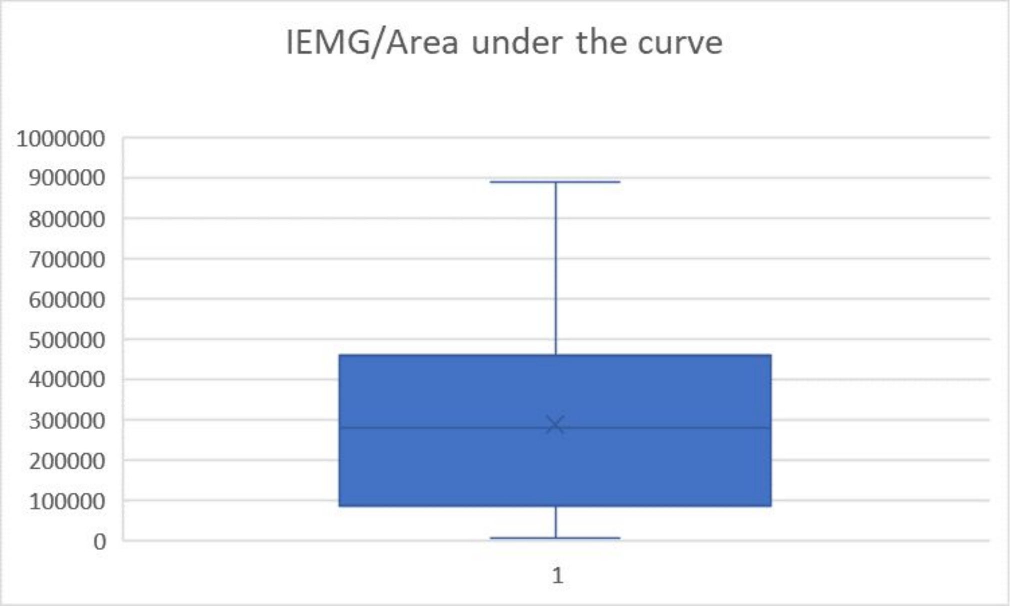

Peak Frequency
180
160
140
120
100
80
60
40
20
0
1


Peak Amplitude
3500
3000
2500
2000
1500
1000
500
0
1


RMS
180
160
140
120
100
80
60
40
20
0
1

Week 4


Mean Absolute Value
60
50
40
30
20
10
0
1


IEMG/Area under the curve
1000000
900000
800000
700000
600000
500000
400000
300000
200000
100000
0
1

Week 4

Firstly preliminary models like Isolation Forests, One-Class SVM, Elliptic Envelope and Local Outlier Factor were applied on features (calculated separately for all 5 electrodes making in total 40 features) extracted from unfiltered and raw data.

Key points, negative scores indicate anomaly. The more a score is away from 1 and close to -1 it indicates an anomaly, threshold is set to 0 by default.

Here are the performances:

1) Isolation Forests, though giving an accuracy of 100% failed to identify neuropathic signal from healthy, and gave a score of 0.08. However if we tweak the threshold from 0 to around 0.08-0.09 the accuracy would drop to 96%(3 normal cases out of 75 would be classified as abnormal), but the model would be able to identify neuropathic signal.
2) One-Class SVM gave an accuracy of 90.66%, and is unable to identify the neuropathic signal as abnormal, giving it a score of 0.09.
3) Local Outlier Factor is a method that prohibits testing new data points for anomaly detection, but when trained on the dataset, it misclassified only label as abnormal on the entire range of normal points.
4) Elliptic Envelope, by far the best method found, gave an accuracy of 96% when trained on the normal data, and when tested on anomalous data like neuropathic signal, it classified it as anomalous with an astounding confidence, making it look very promising.

Further we aim to also apply signal processing techniques, whose pipelines are ready, and apply models on those data. And parallely we are working to extract important or more contributing features for detection via deep learning methods.

Week 4

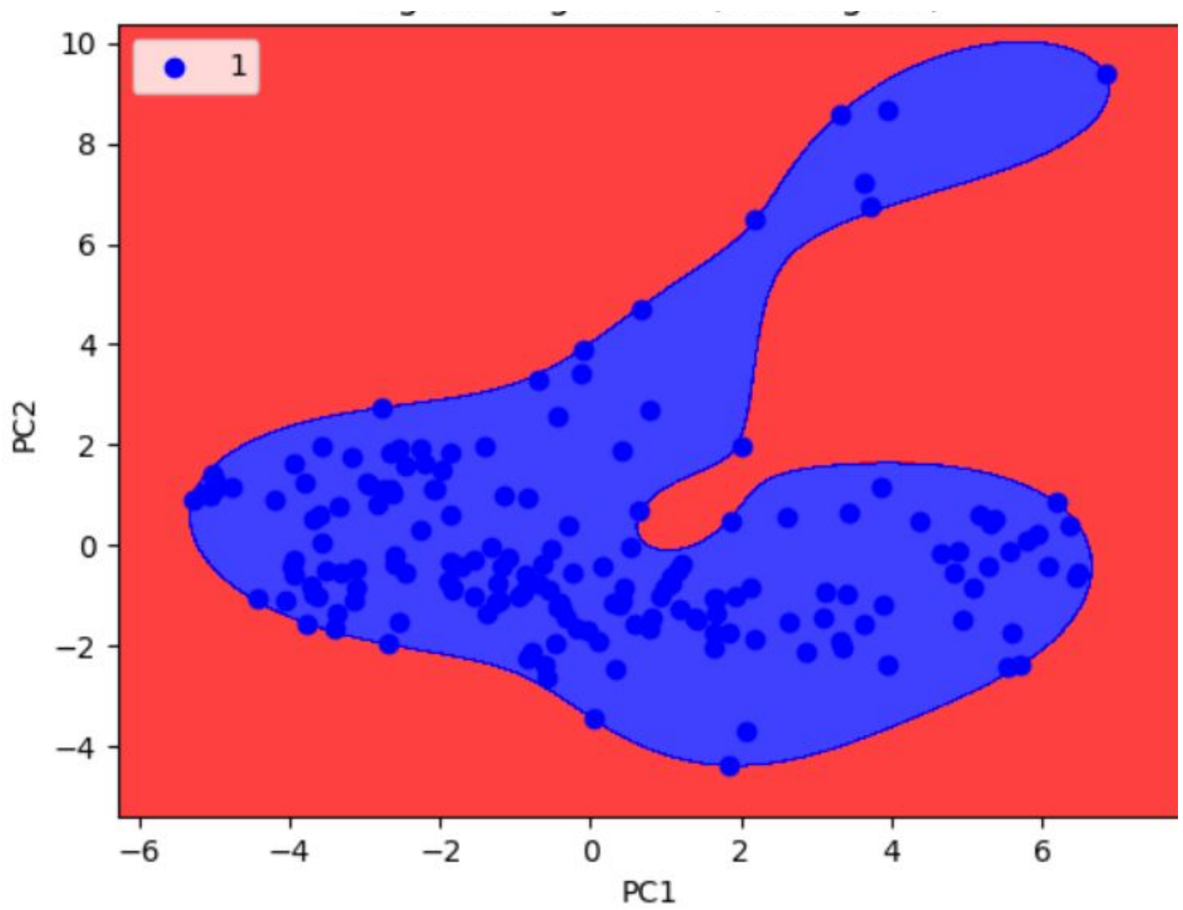
After applying signal processing, and Standard Scaler to the data, many algorithms showed higher accuracies, One Class SVM, also showed higher accuracy . Elliptic Envelope identified neuropathic signal with a evern higher confidence, and its accuracy on the training set increased.

But after just selecting the 5th Electrode's data for action 1 (it was coin tossing, and electrode 5's data corresponded to thumb muscle), the results improved drastically, even One Class SVM began identifying the anomalous neuropathic signal, and Elliptic Envelope's confidence increased plus its accuracy increased to a 100%.

This leads us to two things, choosing the electrode is essential, and we have to make sure that our model is not overfitting, for that we must gather a larger dataset of anomalous signals, or generate one understanding the underlying partitions.

Week 4

Using PCA (Principal Component Analysis) can reduce the dimensions of the dataset from 40 features to any specified number of features. Here's a visualization of 40 features scaled down to 2 features.

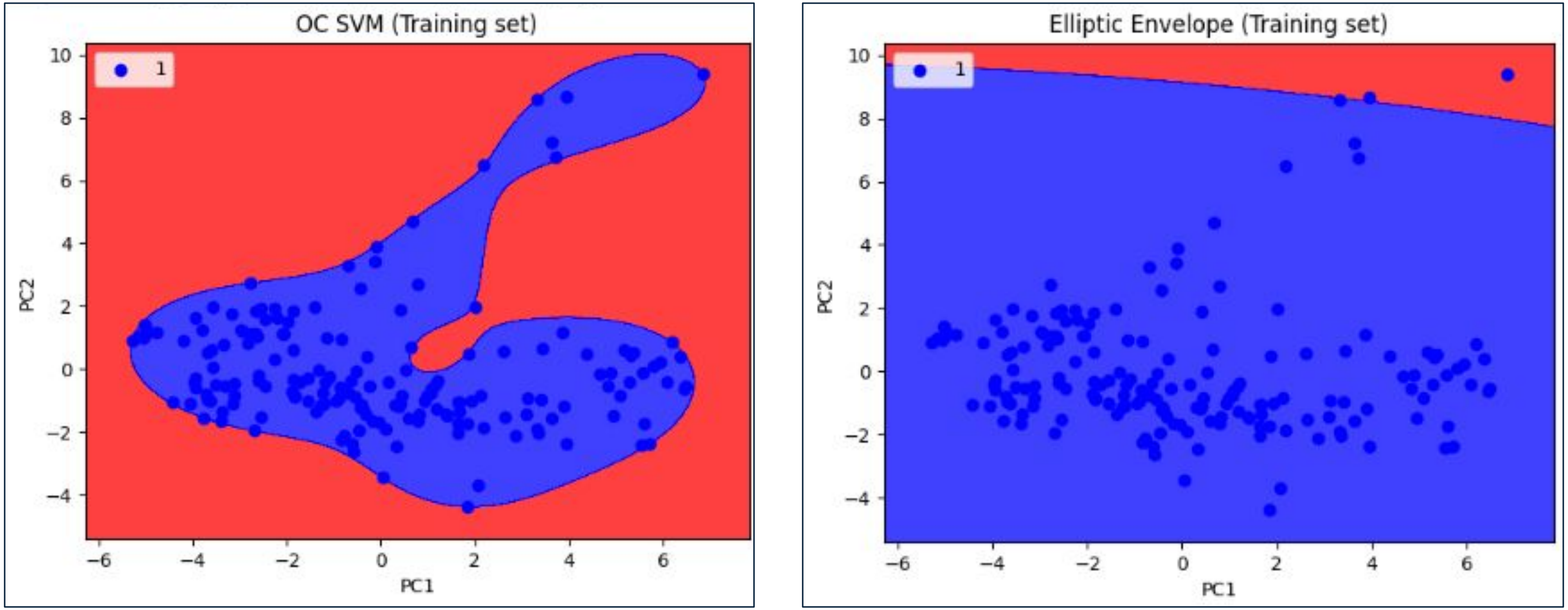


Week 4

This shows that most of the points concentrated at the center form an ellipse, hence elliptic envelope shows a good accuracy and is able to identify anomalous data.

However better accuracies are achieved when 40 features are scaled down to 3 features, in terms of accuracy and identification of anomalies, but as visualization is not possible in 3 dimensions hence the sketch is for 2 features.

PCA Visualization of OC_SVM and Elliptic Envelope



Week 4

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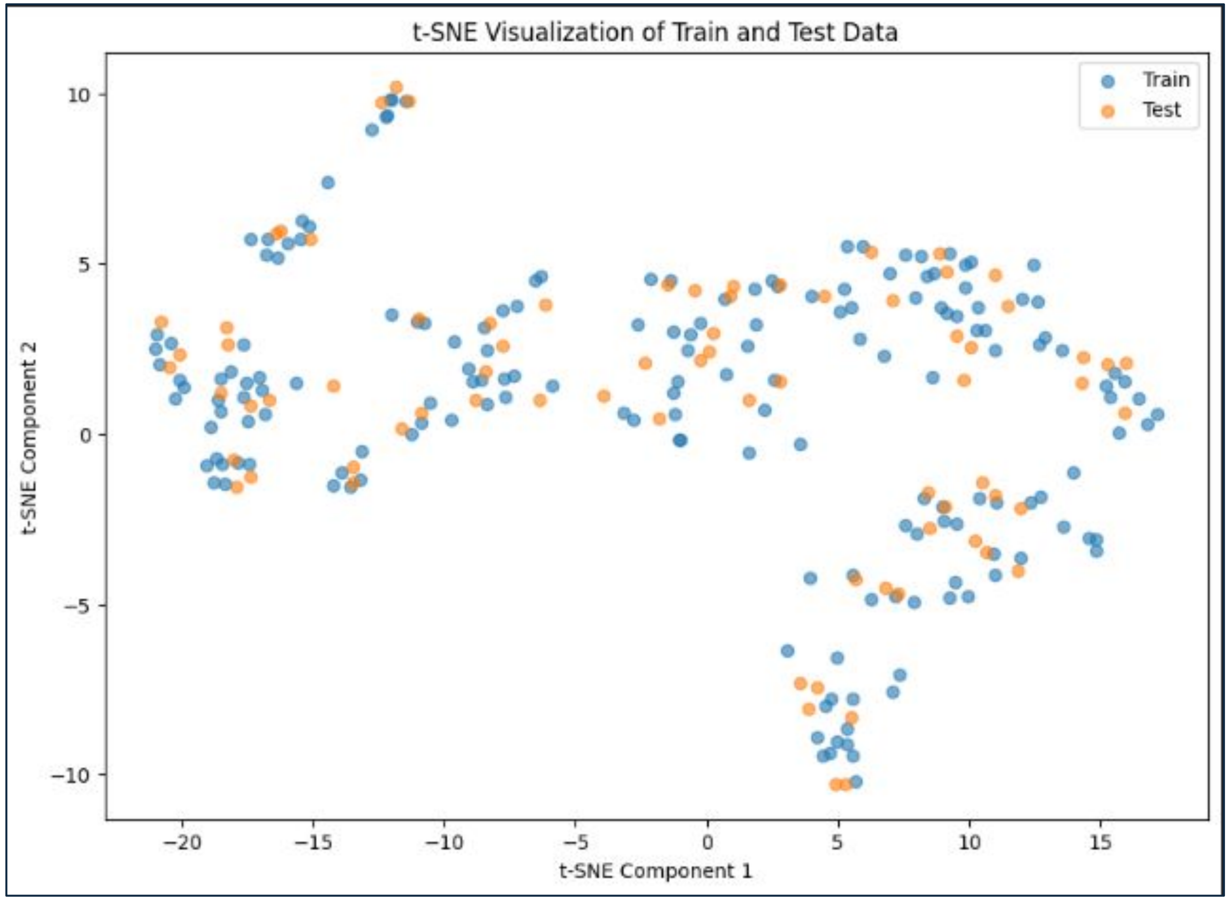
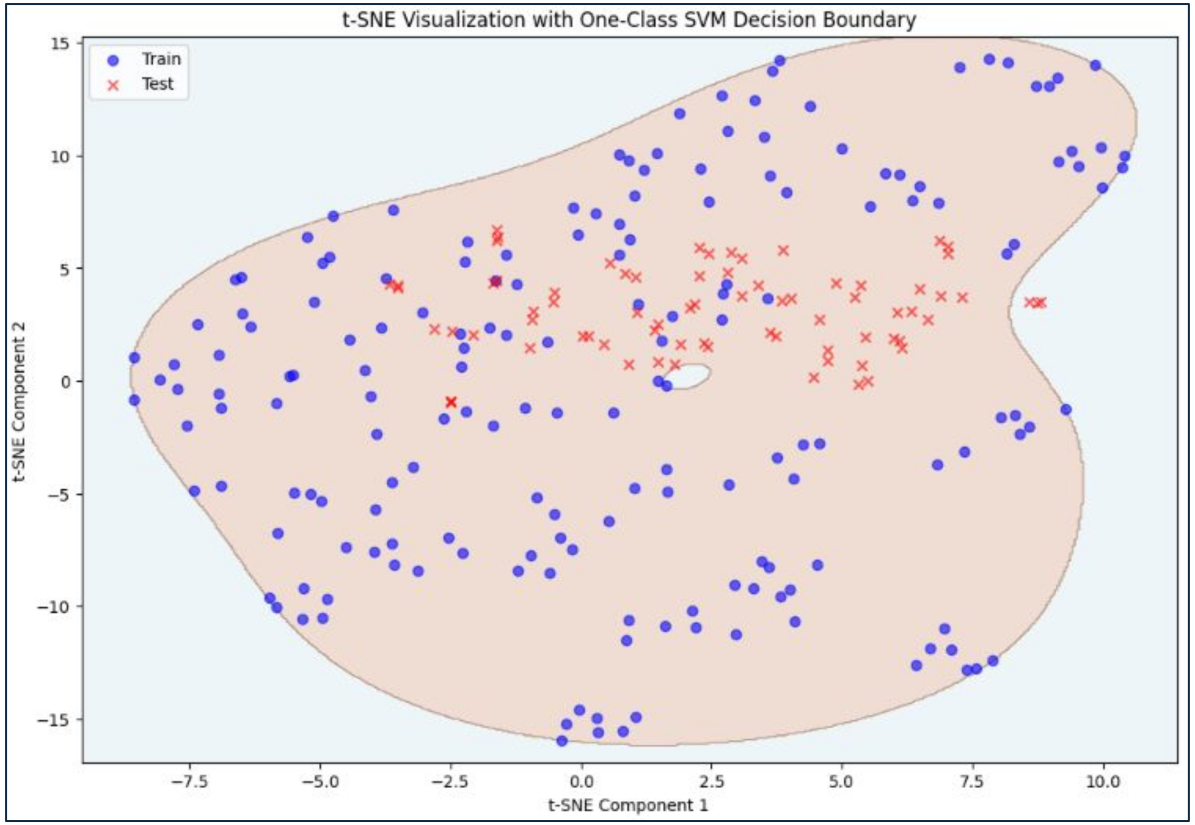
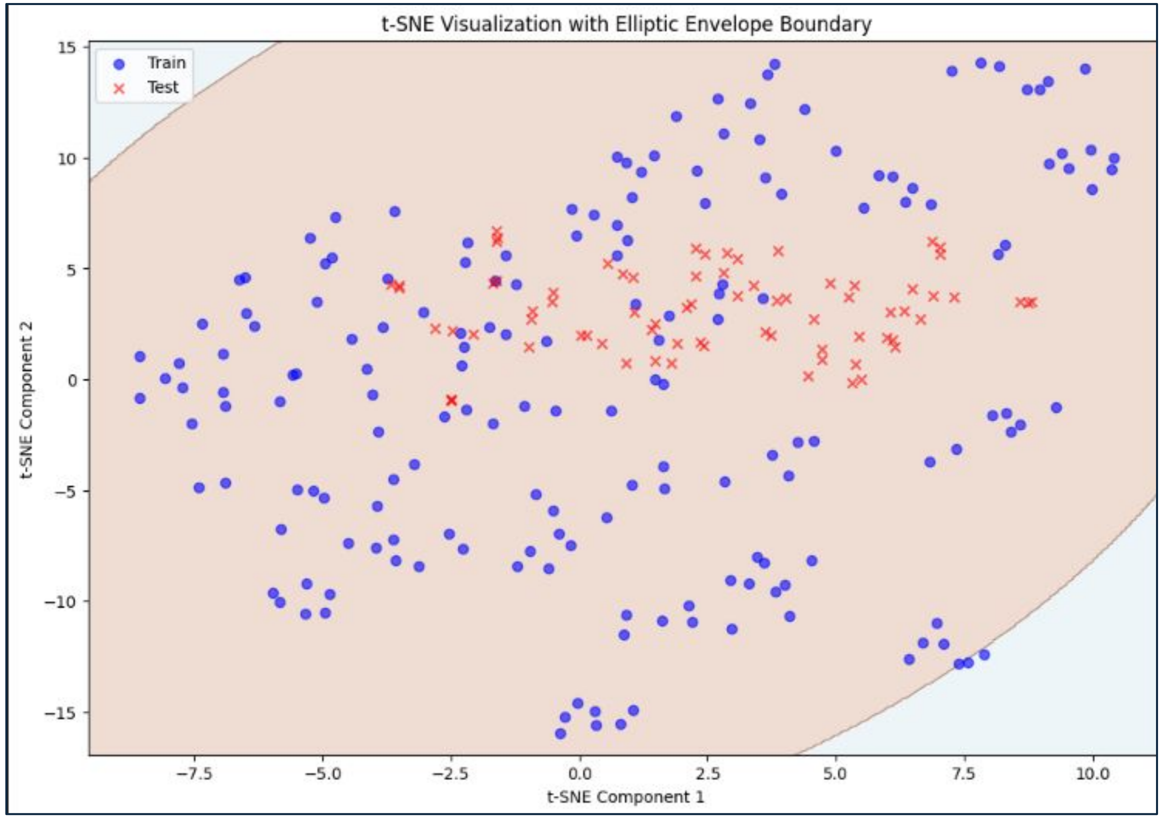
t-SNE Picture of the entire data



t-SNE picture of OC SVM and Elliptic Envelope

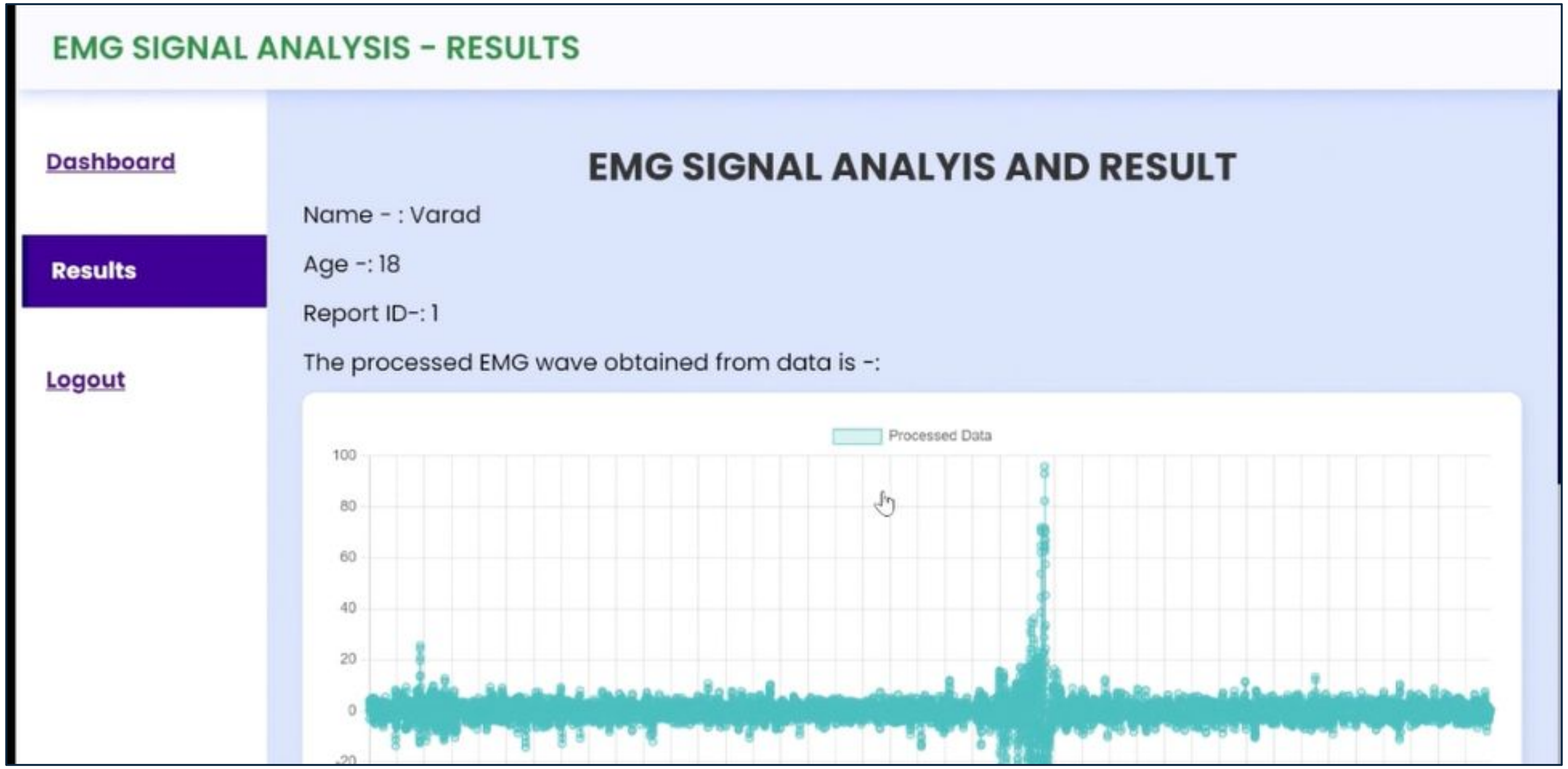




Week 4

Web/App Developments

Improving UI and adding Dashboard and Result pages .



Week 5

The models that we trained till now look good with accuracy as a metric, but the catch about it is, these models may very easily be underfitting or overfitting. And hence we need a robust mechanism that can generate artificial signals, which we can give to our model as anomalous data and evaluate its performance on it. This way our model will be much more robust and would be able to identify anomalies much better.

Out of all the methods found researched,
Generative Adversarial Networks, or GANs are known to generate synthetic EMG Signals, with bits and pieces of the physionet database of myopathic and neuropathic signal, we aim to train a model that can give us more of such signals. Planning to implement it in next phases.

Week 5

Resources explored for synthesizing artificial signals:

1) https://repositorium.hs-ruhrwest.de/frontdoor/deliver/index/docId/742/file/Bachelorarbeit_Mahdi_EL_Mesoudy.pdf

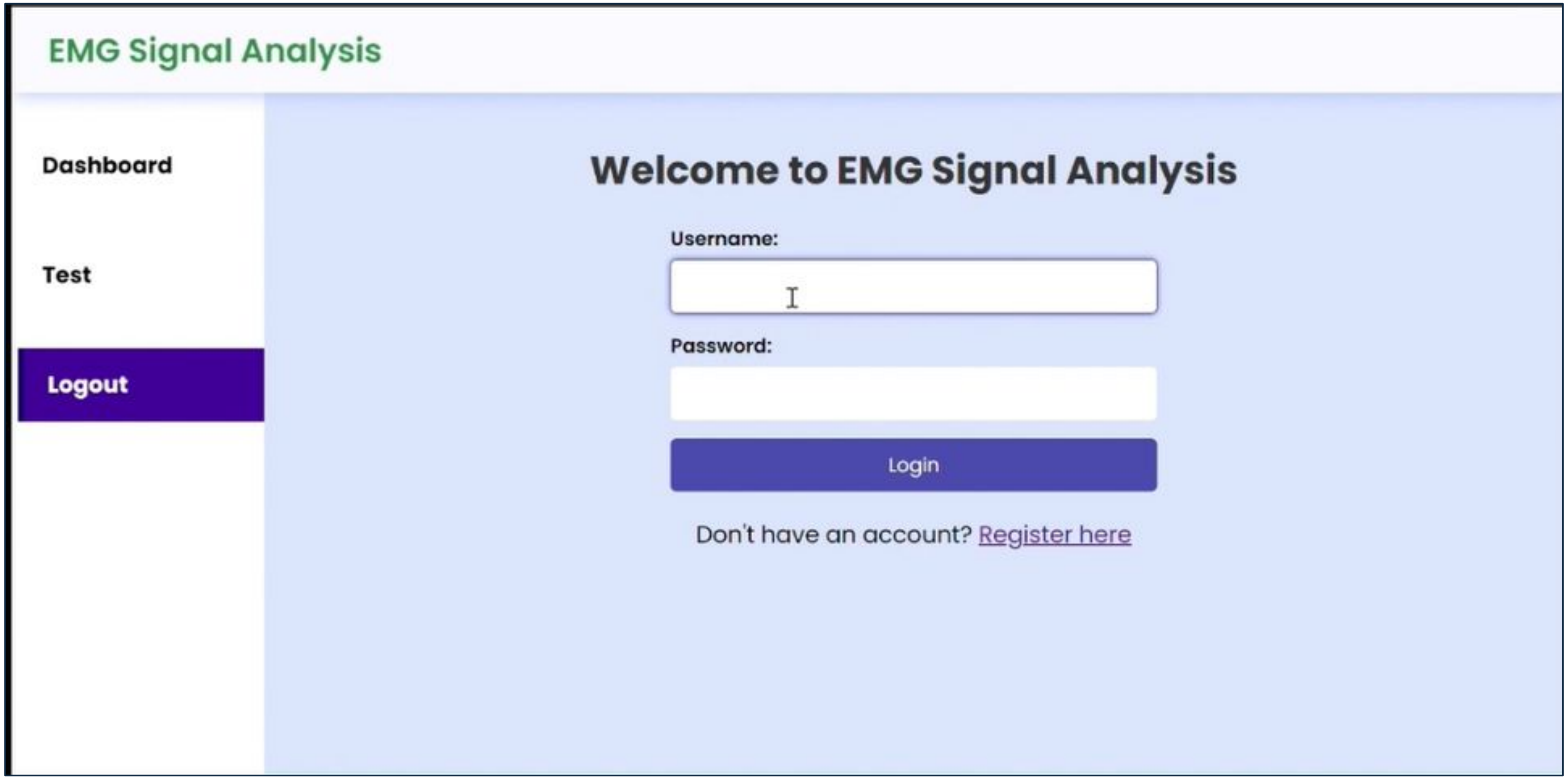
2) https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5481033/#:~:text=Artificial%20EMG%20signals%20are%20then%20generated%20by%20multiplying%20the%20variance,to%20the%20muscle%20activation%20levels

3) https://towardsdatascience.com/hands-on-generative-adversarial-networks-gan-for-signal-processing-with-python-ff5b8d78bd28

4) https://github.com/larocs/EMG-GAN

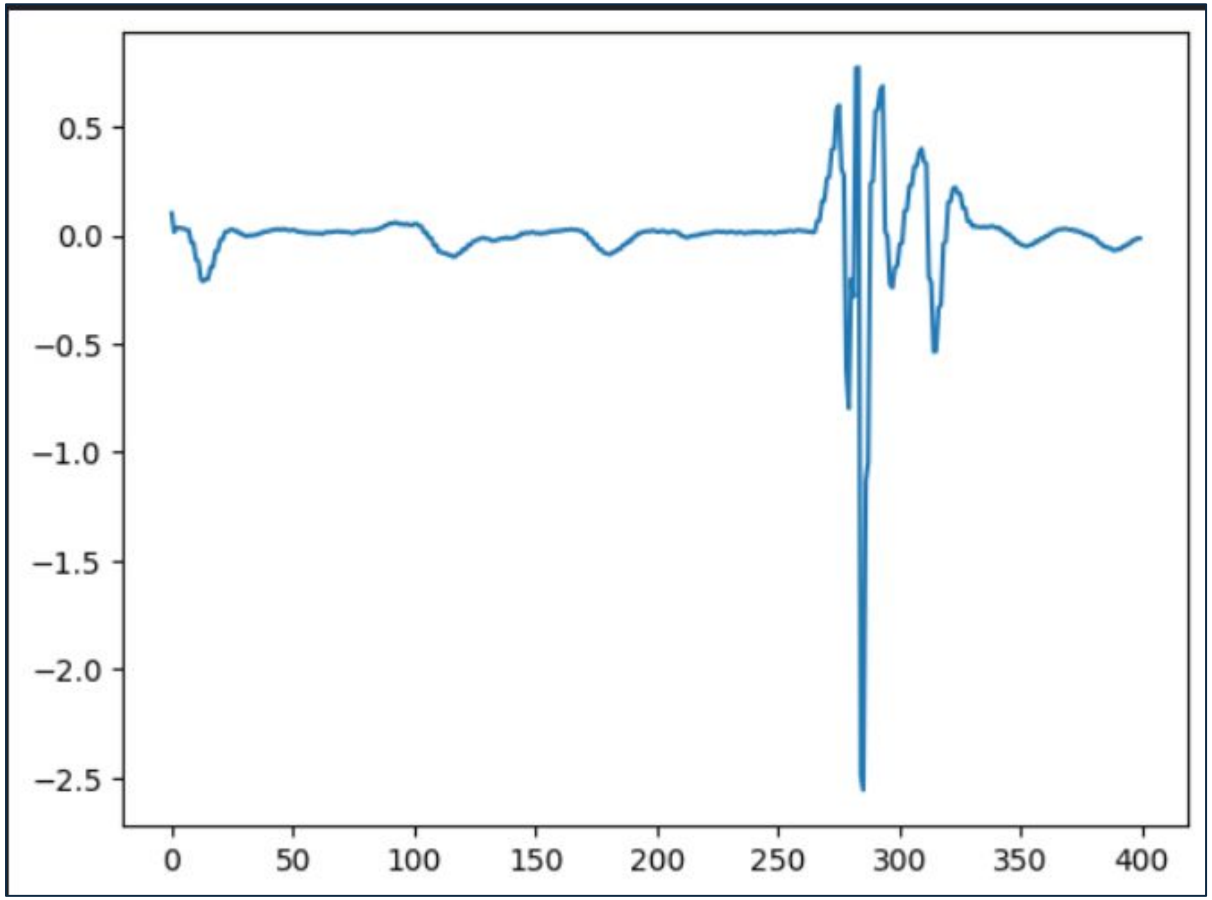
Week 5

Linking with database to store patient history

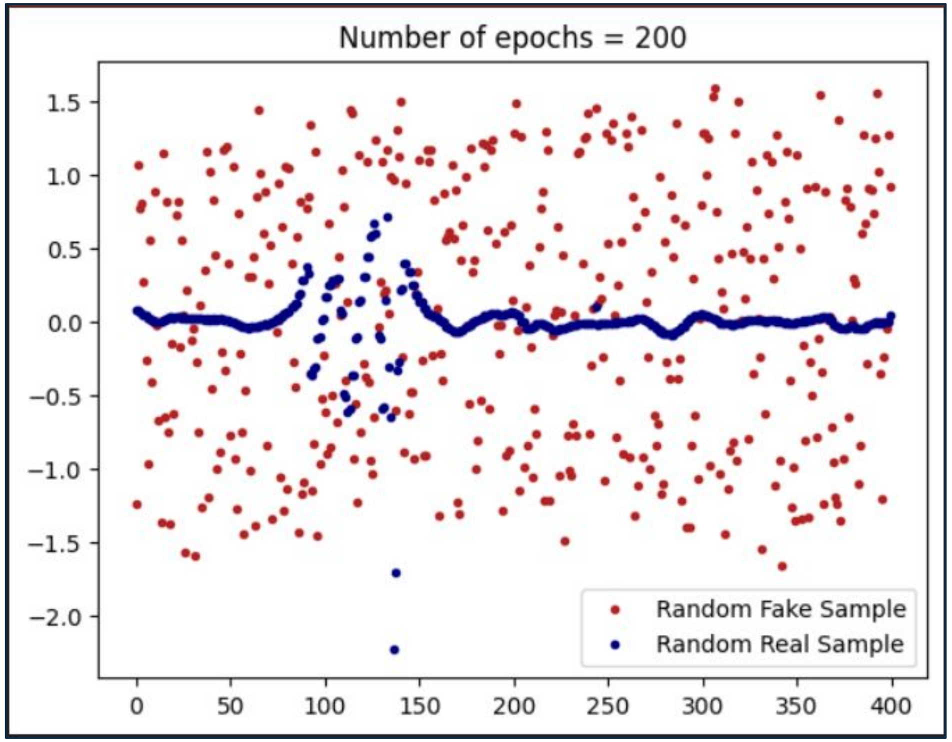


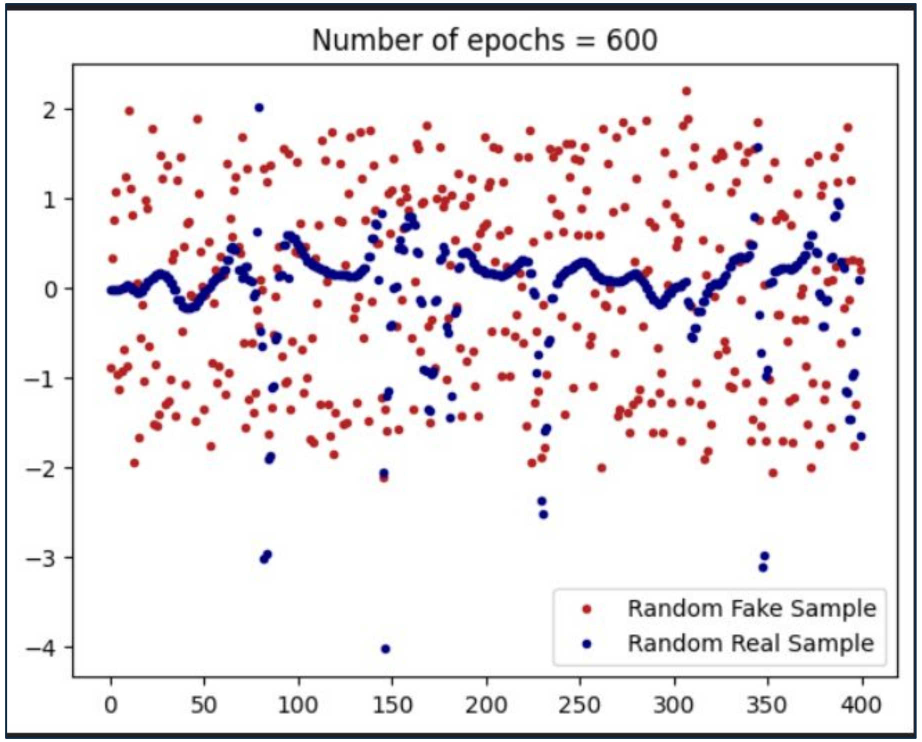
Week 6

EMG GANs code was tried to be implemented,
Here is it’s performance uptil now, we pass in signals in batches of 400 that look like this,



Week 6


Number of epochs = 200
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
0
50
100
150
200
250
300
350
400
Random Fake Sample
Random Real Sample


Number of epochs = 600
2
1
0
−1
−2
−3
−4
0
50
100
150
200
250
300
350
400
Random Fake Sample
Random Real Sample

Week 6

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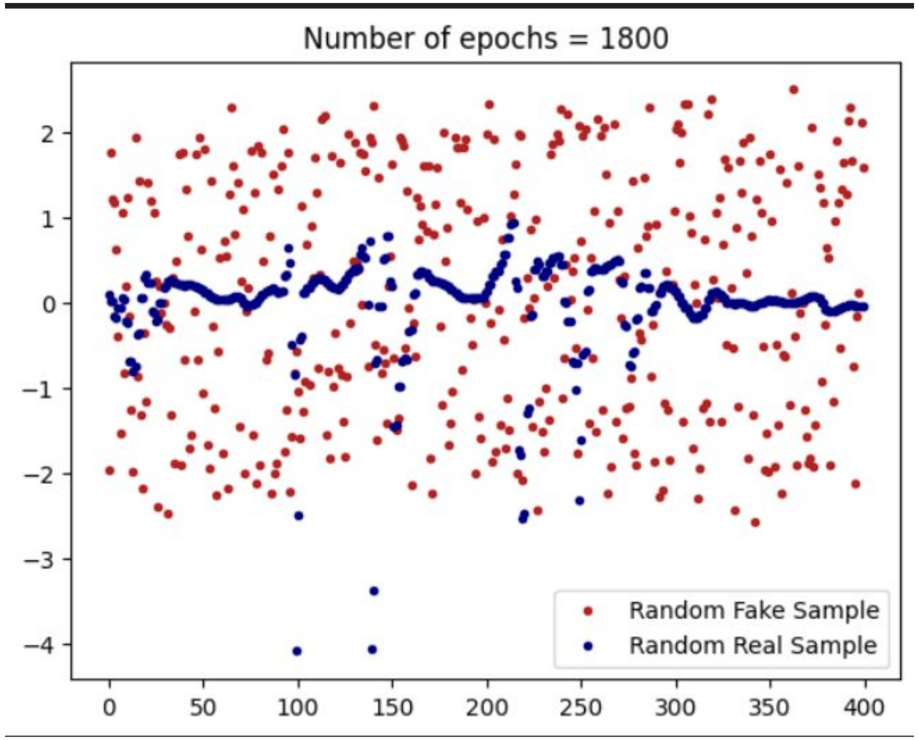
Until now, the model is not able to make a meaningful outcome. The reason for it is that training this GANs it is suggested to run at least 10,000 epochs to visualize even the most common patterns, but at 2000 epochs the RAM gets exhausted. A search for lesser RAM intensive procedure is continued.



Week 6

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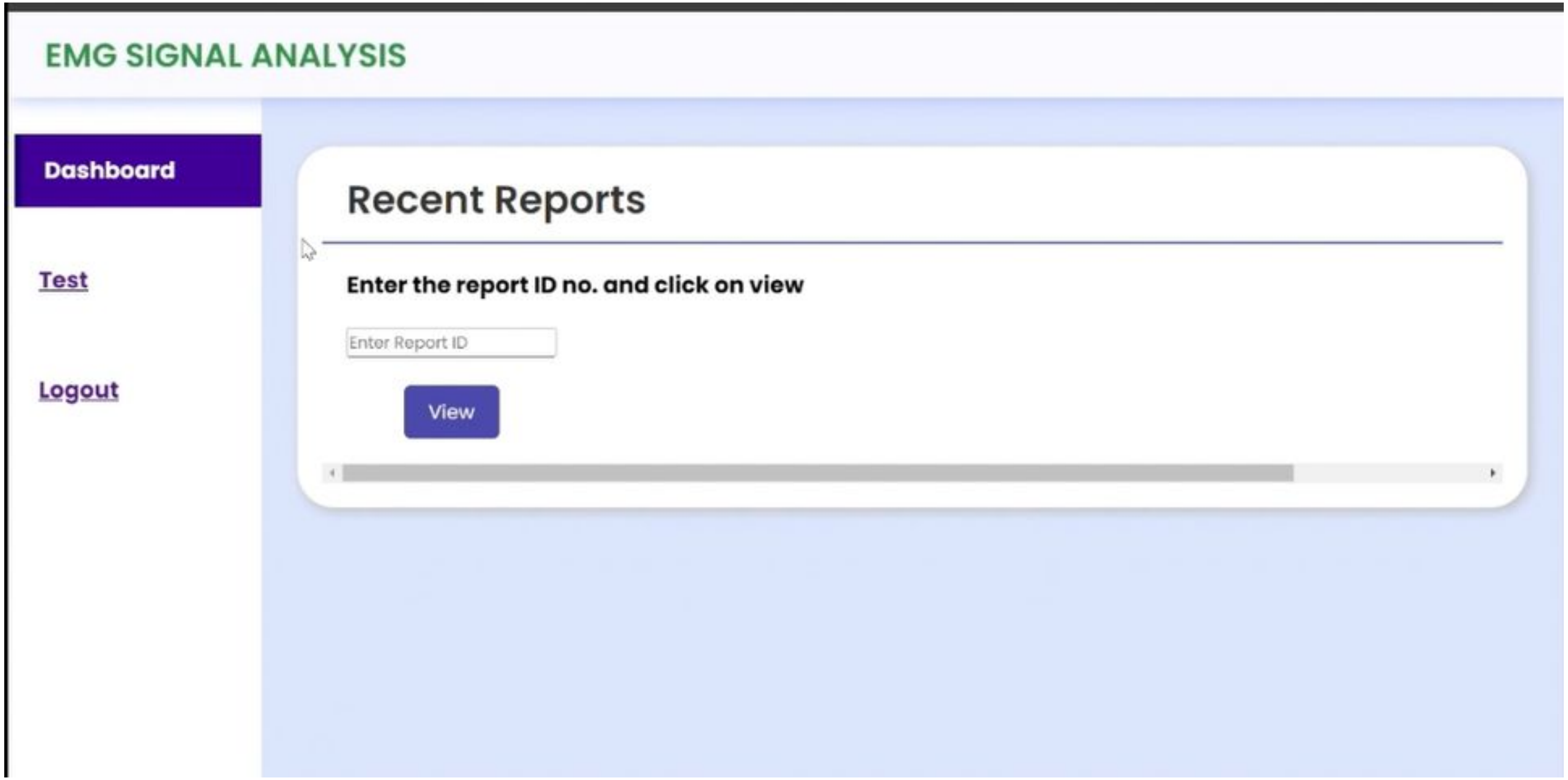
Creating feature for previous report visibility by the user on the app



Week 7

To link the ML models to the web server created, the model of action 1 were converted into .pkl files and shared with the Web/App team for integration.
Simultaneously, experimentations with electrode selections were continued.

For that, a neural network with a bit of GAN generated signals and the anomalous (myopathic and neuropathic) signals of PhysioNet database were combined to form another database. This database had 15 neat anomalous signals.

Another database was created to be fed into a neural network. This database has 16000*5 columns, 16000 data points of one signal, collected over 5 electrodes, and another database had only 16000 data points from electrode 5 of action1(theoretically the most accurate electrode). It had 265 signals in total. A basic CNN-LSTM model was trained on both of them separately, and both of them converged very quickly to close to 100% accuracy. An MLP too was trained which gave an accuracy of 53%.

This showed little to no difference between considering 1 electrode or 5 electrodes.

The test dataset was carefully curated, with having nearly 30% anomalous signals and 70% normal signals. This was done because we understood that the anomalous signals were very very low in number as compared to the normal signals.

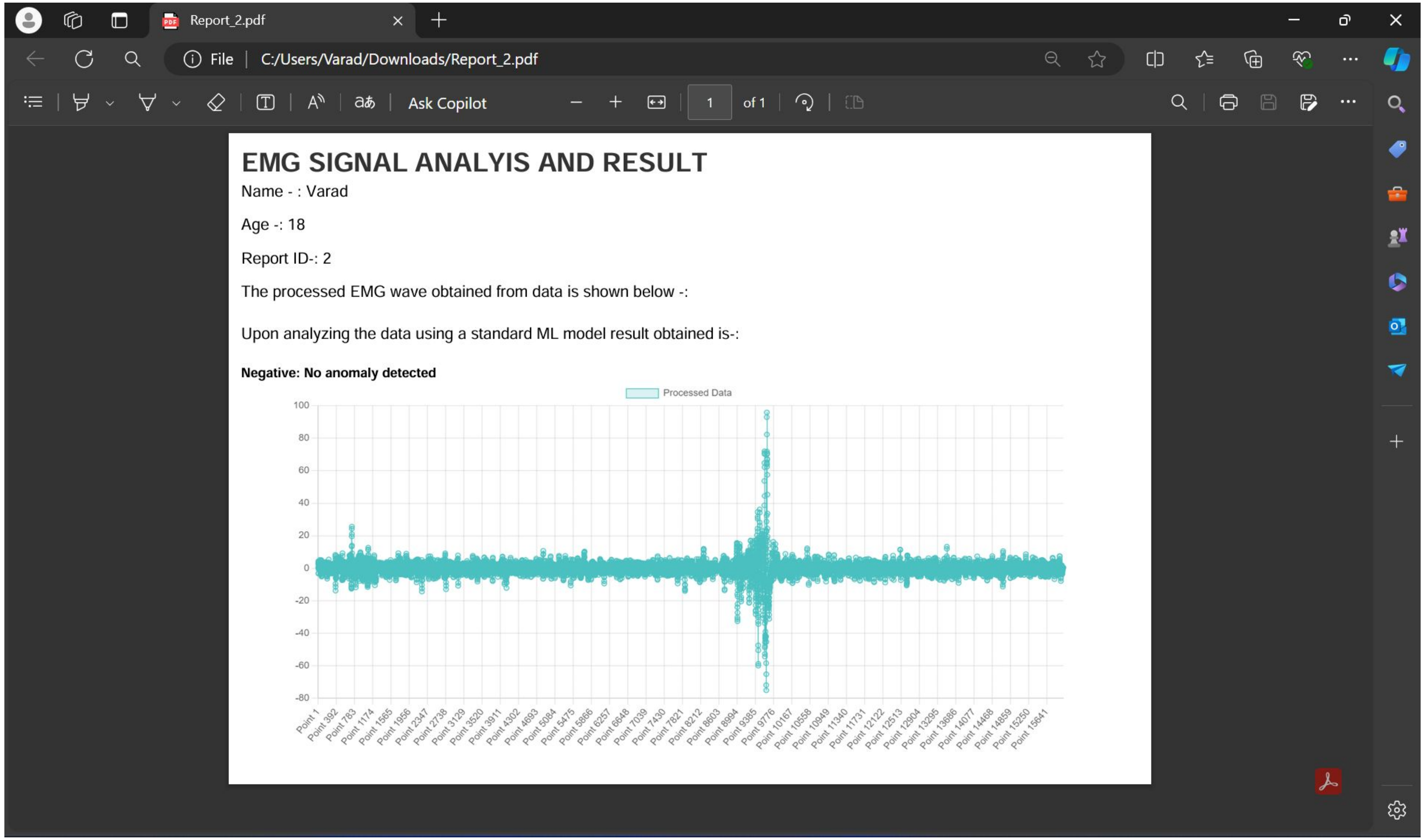
On visualizing the confusion matrix of these models(MLP and CNN-LSTM) which were

```
array([[ 5,  5],        and  array([[ 9,  1],
       [33, 37]])                   [ 0, 70]])
```

A good thing to note about the CNN-LSTM Model is that the false negatives are 0, false negatives in this case are placed first on the lower rung as 0 represents disease and 1 represents normal signal. It is good from a medical point of view to have less false negatives as compared to false positives.

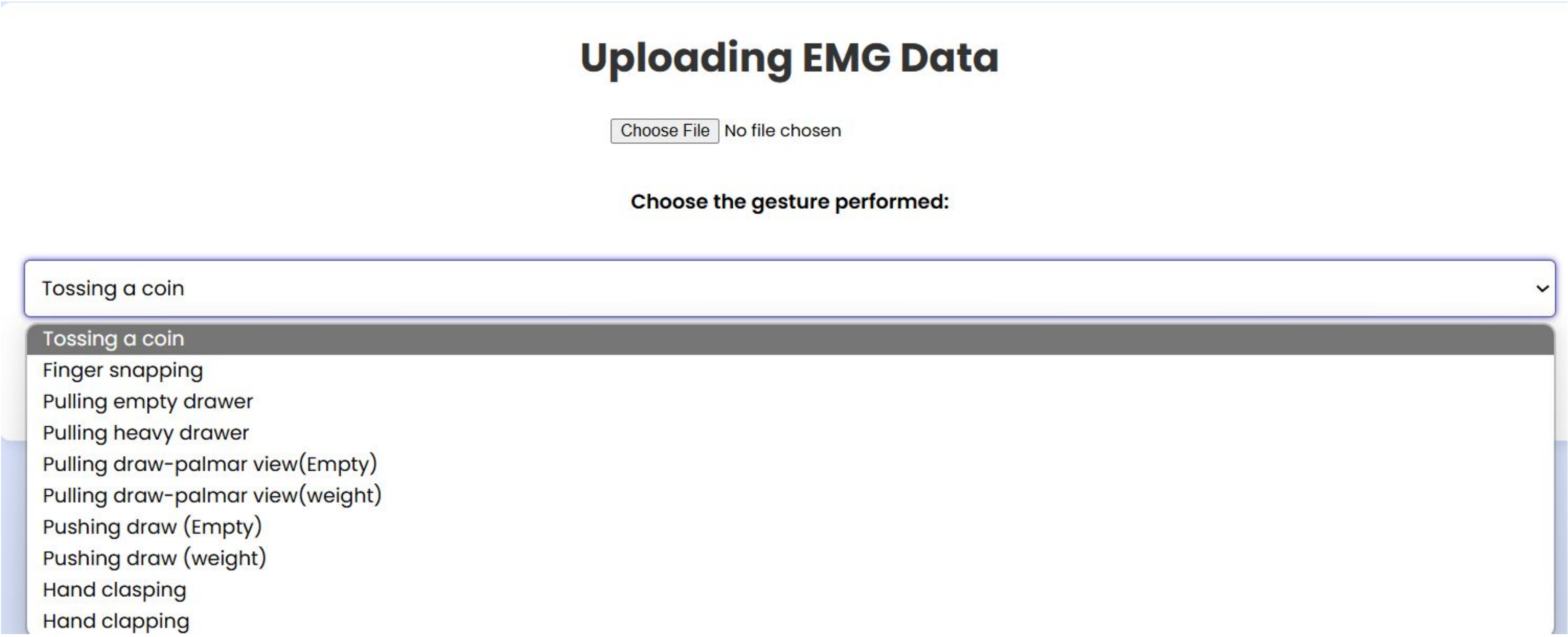
Week 7

Creating feature for saving report in pdf files



Week 8

Final documentation work, debugging the model issues and training all models of different actions database and sharing .pkl files of the models to be integrated with the final Web/App. Extending app interface to all 10 gestures and integrating pkl files of models for all 10 gestures



Week 8

Model Finalization process involved rigorous testing of data over various metrics.

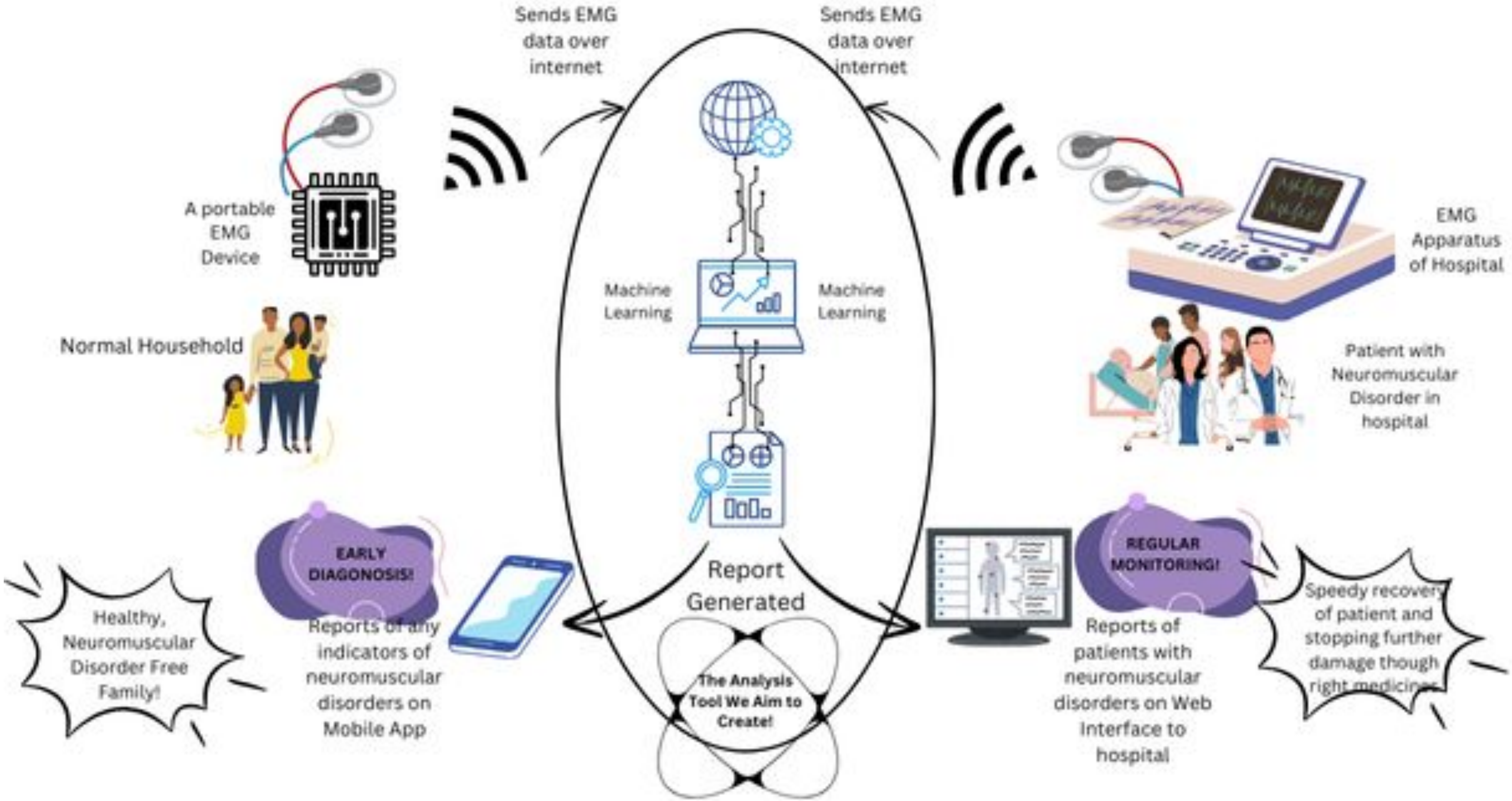
One standard problem with anomaly detection models is misleading metrics. While accuracy of a model is very high, it may mean that it is simply not sketching a good enough boundary.

In absence of test data, validation becomes even harder. Hence we defined 6 functions based on literature review from Electrodiagnosis in Diseases of Nerve and Muscle, Jun Kimura and tested our models on those anomalous signal whether it is able to identify it or not. Here are the metrics.

https://docs.google.com/spreadsheets/d/1GK8E_OhKFIJ29XLF9kQxhPOPJON1MqaIzUSGY8CEDcA/edit?gid=0#gid=0

Solution-at-a-Glance

Solution Overview



Technical Flow and Overview

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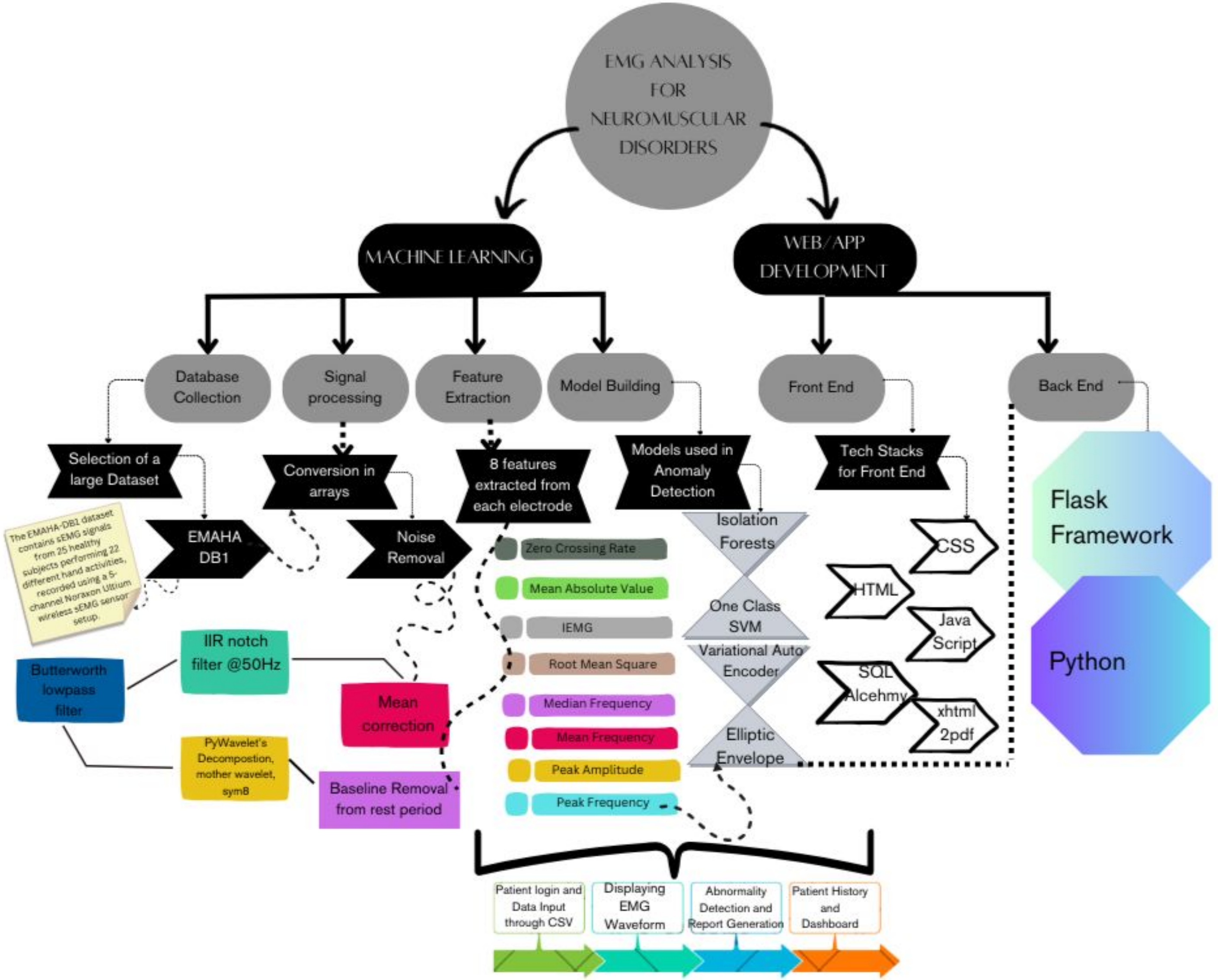

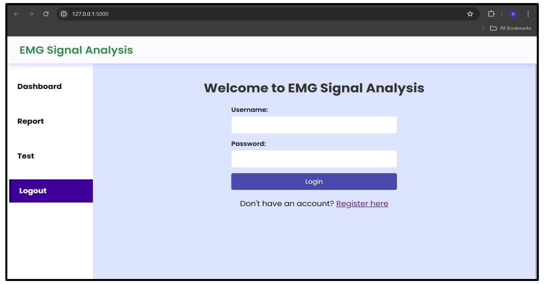

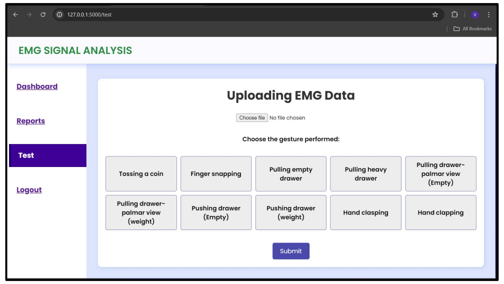

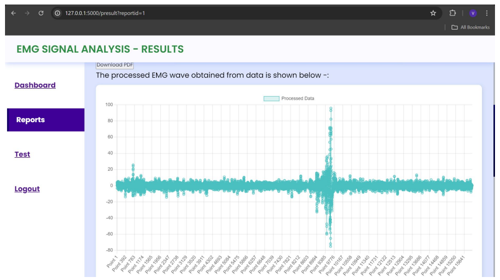

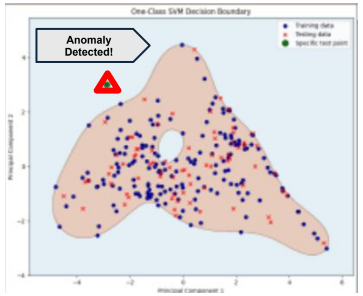

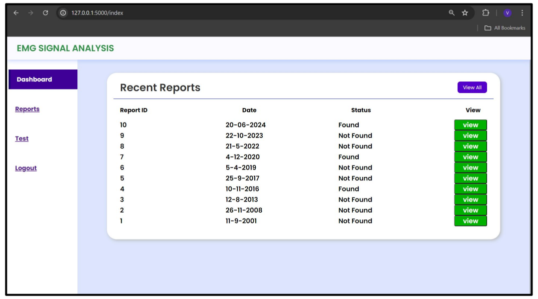

Step 1

Patient Registration and Login on Website

The patients can easily register themselves on the website and login thereafter.

Step 2

Uploading the EMG signal file

The user has to select the action he/she is performing and correspondingly upload the action's EMG file.

Step 3

Signal Processing on Backend

We at backend perform signal processing and remove noise from biomedical signal to make it ready for anomaly detection.This processed signal is displayed.

Step 4

Anomaly Detection using ML Algorithms

Utilizing Elliptic Envelope, heeding to the Gaussian Distribution in database, we tell the patient if any anomaly is detected.

Step 5

Report Generation and Dashboard

A comprehensive report is generated, and can be saved as a PDF file. The patient history gets saved in their accounts and can be accessed any time.

charak

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Thank you!