EMG Signal Acquisition and Processing for Feature Extraction And Detection of Disease

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Abstract

Electromyography (EMG) is a diagnostic procedure for evaluating the health of muscles and the nerve cells that control them. Proper analysis of the results of EMG can reveal muscle dysfunction, nerve dysfunction, or issues with the transmission of nerve-to-muscle signals. This project aims to apply digital filters to a raw sEMG signal, extract time and frequency features and use it to predict the presence of any abnormalities using the sliding window method. This input can assist in training a machine-learning model to distinguish muscular patterns. The frequency range of the acquired data is used to predict if the tremors are in normal or abnormal condition. This project can classify the sEMG data based on frequency to indicate the patient's muscular response or electrical activity. This can help distinguish healthy conditions from Myopathy and Neuropathy. With a refined approach, this model can be used for Real-time detection of Parkinson's disease, ADHD, and other syndromes, providing a ballpark diagnosis for a quick approach to treatment or more refined testing or diagnostic procedures.

Keywords

Electromyography, Machine learning, Pattern recognition , Feature extraction, Real-time detection

Introduction

EMG Pattern Recognition involves detecting human movements through surface electromyographic (sEMG) signals, generated by muscle contractions. It has been deployed in various applications including powered upper-limb prostheses, electric power wheelchairs, human-computer interactions, and diagnoses in clinical applications[1-4]. Compared to other eminent bioelectrical signals (e.g. ECG, EOG, GSR), the study of surface EMG signal is arduous due to its random outcome probability [5].

Existing EMG pattern recognition approaches can be mainly classified into two types:

1. Feature engineering
2. Feature extraction

Machine Learning (ML) algorithms involve significant models like feature engineering and extraction. In EMG analysis, short time windows of the raw EMG signal are used to extract time and frequency features, improving information quality and density. According to numerous studies, both the quality and quantity of features have a significant impact on the performance of EMG pattern recognition [6-9].

EMG pattern recognition systems employ emerging deep learning architectures and methods like Gesture Recognition by Instantaneous Surface EMG Images, EMG-based estimation of Limb Movement Using Deep Learning And CNN, and EMG Pattern Classification Using Deep Belief Networks for Enhanced User Experience, with the introduction of shared larger EMG data sets and recent progress in techniques for addressing overfitting problems [10-12,14]. In few cases, the amalgamation of both feature engineering and extracting is done by inputting pre-processed data or pre-extracted features into a deep learning process with some benefits which have been demonstrated in Deep Learning for Electromyographic Hand Gesture Signal Classification Using Transfer

Learning, EMG-based estimation of Limb Movement Using Deep Learning And CNN, EMG Pattern Classification Using Deep Belief Networks for Enhanced User Experience [11-13].

Interfaces that rely on surface electromyography (sEMG) can be difficult to design because they require a signal function or model that ensures reliable control of a care system. sEMG analysis typically involves three methods to extract information based on the non-stationary signal behaviour: time, frequency, and time-frequency domain[15-17]. However, some practical factors such as changes in arm position may hinder robust myoelectric control. So, machine learning models are used for better results [18]. Overall, non-invasive electromyography (EMG) remains the optimal intuitive and easy-to-use interface for stroke rehabilitation compared to other methods [19-20].

Pattern recognition (PR) is challenging or even impossible in the post-stroke heterogeneous discrepancies in abnormal muscle signals and subject-dependent characteristics[21-24]. Analytically, at the signal preprocessing stage, signal cleaning (rejection, decimation, and down-sampling) and filtering an reduce but not eliminate this distortion[25-27]. Effective signal decoding requires further stages related to feature extraction and classification; however, material limitations are a hindrance [6,14,26-31].

During the learning, most supervised learning (SL) procedures are usually linear and are restricted to an estimate of classified labels [4,27,28]. Nevertheless, a supervised function support vector machine (SVM) permits to evade of linearity (while using non-linear attributes) and is broadly used in neural signal processing [31,32]. After acquiring signal data, it can be denoted by processed features, as the complexity of the raw data degrades the capability of the method to correctly classify [6,28,33]. Those features have small dimensional masses and can reveal exact signal parameters more proficiently (compared to raw signals), but feature selection needs domain skill and remains a tough job [35,6]. Additionally, redundancy and probable computational load (important for real-time use) [34,35] can be caused by extracted feature characteristics from identical and different domains. Lastly, due to model overfitting in practical use, the theoretical number of feature components is limited[14,33].

It is possible to address the challenges associated with EMG signal-based hand gesture recognition by using Machine Learning techniques [36]. SVMs, k-nearest neighbours (k-NN), decision trees, random forests, linear discriminant analysis, artificial neural networks (ANN), convolutional neural networks, and gated recurrent unit networks are some commonly used strategies for hand gesture detection[37-49]. The traditional features used for accurate hand gesture recognition are defined in three domains:

- time domain - mean absolute value (MAV) and zero crossing (ZC) [50]
- frequency domain - median frequency and power spectrum ratio [30]
- time-frequency domain - wavelets [51].

Tremors in neurological patients [52] have clinically described their mode of presentation as

- Rest - appears during rest
- Postural - triggered by maintaining a posture or a position against gravity
- Kinetic tremor - induced by a voluntary movement (maximal near the target) [53]

The prominent frequency and the power spectral density categorize tremors in a clinical setting. Rest tremor frequency is typically in the range of 3–6 Hz and may rise with mental stress or contralateral voluntary motion [53,54]. Idiopathic Parkinson’s Disease is the root cause of rest tremor. Postural tremor frequency lies between 4 and 12 Hz. Postural tremors in the upper limbs lead to many disorders. Essential tremor is the leading cause [55]. Kinetic tremor frequency usually lies between 2 and 7 Hz [53].

The objective of this project is to predict the irregularities or the presence of disorders in the patient's conditions, at an early stage, using the conditional statement of Python programming language. It mainly focuses on the features of the EMG signal, especially the time and frequency domain. The primary reasons that motivated us to pursue this research were

- Increased occurrence of neuromuscular diseases among all age groups in recent years has led to many innovations in medical science. This is also an attempt to make a better service.
- Delayed diagnostic decisions often lead to tragic consequences whereas quality service implies diagnosing patients correctly with effective treatment at the soonest.

- The provision of quality services at affordable costs can be achieved by employing appropriate program-based algorithms and decision support systems.

In this paper, we have used a machine learning model and sEMG signals-based pattern recognition model to achieve real-time response [52]. For data acquisition, we use the sEMG signal data set, but we have also made a feature to incorporate real-time data measured from an indigenously developed sensor. For preprocessing, we use a Butterworth filter to remove noise and smooth the signal. For feature extraction, we use the pre-processed signals in the sliding window. The flow diagram explaining the entire procedure of the feature extraction is shown in Figure 1.

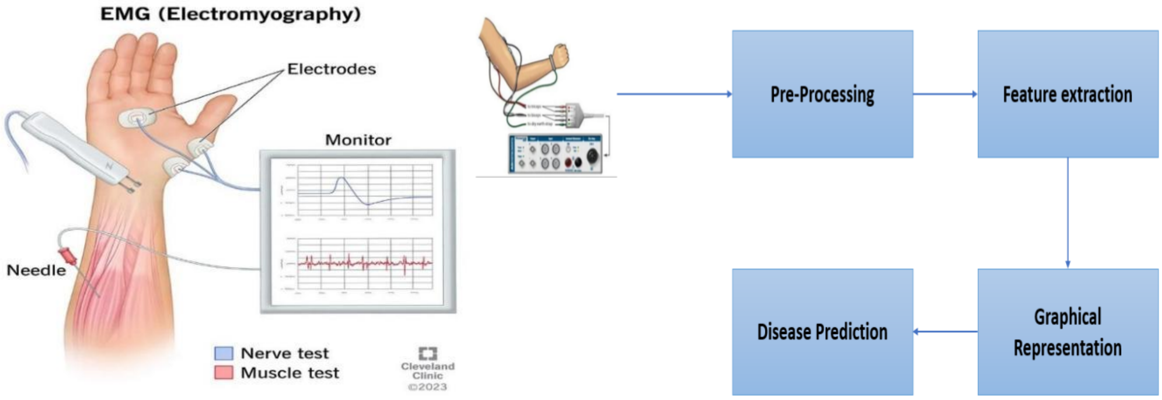

Figure 1 - Flow diagram of Feature Extraction

Materials and Methods

EMG findings in neuropathy and myopathy reflect the underlying pathophysiology of these conditions. Neuropathy is characterised by reduced nerve conduction and denervation-related changes, while myopathy is associated with direct muscle damage and alterations in MUAPs. EMG, besides other diagnostic tests, plays a vital role in distinguishing between these conditions (as shown in Figure 2) and guiding clinicians in the diagnosis and management of neuromuscular disorders. It can be seen that the primary distinguishing factor is frequency in this case.

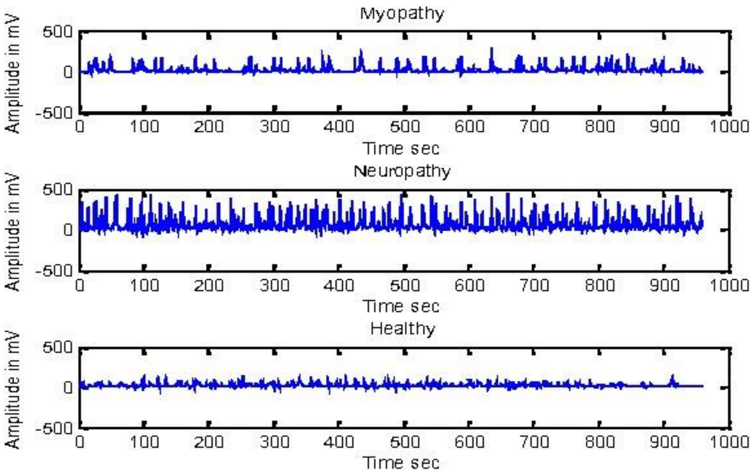

Figure 2 - Graphical Comparison of healthy, neuropathic and myopathic conditions

- **Sensors and Data Acquisition -** To facilitate real-time processing, we use the indigenously developed EMG sensor to acquire the sEMG data [56]. The sensor is developed using Arduino sensors. These sensors measure the electrical activity of the muscles of the palm at a sampling frequency of 2000 Hz. The features are estimated using a frame of 500 and a step of 250. Data from the sensor is transmitted to the computer by the program. For preliminary detection, we have used a readily available data set of EMG. There is a facility for analysing real-time data which can be acquired using the sensor.

- **Method -** The original signal (as shown in Figure 3) is pre-processed for rectification and filtered to remove the noise at first. Then, the time domain features representative of the data are extracted. The proposed approach for classification uses a sliding window protocol for all the features. Our model meticulously presents separate and detailed algorithms for both training and testing.

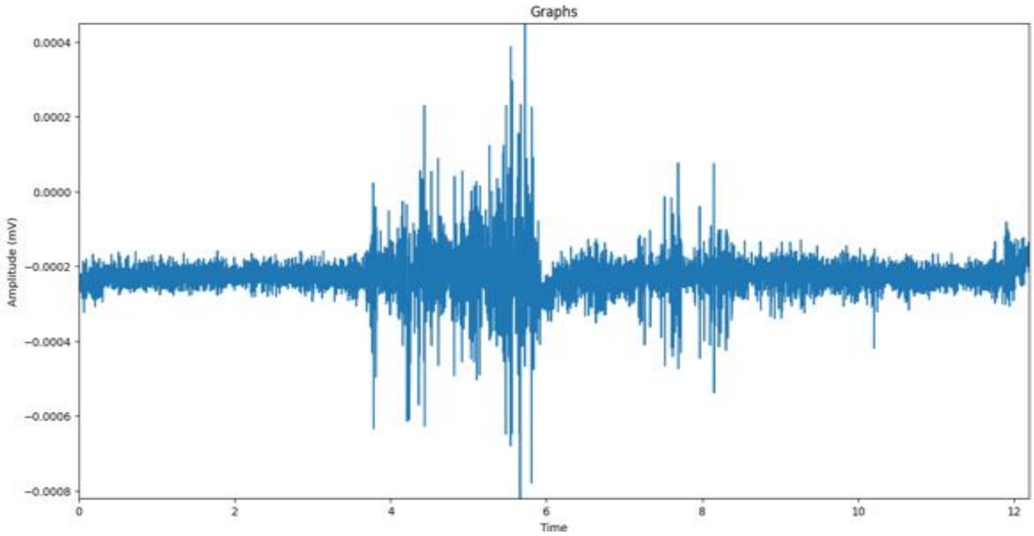

Figure 3 - Raw Data Plot of EMG Signal from the data set

1. **Preprocessing** - The purpose of the preprocessing is to denoise the acquired signal and make it easy to extract features. The original signal has additional noise that can generate invalid features and interfere with the classification. For training, the observed signals are normalised at first, with each element of each matrix being in the range determined by using a notch filter (as shown in Figure 4) [57]. We design the filter to smooth the signal and reduce the noise by analysing the signal frequency component and noise. The cut-off frequency of the 4th-order digital Butterworth filter is set at 10 Hz which is appropriate due to the use of Fourier transform. Then, the detection function removes the signals above the higher cut-off of 500 Hz to extract the muscle activity range[58]. The muscle activity region can be found by calculating the spectrum energy from filtered data, based on sampling intervals that can be extracted. So, the time area of muscle activity can be found. Combining both Butterworth and notch filters and applying filters both forward and backward on a signal help eliminate phase lag and give better results. This combination ensures the correct amplitude and phase relationships across a wide tuning range to create adjustable Z-transforms without sacrificing the gain of the passband.

```
from scipy import signal
import matplotlib.pyplot as plt
import numpy as np
import jwt


2 usages
def notch_filter(x, samplerate, plot=False):
    x = x - np.mean(x)

    high_cutoff_notch = 59 / (samplerate / 2)
    low_cutoff_notch = 61 / (samplerate / 2)

    [b, a] = signal.butter( N: 4,  Wn: [high_cutoff_notch, low_cutoff_notch], btype='stop')

    x_filt = signal.filtfilt(b, a, x.T)
    #Applies a digital filter forward and backward to a signal
```

Figure 4 - A snippet of the code from Digital Processing

2. **Noise minimization** - Tremor time series need noise removal, achieved using Frequency-selective filters or adaptative filters [54]. Wavelet (time-scale distribution) denoising may act as a band-pass filter for a given signal. Wavelet transforms exist in both frequency and time domains and are effective for random signals like neurological tremors [59]. Wavelets express a signal as a linear combination of given sets of functions (wavelet

transform). The mother wavelet function can be shifted and dilated to form the transforms. Wavelet-based denoising can efficiently isolate activities of interest such as EMG discharges (as shown in Figure 5), from noise in the tremor signal [54]. The noise (amplitude-based) and the desired signal (frequency-based) can be elucidated using graphical representation.

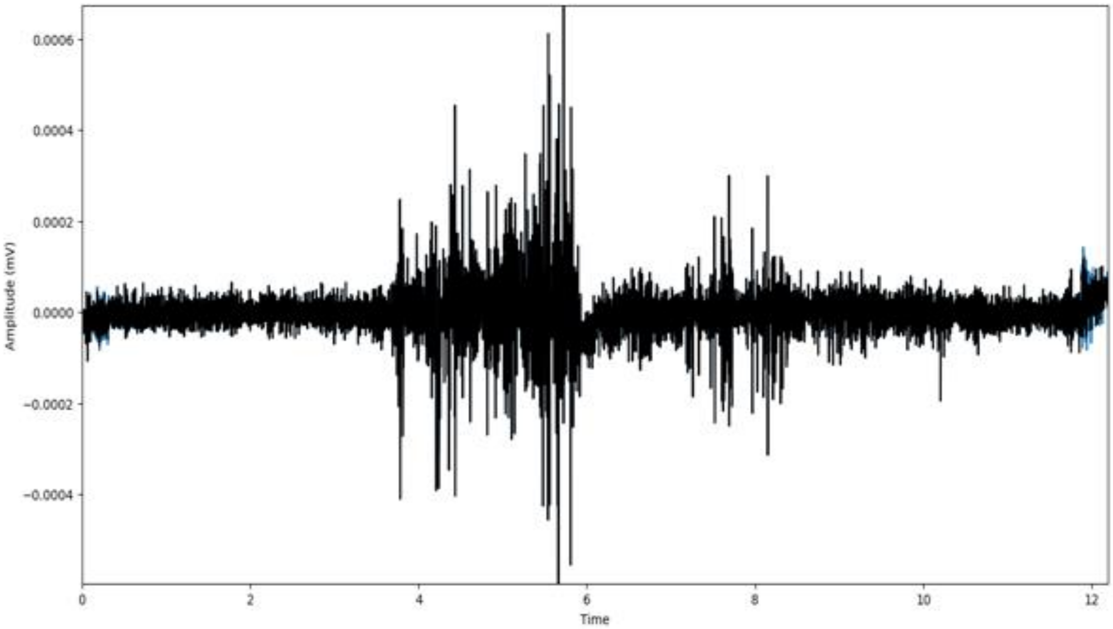

Figure 5 - Filtered and Processed Signal from the data set

3. **Feature Extraction** - For feature extraction, the sliding window technique is used. The data set is divided into data segments. For accuracy in real-time, the step size of the two consecutive sliding windows is set, based on the frames. For extracting features in the sliding window, to reduce the room for error, we select ten features in the time domain: Variance, RMS, MAV, Wavelength, ZCR, Wilson amplitude, AAC Myo-pulse percentage rate, log detector, and integrated EMG [60-62]. The formulae for these features are discussed in Table 1.

Table 1: Time-domain Indicators for EMG Signal Processing

Features	Formula	Denotation
Variance	$\mathrm{VAR(s(k))} = \frac{1}{\mathrm{N}-1}\sum_{\mathrm{k-1}}^{\mathrm{N}} \mathrm{s(k)}^2$	s(k) - k-th voltage value that makes up the signal N- number of elements
RMS	$\mathrm{R} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{k=1}}^{\mathrm{N}} \mathrm{s(k)}^2}$	L- total length of the curve or the sum of the Euclidean distances between successive points m- diameter of the curve N- number of steps in the curve
MAV	$\mathrm{M} = \frac{1}{\mathrm{N}}\sum_{\mathrm{k=1}}^{\mathrm{N}} \lvert \mathrm{s(k)} \rvert$	s(k) - k-th voltage value that makes up the signal N- number of elements
Wavelength	$\mathrm{W} = \sum_{\mathrm{k=2}}^{\mathrm{N}} \lvert \mathrm{s(k)} - \mathrm{s(k-1)} \rvert$	s(k) - k-th voltage value that makes up the signal
Zero crossing	$\mathrm{zcr} = \frac{1}{\mathrm{T}-1}\sum_{\mathrm{t=1}}^{\mathrm{T-1}} 1_{\mathrm{R<0}}(\mathrm{S_t S_t} - 1)$	s is a signal of length T and $1_{R<0}$ is an indicator function
Wilson Amplitude	$\mathrm{WAMP} = \sum_{\mathrm{n=1}}^{\mathrm{N-1}} f(\lvert x_n - x_{n+1} \rvert)$	x_n - n-th voltage value that makes up the signal N- number of elements

	$f(x) = \begin{cases} 1 & \text{if } (x \geq y) \\ 0 & \text{otherwise} \end{cases}$	
AAC	$i_{Avg} = \frac{1}{N}\sum_{t=1}^{N} x_t$	x_t - instantaneous values in the EMG time signal N- number of elements
MYOP	$\mathrm{MYOP} = \frac{1}{N}\sum_{k=1}^{N} \Phi(x_k)$ $\Phi(x) = \begin{cases} 1 & \text{if } x > L, \\ 0 & \text{otherwise} \end{cases}$	x_k - k-th voltage value that makes up the signal
LOG	$\mathrm{LOG} = \exp\left(\frac{1}{N}\sum_{k=1}^{N} \log(\lvert x_k \rvert)\right)$	x_k- k-th voltage value that makes up the signal
IEMG	$\mathrm{IEMG} = \sum_{k=1}^{N} \lvert x_k \rvert$	x_k - k-th voltage value that makes up the signal

Similarly, we select six features in the frequency domain: Frequency rate, Mean and Total power, Mean, Median, and Peak frequency [63]. The formulae for the frequency features are discussed in Table 2.

Table 2: Frequency-domain Indicators for EMG Signal Processing

Features	Formula	Denotation
FR	$\mathrm{FR} = \sum_{j=LLC}^{ULC} P_j \Big/ \sum_{j=LHC}^{UHC} P_j$	LLC and ULC - lower and upper cut-off frequency P_j - EMG power spectrum at frequency bin j
MNP	$\mathrm{MNP} = \sum_{j=1}^{M} P_j \Big/ M$	Pj - EMG power spectrum at frequency bin j
TTP	$\mathrm{TTP} = \sum_{j=1}^{M} P_j = \mathrm{SM0}$	SM0 – zero spectral moment
MNF	$\mathrm{MNF} = \sum_{j=1}^{M} f_j P_j \Big/ \sum_{j=1}^{M} P_j$	fj- frequency value of EMG power spectrum at frequency bin j
MDF	$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j$	Pj - EMG power spectrum at frequency bin j
PKF	$\mathrm{PKF} = \max(P_j), j = 1, \ldots, M$	Pj - EMG power spectrum at frequency bin j

To improve the accuracy, besides using the feature parameters, we also extract the pre-processed signals through the sliding windows and put them together to form the final matrix used in the classifier.

Machine learning (ML) models are increasingly being used in the processing and feature selection of electromyography (EMG) signals to enhance the accuracy and efficiency of tasks such as pattern recognition, classification, and identification of muscle activities [29, 36, 37]. Here are some common machine-learning models and techniques used in EMG signal processing:

1. Support Vector Machines (SVM): SVM is a popular supervised learning algorithm used for classification tasks. It has been employed in EMG signal processing to classify different muscle activities or to identify specific patterns associated with certain neuromuscular disorders [31,32].
2. Artificial Neural Networks (ANN): ANNs, particularly deep learning models, have shown success in processing complex EMG signals [45, 46]. Deep learning architectures like convolutional neural networks

(CNNs) are capable of automatically learning hierarchical features from raw EMG data, eliminating the need for manual feature extraction [11].

3. Random Forests: Random Forest is an ensemble learning method that combines the predictions of multiple decision trees. It can be used for classification tasks in EMG signal processing, especially in scenarios where interpretability is important.
4. K-Nearest Neighbors (KNN): KNN is a simple and effective algorithm for classification tasks. It has been applied to EMG data for pattern recognition and muscle activity classification.
5. Hidden Markov Models (HMM): HMMs are probabilistic models that have been used in the analysis of time-series data, including EMG signals. They can be employed for gesture recognition or identifying patterns in sequential muscle activities.
6. Principal Component Analysis (PCA): PCA is a dimensionality reduction technique used to transform high-dimensional data into a lower-dimensional space. It has been applied to EMG data for feature selection and to reduce the dimensional complexity of the dataset [6].
7. Wavelet Transform: The wavelet transform is a time-frequency analysis technique that has been used to extract features from EMG signals. It allows for the representation of signal characteristics at different time scales, which can be useful in capturing dynamic changes in muscle activity [35].
8. Autoencoders: Autoencoders are a type of neural network used for unsupervised learning. They can be employed for feature learning and representation of EMG signals, helping to discover meaningful patterns in the data [24]. However, in this project, we have used Sliding Window Protocol which allows even better data transmission.
9. Genetic Algorithms: Genetic algorithms can be applied to optimize feature selection for EMG signal processing. They help identify the most relevant features that contribute to the discrimination of different muscle activities.

These machine-learning models and techniques play a crucial role in the development of intelligent systems for EMG signal analysis, classification, and feature selection. The choice of a specific model depends on the nature of the task, the complexity of the data, and the goals of the analysis.

Results and Discussion

First, the raw data is processed by noise removal and filtered. Now this filtered data will be used to extract features useful for diagnosis. We cannot get all the features as they are very complex but a ball-park diagnosis can be provided using this project. The frequency can tell if the tremors are in normal range or less or more. Now for visual representation, we have used graphs so that people can easily understand because values would not mean anything to most people but looking at differences between healthy and diseased graphs will hold meaning. The results obtained in electromyography (EMG) signal feature extraction involve the identification and quantification of relevant characteristics within the EMG signals [1,6-9]. Feature extraction is a crucial step in processing EMG data as it transforms raw signals into a set of discriminative features that can be used for analysis, classification, or further interpretation. By extracting relevant features from EMG signals, researchers and clinicians gain insights into the underlying patterns of muscle activity, which can aid in understanding motor control, diagnosing disorders, and developing effective rehabilitation strategies. The choice of features depends on the specific goals of the analysis and the characteristics of the EMG signals under investigation.

Electromyography is used for recording the electrical activity produced by skeletal muscles. It can distinguish myopathy from neurogenic muscle wasting and weakness. The frequency range for healthy conditions is 8-12 Hz, but for myopathic conditions, the range is from up to 3hz and for neuropathy it is beyond 12hz up to 16hz. By combining Butterworth and Notch filters and applying digital filters forward and backwards on a signal we can detect these (as shown in Figure 6).

This combination ensures the correct amplitude and phase relationships across a wide tuning range to create adjustable Z-transforms without sacrificing the gain of the passband. Butterworth filter gives a smooth output. This eliminates phase lag and gives better results.

The recommended cutoff frequency f_c for the high pass filter for attenuating these low-frequency artefacts is within the range of 5–30 Hz for conductive EMG sensors. A 400–500 Hz lowpass filter f_c is recommended for filtering high-frequency noise while maintaining EMG signal power.

The project uses the Denoising Wavelet of MATLAB to suppress the noise part of the signals and to recover f. It uses Sliding Window Protocol instead of autoencoders to select the appropriate size of data transmission.

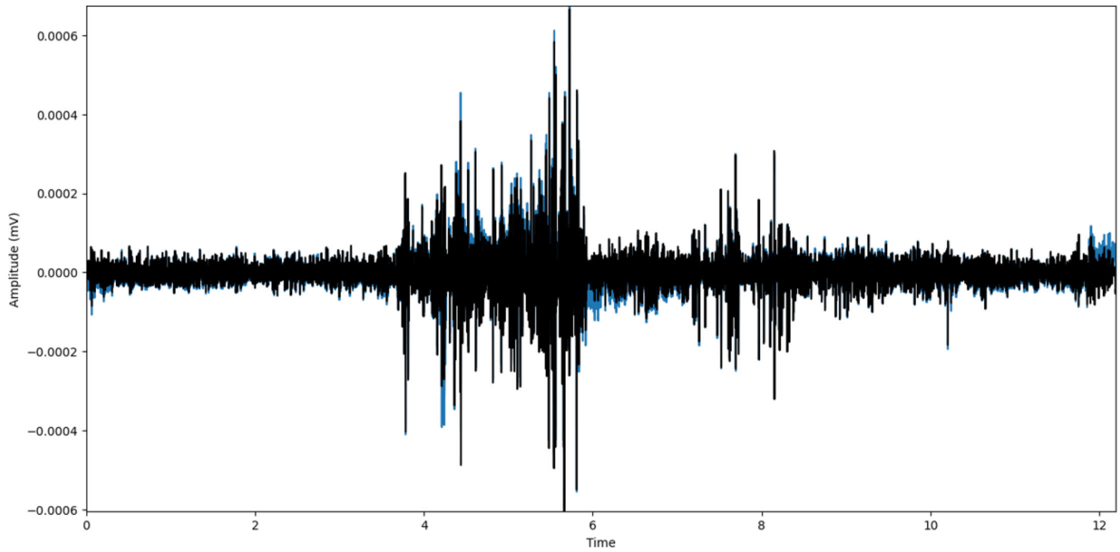

Figure 6 - Feature Extracted Signal from the data set

Real-time processing and outputs

- **Data Acquisition -** To collect the real-time EMG data a unique EMG sensor is used that interprets the biosignal acquired through the surface electrode and relays it to the Arduino circuit for digitization and further display through the program. Filters are also present within the sensor circuit which helps to minimize the noise. An unknown subject is seated in a resting condition and dirt is cleaned if present, which might affect the electrodes. Then the surface electrodes are applied to specific positions on the palm and hand as recommended by medical professionals. There are two polar electrodes, Bio-positive and Bio-negative, and a reference electrode that is placed on a bony region on the hand. After the electrode placement, EMG signal acquisition can be started by simply executing the Arduino program and checking the Serial Monitor for graphical output. A real-time frequency graph is obtained according to the muscular condition of the subject, which is then introduced to the Machine Learning model for further classification of the data. The settings to obtain the data are shown in Figure 7.

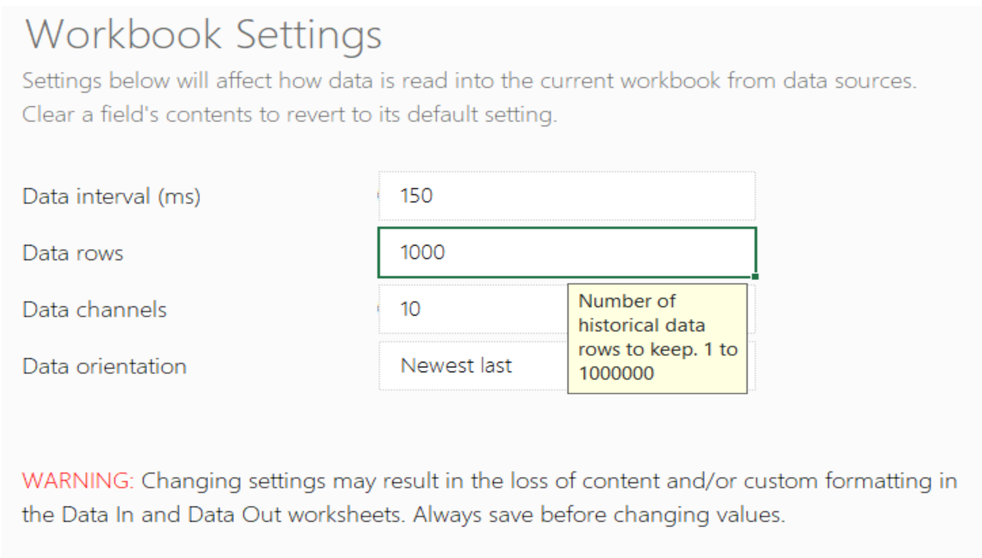

Figure 7 - Settings to acquire real-time data from the sensor

- **Data Segregation -** The Machine Learning program is designed to process data in the form of a 1D array. All the values in the rows of a column are treated as a 1D array for further processing. Now, since the real-time data acquired from the device, saved in the Excel format, has 2 columns (timestamp and values) it can't be used in the program to do further analysis (as shown in Figure 8). To make sure that the code works efficiently the data present only in the values column is taken and a separate file is created. When this file is fetched by the code, it can be read and processed easily as it is in the form of a 1D array.

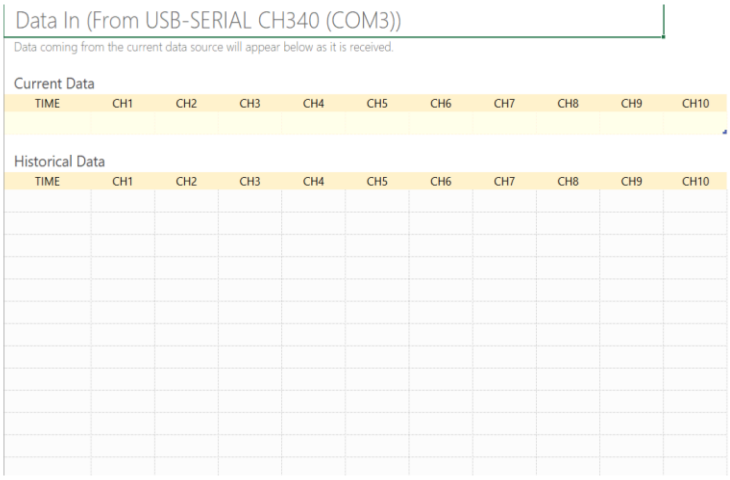

Figure 8 – Format to record data for sEMG of patients

Using the code on real-time data for the diagnosis of disease in patients, in real-time we have derived similar results as the available data sets. This also confirms this system's high accuracy and precision rate concerning other models using ML and Python for sEMG analysis. The results for the real-time voluntary subjects are provided below. First, the raw data, from the Excel sheet, is plotted graphically (as shown in Figure 9). After this, a combination of filters filters out the desired signal from background noise to plot another graph (as shown in Figure 10). The filtered data is again subjected to processing through Machine Learning Algorithms and the formulas provided in Tables 1 and 2. Lastly, the feature-extracted signal is plotted forming a superpositioned graph on raw data to display how the program works efficiently to eliminate noise and extract necessary signals for disease prediction applications (as shown in Figure 11). Here, the amplitude reduction represents that the noise has been filtered out because the noise has a higher amplitude than the required signal. However, there is no loss of frequencies from the data due to the proper transmission using the Sliding Window Protocol. This ensures that there is no data loss which might lead to wrong analysis and predictions in ball-park diagnosis of diseases.

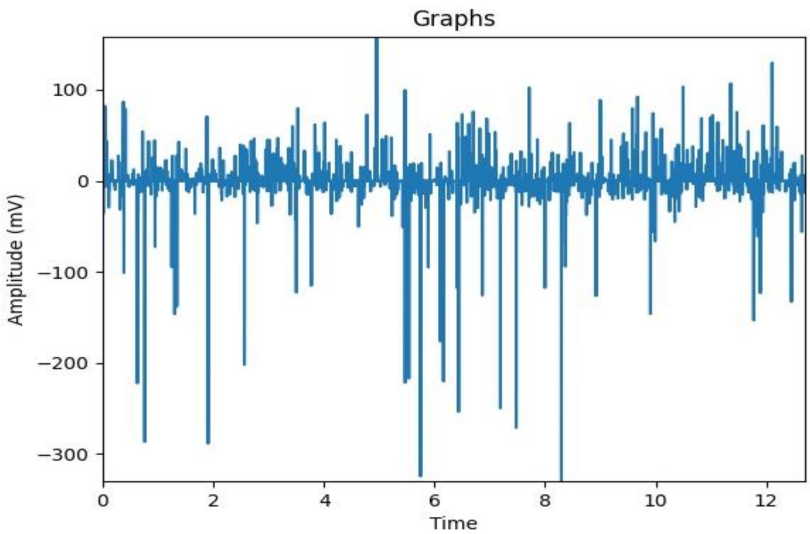

Figure 9 - Raw Data Plot of EMG Signal from the real-time data

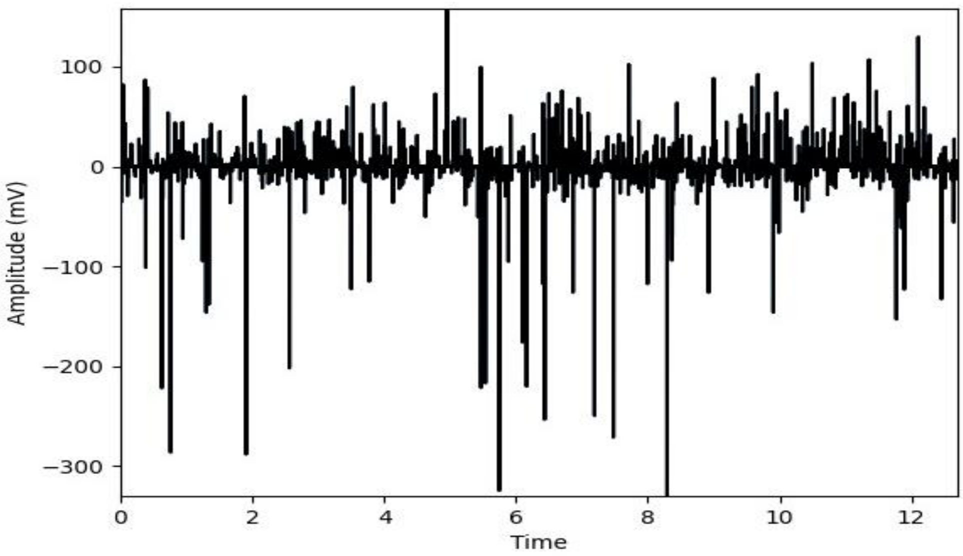

Figure 10 - Filtered and Processed Signal from the real-time data

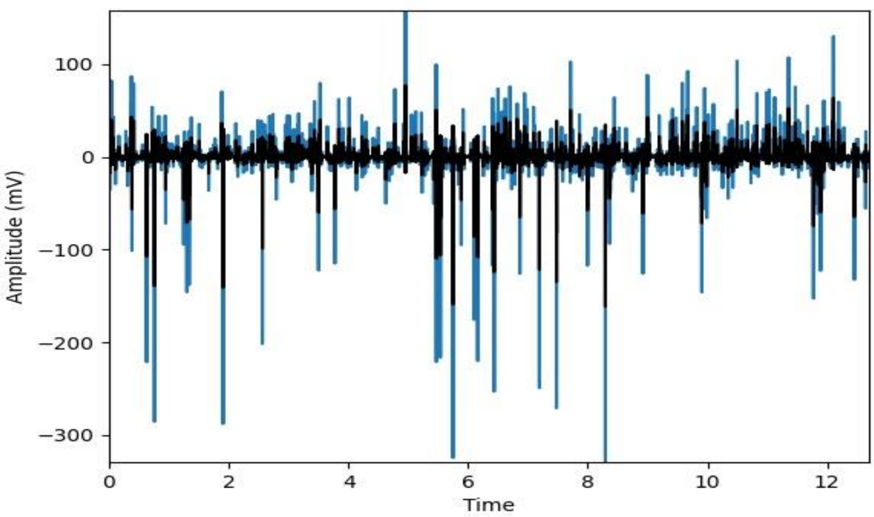

Figure 11 – Distinction of Feature Extracted Signal from the real-time data

Conclusion

The project aims to explore the intricacies of electromyography (EMG) signal acquisition and processing, focusing on robust feature extraction and graphical representation. Electromyography is a valuable technique for capturing electrical activity generated by muscles, providing a window into the neuromuscular system's functionality [31,32]. This project seeks to advance our understanding and application of EMG signals by developing a comprehensive framework that combines signal acquisition, processing, feature extraction, and graphical representation.

This project seeks to contribute to biomechanics and neuromuscular research by providing an advanced and comprehensive framework for EMG signal processing [54,59]. The outcomes of this project could have far-reaching implications, from improving our understanding of motor control to enhancing the development of intelligent systems for human-machine interaction. The combination of advanced signal processing techniques, feature extraction methods, and innovative graphical representations is expected to open new avenues for research and applications in the broader domain of biomedical engineering.

Discussion:

Electromyography is used for recording the electrical activity produced by skeletal muscles. It can distinguish myopathy from neurogenic muscle wasting and weakness. The frequency range for healthy conditions is 8-12 Hz, but for myopathic conditions, the range is from up to 3hz and for neuropathy it is beyond 12hz up to 16hz. By combining Butterworth and Notch filters and applying digital filters forward and backwards on a signal we can detect these (as shown in Figure 6).

This combination ensures the correct amplitude and phase relationships across a wide tuning range to create adjustable Z-transforms without sacrificing the gain of the passband. Butterworth filter gives a smooth output. This eliminates phase lag and gives better results.

The recommended cutoff frequency f_c for the high pass filter for attenuating these low-frequency artefacts is within the range of 5–30 Hz for conductive EMG sensors. A 400–500 Hz lowpass filter f_c is recommended for filtering high-frequency noise while maintaining EMG signal power.

The project uses the Denoising Wavelet of MATLAB to suppress the noise part of the signals and to recover f. It uses the Sliding Window Protocol instead of autoencoders to select the appropriate data transmission size. For now, it is best suited for ball-park diagnosis but with further modifications and training the model with diseased data sets, auto-analysis of graphs can be achieved eliminating the need for specialists to analyse the data for disease prediction.

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- **Ethical Approval**: Ethical Approval by an institutional review board or equivalent ethics committee was not applicable for this article as it does not involve any experiments involving interventions in human tissue.

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