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Machine Learning-Based Feature Extraction and Classification of EMG Signals for Intuitive Prosthetic Control

Chiang Liang Kok [1,*], Chee Kit Ho [2], Fu Kai Tan [3] and Yit Yan Koh [1]

1 College of Engineering, Science and Environment, University of Newcastle, Callaghan, NSW 2308, Australia
2 Engineering Cluster, Singapore Institute of Technology, Singapore 138683, Singapore
3 School of Science and Technology, Singapore University of Social Sciences, Singapore 599494, Singapore; philiptan004@suss.edu.sg
* Correspondence: chiangliang.kok@newcastle.edu.au

Abstract: Signals play a fundamental role in science, technology, and communication by conveying information through varying patterns, amplitudes, and frequencies. This paper introduces innovative methodologies for processing electromyographic (EMG) signals to develop artificial intelligence systems capable of decoding muscle activity for controlling arm movements. The study investigates advanced signal processing techniques and machine learning classification algorithms using the GRABMyo dataset, aiming to enhance prosthetic control systems and rehabilitation technologies. A comprehensive analysis was conducted on signal processing techniques, including signal filtering and discrete wavelet transform (DWT), alongside a composite feature set comprising Mean Absolute Value (MAV), Waveform Length (WL), Zero Crossing (ZC), Slope Sign Changes (SSC), Root Mean Square (RMS), Enhanced Waveform Length (EWL), and Enhanced Mean Absolute Value (EMAV). These features, refined through Linear Discriminant Analysis (LDA) for dimensionality reduction, were classified using Support Vector Machine (SVM) algorithms. Signal filtering and DWT improved signal quality, facilitating better feature extraction, while the diverse feature set enhanced classification accuracy. LDA further improved accuracy by isolating the most informative features, and the SVM achieved optimal performance in decoding complex EMG patterns. Machine learning models, including K-Nearest Neighbor (KNN), Naïve Bayes (NB), and the SVM, were evaluated, with the SVM outperforming the others. The significance of these results lies in their potential applications in prosthetic control systems and rehabilitation technologies. By accurately decoding muscle activity, the developed systems can facilitate more intuitive and responsive robotic arm movements, contributing to the advancement of innovative solutions for individuals requiring prosthetic devices or undergoing rehabilitation, hence improving the quality of life for users. This research marks a significant step forward in the integration of advanced signal processing and machine learning in the field of EMG analysis.

Keywords: machine learning; signal processing; electromyography (EMG)

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1. Introduction

Signals are the backbone of science, technology, and communication, serving as the fundamental carriers of information that enable processes and facilitate understanding. At their core, signals transmit messages through changing patterns, amplitudes, and frequencies over time. In the realm of deep learning, accurately modeling these signals is critical, as it requires identifying the key factors of each algorithm and understanding the relationships between different signals and features. This understanding is crucial for making accurate predictions. Surface Electromyography (SEMG) based Hand Gesture Recognition (HGR) has shown limitations due to individual variability in EMG signals [1]. Each person's unique EMG signal necessitates personalized HGR systems. Recent studies highlight the potential of fusing SEMG with electroencephalography (EEG) signals to enhance the flexibility and accuracy of arm motion recognition. This fusion, facilitated by advanced techniques like Graph Convolutional Networks (GCNs) and Functional Connectivity, establishes a deeper link between brain signals (EEG) and motor neuron signals (SEMG) [2]. Technological advancements now allow for the non-invasive capture of high-definition SEMG signals with minimal noise, providing new insights for neuroscientists. These signals are integral to Human–Machine Interfaces (HMI) [3], which rely on the brain's bio-signal processing and represent the future of biocybernetics. For individuals without hands, EMG technology plays a pivotal role by enabling the control of prosthetic limbs or assistive devices through muscle activity detection. This technology translates muscle signals into meaningful commands, allowing for the precise control of prosthetic hands, thereby enhancing autonomy and quality of life. This research aims to harness advanced signal feature extraction methodologies and machine learning algorithms to analyze the GRABMyo dataset, which contains unique EMG signals from the forearm. The dataset includes three sessions with 43 participants, each performing 16 gestures, captured seven times per gesture. By employing signal processing techniques such as Mean Absolute Value (MAV), Waveform Length (WL), Zero Crossing (ZC), Slope Sign Change (SSC), Root Mean Square (RMS), Energy of Wavelet Coefficients (EWLs), and Enhanced Mean Absolute Value (EMAV), this study seeks to uncover nuanced patterns within the EMG signals indicative of forearm muscle activity. Dimensionality reduction techniques like Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) will refine the extracted features, enhancing their discriminative power. Machine learning models will then be used to predict various forearm muscle movements based on these features, potentially advancing the development of intuitive prosthetic control systems and rehabilitation technologies. The research will involve preprocessing raw EMG signals, decomposing and reconstructing them using the Biorthogonal 3.3 Discrete Wavelet Transform (DWT), and implementing feature extraction and dimensionality reduction. Finally, classification algorithms will predict specific hand gestures from the optimized dataset, focusing on five primary gestures: Little Finger Extension (LFE), Index Finger Extension (IFE), Thumb Extension (TE), Hand Open (HO), and Hand Close (HC). Despite potential limitations, such as the quality of the dataset and variability in EMG signals, this research aims to enhance our understanding of forearm muscle signals and improve the accuracy of gesture predictions, ultimately contributing to the advancement of assistive technologies.

Feature Extraction

Signal Processing

2. Literature Review

The literature on machine learning-based feature extraction and classification of EMG signals for intuitive prosthetic control has expanded significantly in recent years, reflecting the growing interest in developing advanced assistive technologies. Traditional approaches to EMG signal analysis often relied on basic statistical methods and manual feature selection, which posed limitations in capturing the complex patterns inherent in EMG signals. Recent advancements have introduced more sophisticated techniques, such as time–frequency analysis and wavelet transform, to better characterize EMG signals. For instance, this work [3] emphasized the importance of feature extraction methods like Mean Absolute Value (MAV), Zero Crossing (ZC), and Root Mean Square (RMS) for enhancing signal interpretation. These methods, when combined with machine learning algorithms, have shown promising results in classifying various hand gestures and muscle movements. Machine learning [4,5], particularly deep learning, has revolutionized EMG signal processing by automating feature extraction and improving classification accuracy. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been employed to learn spatial and temporal dependencies in EMG data, leading to significant improvements in gesture recognition tasks. This work [6] demonstrated that CNNs could effectively capture the spatial patterns of EMG signals, resulting in a higher classification performance compared to traditional methods. Similarly, the paper [7] utilized Support Vector Machines (SVMs) and Random Forests to classify EMG signals from the Ninapro database, achieving high accuracy and robustness. The integration of EMG with other bio signals, such as elec-

Feature Extraction once after Signal Processing troencephalography (EEG), has also been explored to enhance prosthetic control systems. Other research [8–11] investigated the fusion of SEMG and EEG signals using Graph Convolutional Networks (GCNs) to improve the recognition of complex arm movements. This multi-modal approach leverages the complementary information provided by different types of bio signals, leading to more reliable and flexible control mechanisms. Additionally, feature selection and dimensionality reduction techniques, such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), have been applied to optimize the features extracted from EMG signals, reducing computational complexity while maintaining high classification accuracy. The application of these advanced techniques has significant implications for the development of intuitive prosthetic control systems. By enabling a more accurate and responsive control of prosthetic limbs, these methods can substantially improve the quality of life for individuals with limb loss. Future research is likely to focus on further refining machine learning models, exploring new feature extraction methods, and integrating additional bio signals to enhance the functionality and usability of prosthetic devices. Overall, the convergence of machine learning and EMG signal processing represents a promising frontier in the field of assistive technology, with the potential to deliver more natural and effective prosthetic control solutions.

Figure 1 depicts the comprehensive process diagram outlining the distinct phases of the research from Signal Processing to Machine Learning.

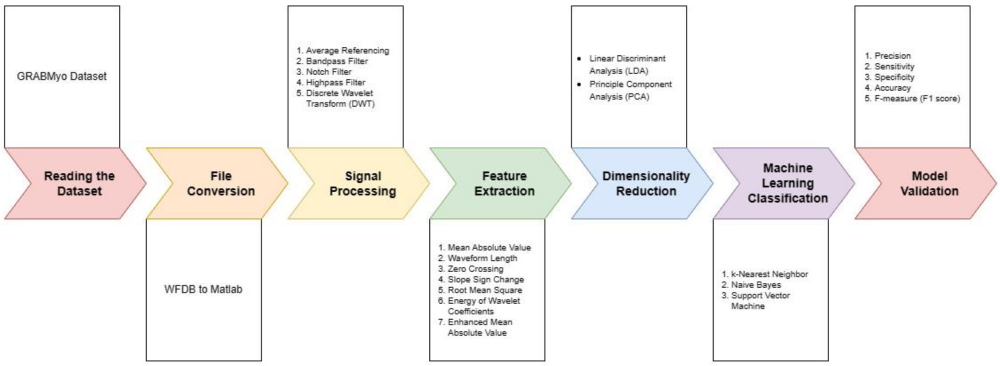


Figure 1. Overall process diagram for the approach of the research.

A thorough exploration of the key concepts and methods applied will be addressed in the subsequent sections, namely Sections 3 and 4.

3. Overview: GRABMyo Dataset

In this study, we utilized the Gesture Recognition and Biometrics ElectroMyogram (GrabMyo) dataset, a comprehensive collection of electromyographic (EMG) signals recorded during various hand gestures. The dataset, presented by researchers at the University of Waterloo, comprises EMG data captured from multiple sensors worn on the forearm, along with corresponding labels for different hand movements. The GrabMyo dataset offers valuable insights into human hand motor control and has been widely used for gesture recognition and prosthetic device development [12].

3.1. Device Information

The device used to capture signals from the participant's forearm, as shown in Figure 2, is a multi-channel amplifier manufactured by OTBioelettronica. The model EMG-USB2+ is a bioelectrical signal amplifier capable of measuring surface electromyography (sEMG) signals, intramuscular electromyographic (iEMG) signals, electroencephalographic (EEG) signals, and electrocardiographic (ECG) signals. Table 1 outlines the configurations used in the device for capturing EMG signals in the GRABMyo dataset [12].

Figure 2. EMG-USB2+ multichannel amplifier by OTBioelecttronica [12].

Table 1. Configurations used in the device for capturing the EMG signals [12].

Sampling Frequency	2048 Hz
Bandpass Filter (Hardware)	10–450 Hz
Gain (Hardware)	500 Hz
Number of Channels	32 Channels

3.2. Forearm Electrode Locations

A total of 28 electrodes were placed at four main points on the forearm: the proximal wrist, distal wrist, distal forearm, and proximal forearm. The table and image below illustrate the number and locations of these electrodes. Figure 3 visually depicts the forearm with the electrodes attached. Table 2 provides details on the configuration for setting up the electrodes with the corresponding channels available in the EMG-USB2+ multichannel amplifier [12].

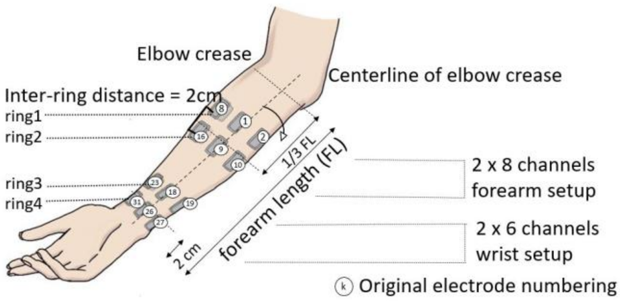


Figure 3. GRABMyo dataset setup for electrodes on the forearm [12].

Table 2. Setup location for electrodes on the forearm (from the electrodes on the left to the electrodes on the right) [12].

Location of Electrodes	Number of Channels	Channels	Corresponding Column Number
Proximal wrist (Ring 4)	6-channel wrist setup	{W7–W12}	{26, 27... 31}
Distal wrist (Ring 3)	6-channel wrist setup	{W1–W6}	{18, 19... 23}
Distal forearm (Ring 2)	8-channel forearm setup	{F9–F16}	{9, 10... 16}
Proximal forearm (Ring 1)	8-channel forearm setup	{F1–F8}	{1, 2... 8}
Unassigned channels	4 channels not setup	{U1–U4}	{17, 24, 25, 32}

3.3. Analysis of GRABMyo Dataset

The GRABMyo dataset consists of signals recorded from trials involving 43 healthy male and female participants, repeated across three sessions. In each session, all 43 participants perform 16 gestures, which are recorded over seven trials [12]. Figure 4 provides an overview of the folder structure after extracting the compressed GRABMyo dataset.

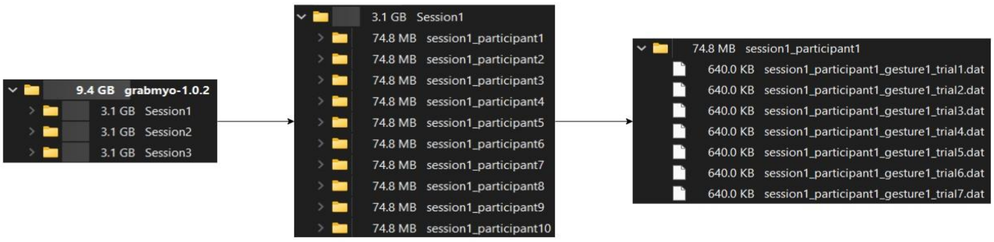


Figure 4. GRABMyo dataset folder and file exploration.

Electromyography signals are sampled at a rate of 2048 Hz. In each trial, data is recorded from 28 forearm channels over 5 s intervals, resulting in 10,240 samples per channel, and a total of 286,720 samples for all 28 channels [12]. Figure 5 presents a flowchart outlining the comprehensive process for capturing signals. This includes the initial data acquisition from various sensors, recording of hand gestures over specified sample periods, and final data storage in a structured database format. The flowchart ensures a clear understanding of each phase, from raw signal collection to the preparation of the dataset for analysis.

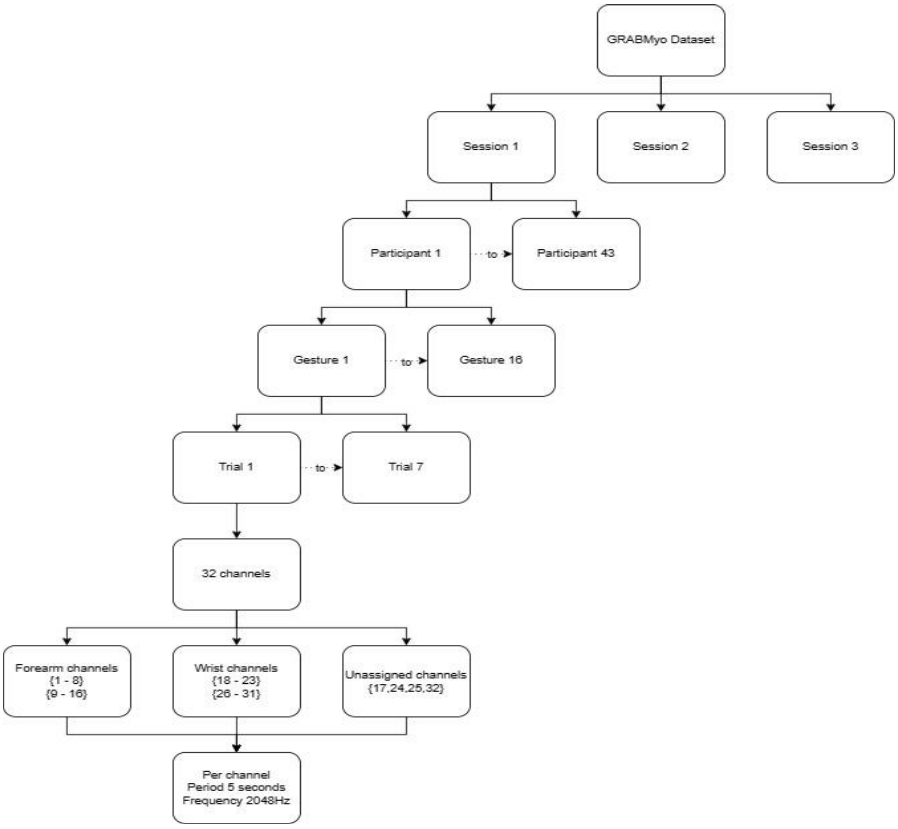
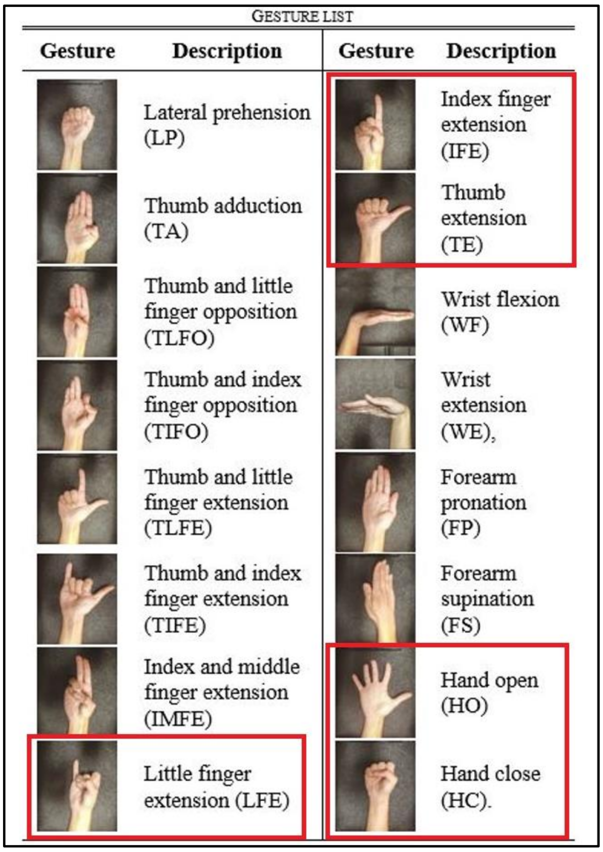


Figure 5. GRABMyo dataset flowchart for signal acquisition.

3.4. Hand and Fingers Gesture List

The GRABMyo dataset includes a total of 16 gestures [13–17], representing the research focus on gathering data on these specific movements. These gestures are sampled at 5 s intervals for each trial. This research will concentrate on five selected gestures chosen specifically to comprehend more generalized hand movements commonly used in daily activities. The selected hand gestures include Little Finger Extension (LFE), Index Finger Extension (IFE), Thumb Extension (TE), Hand Open (HO), and Hand Close (HC).

This proposed work involves the use of the GRABMyo dataset. The GRABMyo dataset is an open-source collection of electromyographic (EMG) signals recorded from multiple participants during various hand gestures. This suggests that the data used in the research come from a pre-existing dataset and do not involve new human participants for the study. For further clarity on data reuse and the consensus required, we have referred to the terms and conditions under which the GRABMyo dataset, shown in Figure 6, was originally published and studied how the data can be used. We have also followed the guidelines carefully and have included a proper citation in the paper.


GESTURE LIST

Gesture	Description	Gesture	Description
	Lateral prehension (LP)		Index finger extension (IFE)
	Thumb adduction (TA)		Thumb extension (TE)
	Thumb and little finger opposition (TLFO)		Wrist flexion (WF)
	Thumb and index finger opposition (TIFO)		Wrist extension (WE),
	Thumb and little finger extension (TLFE)		Forearm pronation (FP)
	Thumb and index finger extension (TIFE)		Forearm supination (FS)
	Index and middle finger extension (IMFE)		Hand open (HO)
	Little finger extension (LFE)		Hand close (HC).

Figure 6. Available gesture list and selected research gestures.

3.5. Raw Signals Extracted from GRABMyo Dataset

This section provides an insightful examination of the raw EMG signals extracted from the GRABMyo dataset. Figures 7 and 8 depict raw EMG signals from the forearm and wrist regions in the time domain, while Figures 9 and 10 illustrate the signals in the frequency domain, which will be the focus of our signal processing efforts. Processing signals in the frequency domain offers a powerful and versatile approach to signal analysis and manipulation. These visuals offer a representation of the initial raw EMG signals, providing insights into the spatial distribution and waveform characteristics across various anatomical segments. The raw EMG data images serve as the foundation for subsequent processing and analysis, guiding our exploration into the intricate patterns of muscle activity within the forearm.

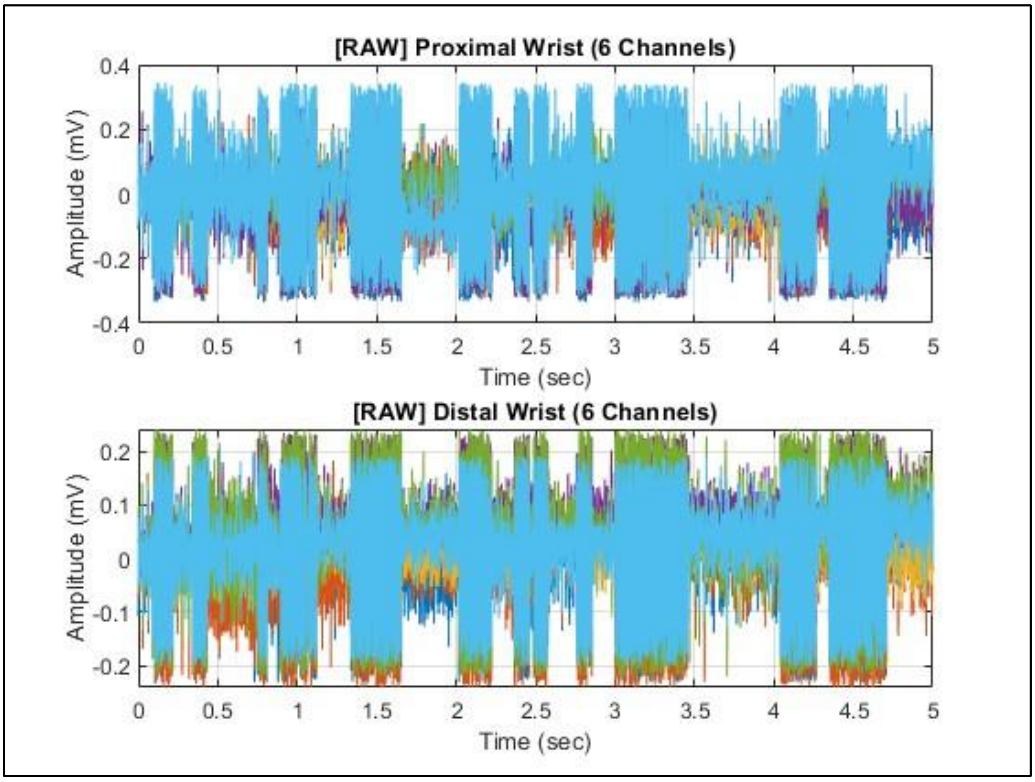


Figure 7. Raw EMG signals captured from the wrist in the time domain.

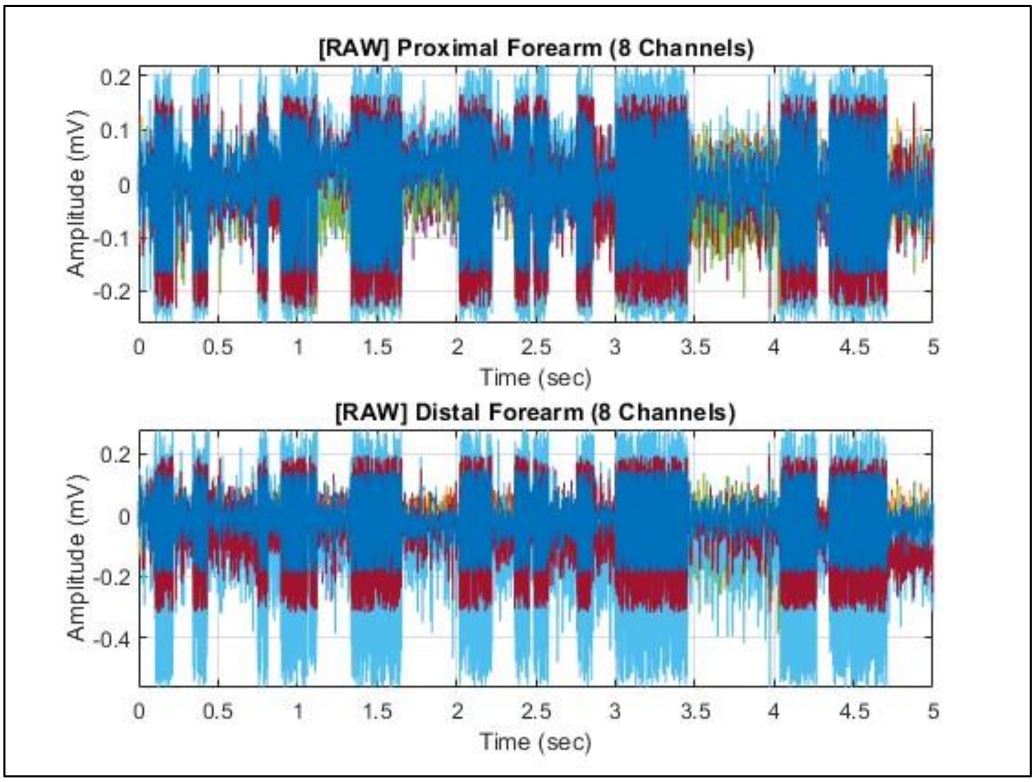


Figure 8. Raw EMG signals captured from the forearm in the time domain.

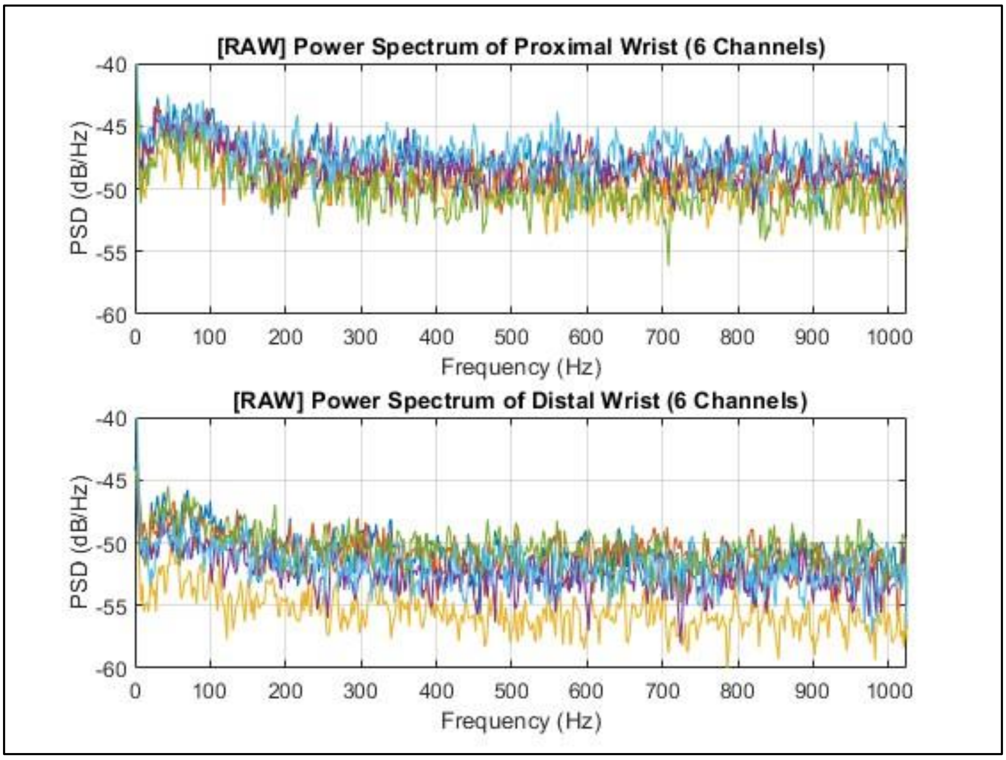


Figure 9. Power Spectrum Density (PSD) analysis of raw EMG signals captured from the wrist in the frequency domain.

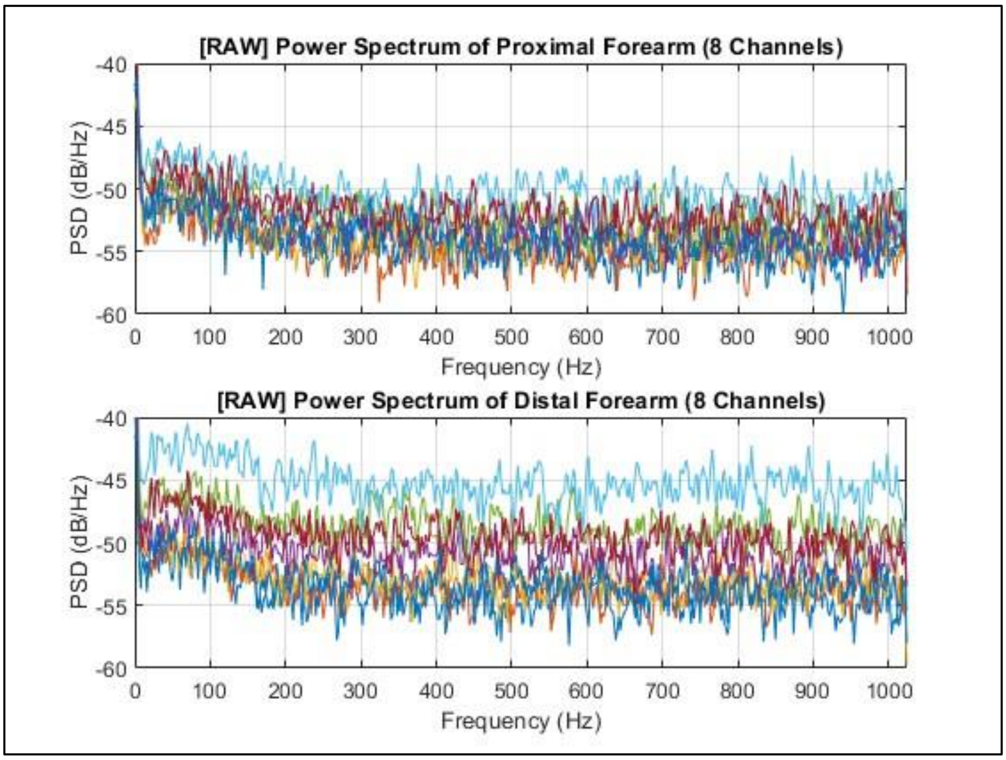


Figure 10. Power Spectrum Density (PSD) analysis of raw EMG signals captured from the forearm in the frequency domain.

4. Overview: Signal Processing Methods

Signal processing [18–20] is essential for analyzing and interpreting raw data by extracting meaningful information, reducing noise, and identifying patterns from input signals. This process enhances data quality, enables efficient storage and transmission, and facilitates subsequent analysis and interpretation in various applications.

4.1. Average Referencing

Average referencing is commonly used in signal processing for EEG and EMG to improve the accuracy of the recorded signals. It is a technique used to remove common noise present across multiple channels in a signal. Averaging is done by calculating the average of all channels at each point of time and subtracting this average from each individual channel. With the common noise shared among the channels effectively removed, the signal-to-noise ratio and quality of recorded data are improved and the data are ready for further processing. The GRABMyo dataset consists of 28 electrodes capturing signals from the forearm. The captured signals often contain the desired signal data along with background or random noises, either from the environment or interference from nearby electrodes. When average referencing is applied among multiple electrodes, such as the 16 channels from the forearm and 12 channels [12,21–24] from the wrist in the GRABMyo dataset, it becomes particularly useful for improving the quality of the recorded signals. Average referencing helps in reducing common noise that may be present across the 28 electrodes. By subtracting the average signal from each channel, it cancels out common noise sources among the electrodes, enhancing the signal-to-noise ratio. By aligning the signals from different electrodes around a common reference point, zero, average referencing contributes to signal consistency. This is beneficial when analyzing patterns or trends that involve the interaction of signals from the 28 electrodes. Averaging referencing is particularly beneficial when dealing with uncorrelated or random noise present in signal data. It helps to enhance the clarity and accuracy of the desired signal representation, as demonstrated in Figures 11 and 12 compared to Figures 9 and 10.

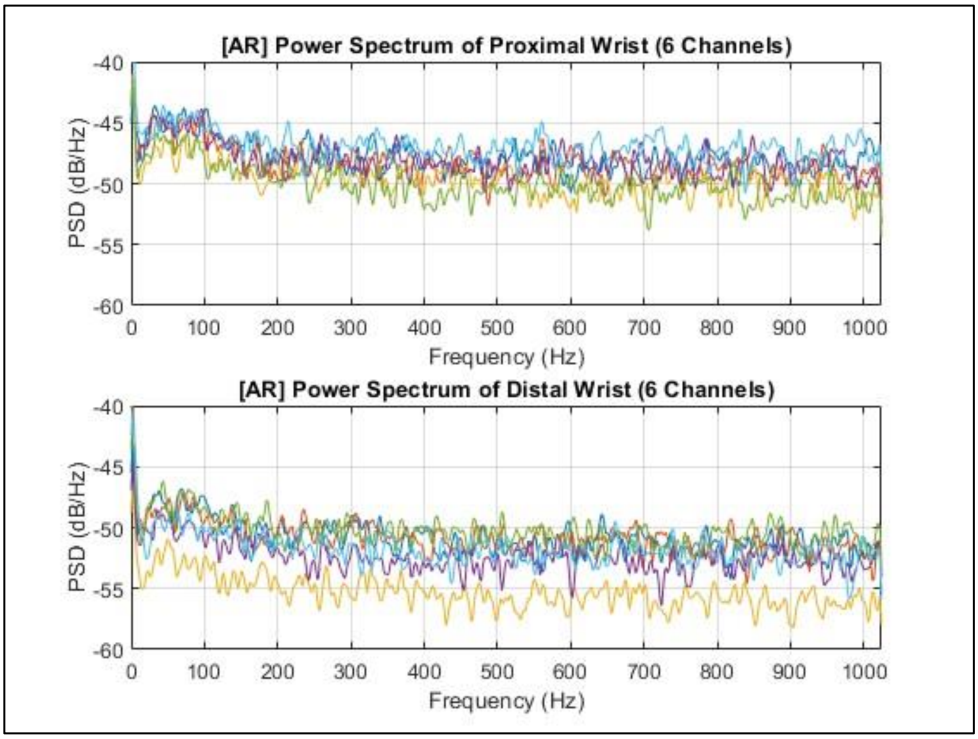


Figure 11. PSD analysis of EMG signals captured from the wrist after average referencing.

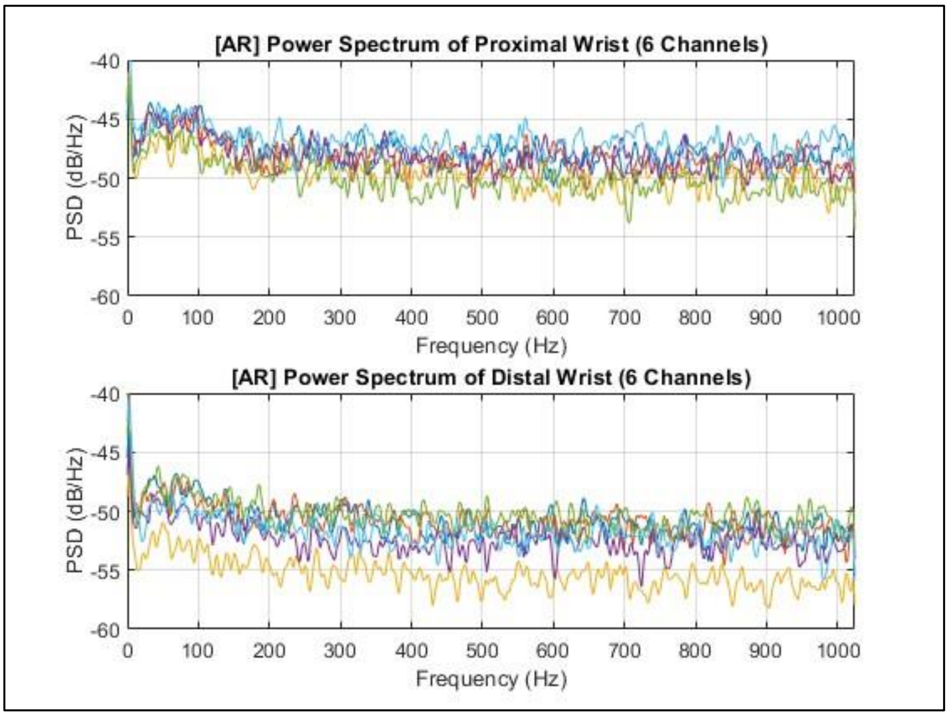


Figure 12. PSD analysis of EMG signals captured from the forearm after average referencing.

4.2. Filters Applied

The research will implement common filters utilized for EMG signals, which include the Band-pass filter, Notch filter, and High-pass filter. These filters are instrumental in eliminating unwanted common noise sources and narrowing down the frequencies to the range of the EMG signals.

4.2.1. Band-Pass Filter with a Range of 10 to 450 Hz

The frequency range of EMG signals varies depending on the type of gesture being recorded. Each gesture activates a unique range of muscle groups with varying frequencies. In general, EMG signals can range from approximately 10 Hz to 450 Hz, with higher frequencies often associated with more forceful or rapid muscle contractions. However, in certain cases or pathological conditions, the EMG signals may display frequencies beyond the usual range. In Figure 13, point 1 highlighted in red represents the signal range preserved between 10 Hz and 450 Hz.

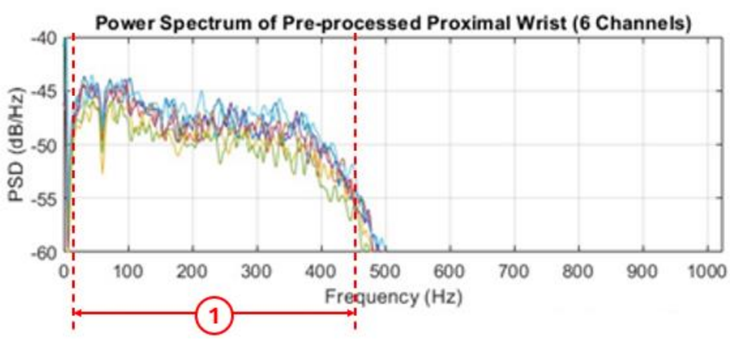


Figure 13. PSD analysis of EMG signals captured from the wrist after the application of a Band-pass filter with a range of 10 Hz to 450 Hz.

4.2.2. 60 Hz Notch Filter

Typically, a notch filter is employed to eliminate noise generated by power lines, which normally falls within the 50 Hz to 60 Hz range. When recording raw or any biomedical signals, there is a chance of encountering power line noise in the room. If this noise falls within the frequency band of interest, such as the EMG range (which also starts from 50 to 60 Hz), a notch filter is utilized to specifically remove the power line noise without affecting the actual muscle activity in the EMG signal. In Figure 14, point 2 highlighted in red represents the removal of the 60 Hz signal.

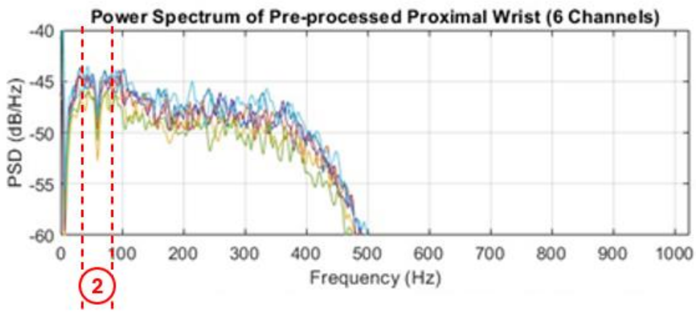


Figure 14. PSD analysis of EMG signals captured from the wrist after the application of the 60 Hz Notch filter.

4.2.3. High-Pass Filter with a Cutoff of 0.1 Hz for DC Removal

A high-pass filter is used to remove DC components from the signal. During the capturing of the EMG signals, these DC components may arise due to factors such as electrode offset or baseline drift. These DC components can interfere with the analysis of the EMG signal when focusing on changes or variations in muscle activity over time. By applying a high-pass filter with a cutoff frequency of 0.1 Hz, the low frequency DC components (typically known to be 0 Hz) can be attenuated or removed from the signal while preserving the higher frequency components that represent the muscle activity. This aids in eliminating any DC offset or baseline variations that could distort information about muscle contractions, thus ensuring an accurate reading.

4.3. Signals after Pre-Proccessing with Filtering

In Figures 15 and 16, the signals are depicted after undergoing filtering, preparing them for subsequent analysis using the Discrete Wavelet Transform (DWT). Filtering plays a crucial role in enhancing signal quality by removing noise, artifacts, and extraneous components. This ensures that the application of the DWT is effective and precise.

4.4. Discrete Wavelet Transform—Biorthogonal 3.3

The Fourier transform stands as a powerful tool for data analysis, yet it lacks efficiency in representing abrupt changes. This limitation arises because the Fourier transform represents data as a sum of infinite sinusoids, which do not inherently consider time or spatial localization. Representing the signals in the time–frequency domain proves beneficial, particularly for non-stationary signals. In wavelet analysis, two primary transforms exist: the discrete wavelet transform, and the continuous wavelet transform. These transforms diverge in terms of how the wavelets are scaled and shifted. The DWT was selected due

My part

to its explicit utility in analyzing bioelectrical signals. As a novel signal processing tool, the DWT technique offers advantages in decomposing signals and images into different frequency bands, enabling efficient analysis while preserving crucial information. This method, characterized by its dual filter bank structure, stands out for its ability to maintain a balance between time and frequency localization, allowing for enhanced feature extraction and denoising capabilities across various domains. By comprehensively delving into the intricacies of this transformative method, the research aims to harness its potential in diverse applications, spanning from biomedical signal processing to image compression, with a focus on optimizing its functionalities for real-world scenarios. The DWT filters the signal using both a low-pass filter and a high-pass filter, followed by down sampling. This separation of frequency components results in the high-pass components known as detail coefficients and the low-pass components known as approximate coefficients. The filtering process occurs iteratively and can be conceptualized as involving multiple filter banks. The formula for the DWT that involves multiple levels of decomposition can be split into approximate (low-frequency components) (1) and detail (high-frequency components) (2) components.

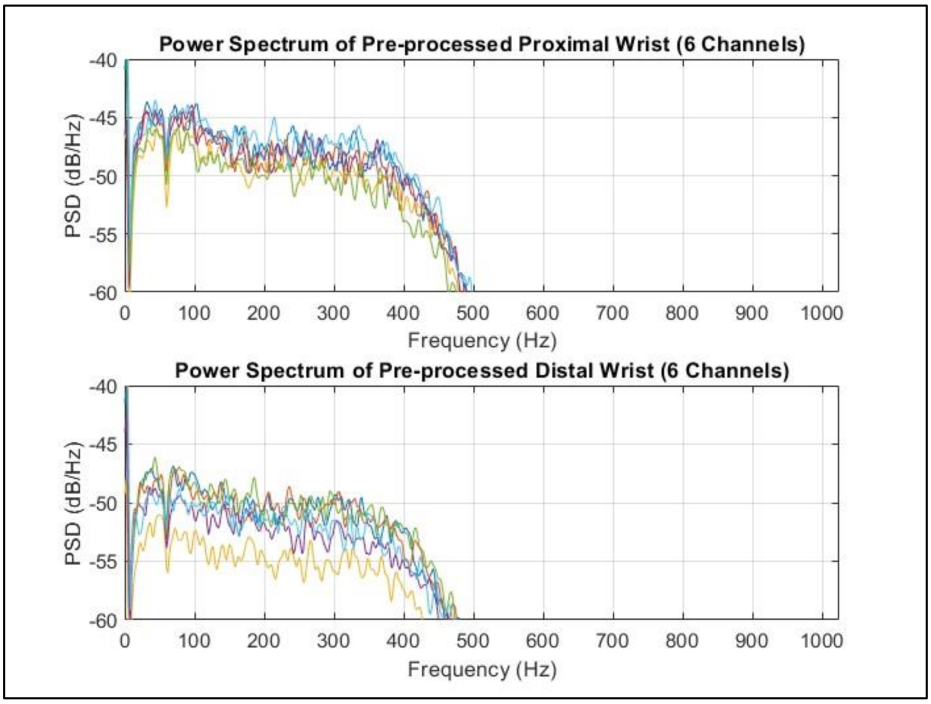


Figure 15. PSD analysis post filtering of EMG signals captured from the wrist.

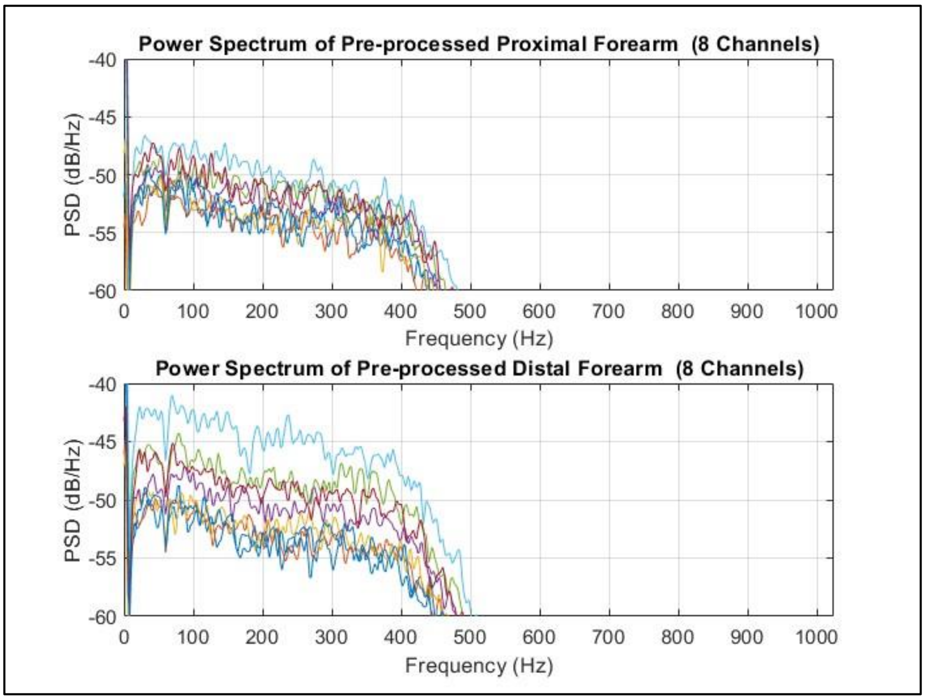


Figure 16. PSD analysis post filtering of EMG signals captured from the forearm.

$$Approximate \rightarrow y[n] = \sum_{k=-\infty}^{\infty} x[k] \cdot g[2n-k] \quad (1)$$

where g represents the high-pass filter coefficients.

$$Detail \rightarrow y[n] = \sum_{k=-\infty}^{\infty} x[k] \cdot h[2n-k] \quad (2)$$

where g represents the high-pass filter coefficients.

The research initially utilized 6 levels of DWT decomposition. However, considering EMG's higher frequency range, it was determined that employing 4 levels of DWT decomposition would yield superior results. Figure 17 illustrates the process of 4-level DWT decomposition.

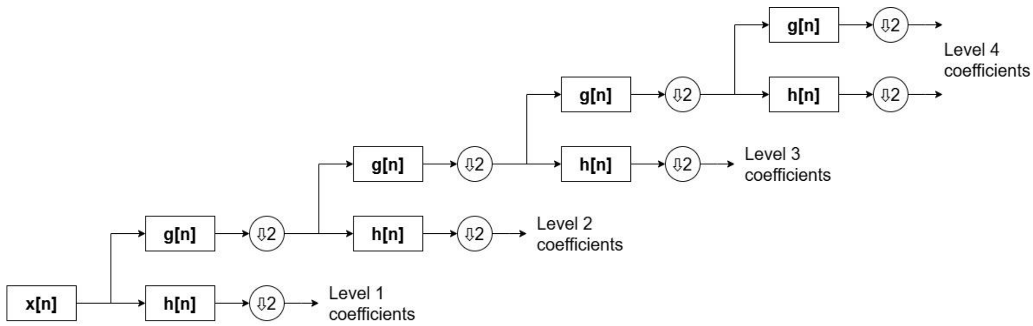


Figure 17. Discrete Wavelet Transform decomposition, block diagram form, with 4 levels of decomposition.

In the reconstruction phase of wavelet signal processing using Biorthogonal 3.3 DWT, the approximation and detail coefficients obtained during the decomposition phase are utilized. These coefficients represent the different frequency components of the original signal at various levels of resolution. Biorthogonal wavelets provide a balanced reconstruction process by utilizing synthesis filters that complement the analysis filters employed during decomposition. Subsequently, through an inverse wavelet transform, the approximation and detail coefficients are merged to reconstruct the original signal. Biorthogonal 3.3 DWT offers an accurate reconstruction, preserving essential signal characteristics while effectively compressing the data. This phase plays a crucial role in recovering the original signal from its decomposed components, ensuring fidelity and reliability in signal reconstruction. An illustration of wavelet decomposition using DWT at the sixth level is shown in Figure 18, while Figure 19 depicts wavelet decomposition at the fourth level. It is evident that over-decomposition occurs at levels 5 and 6 of the detail coefficients. In contrast, decomposition at level 4 is optimal as it retains the unique characteristics that capture the essential information in the signal.

4.5. Signal Feature Extraction Methods

As per the findings cited in the journal, feature extraction techniques yielding the highest accuracy include methods like Mean Absolute Value (MAV), Waveform Length (WL), Zero Crossing (ZC), Slope Sign Change (SSC), Root Mean Square (RMS), Energy of Wavelet Coefficients (EWLs), and Enhanced Mean Absolute Value (EMAV).

Mean Absolute Value (MAV) calculates the average magnitude of a signal by averaging the absolute values of its data points. MAV is commonly used in electromyography (EMG) analysis to assess muscle activity by measuring the overall muscle contraction level.

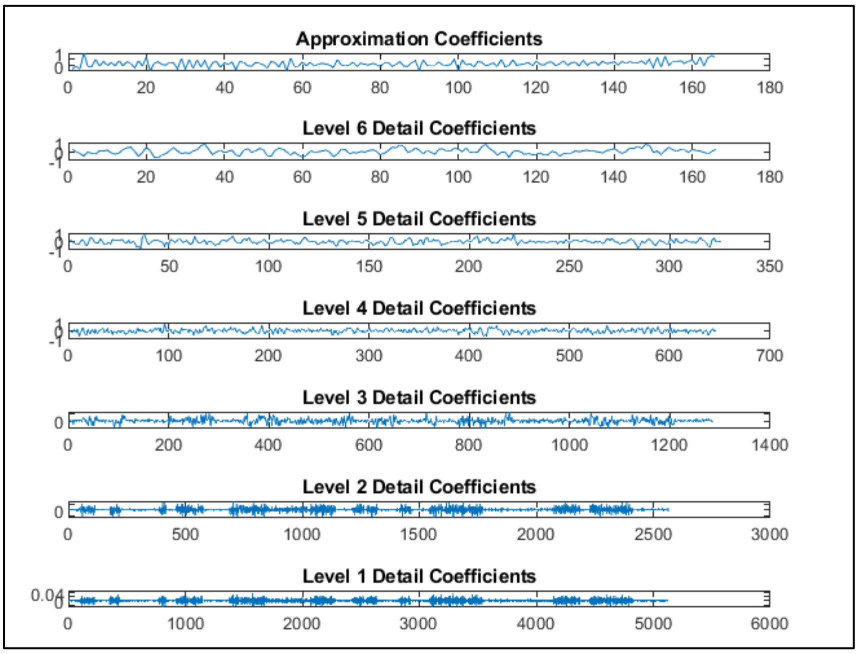


Figure 18. Discrete Wavelet Transform decomposition with 6 levels of decomposition.

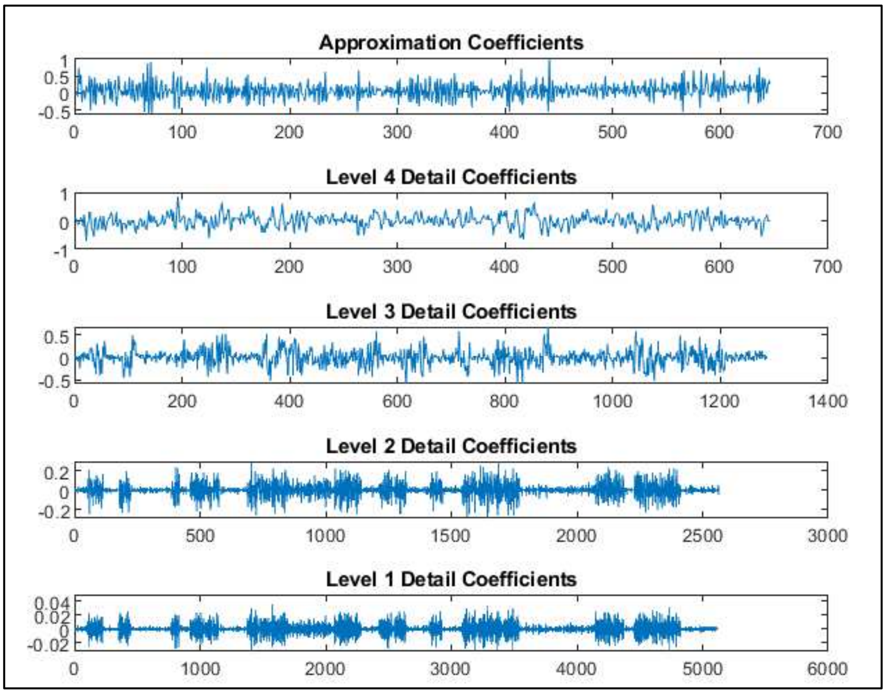


Figure 19. Discrete Wavelet Transform decomposition, analysis form, with 4 levels of decomposition.

$$MAV = \frac{1}{L}\sum_{i=1}^{L}|x_i| \tag{3}$$

Wavelength (WL) quantifies the cumulative length of waveform oscillations by summing the distances between successive peaks or troughs in the EMG signal.

$$WL = \sum_{i=2}^{L}|x_i - x_{i-1}| \tag{4}$$

Zero Crossing (ZC) refers to the points in a signal where the amplitude changes its sign, where the signal crosses the zero-amplitude axis.

$$ZC = \sum_{i=1}^{L-1} f(x_i)$$
$$where\ f(x_i) = \begin{cases} 1,\ if\{(x_i > 0\ \&\ x_{i+1} < 0)|\ (x_i < 0\ \&\ x_{i+1} > 0)\} \ldots \\ \&\ |x_i - x_{i+1}| \geq T \\ 0,\ otherwise \end{cases} \tag{5}$$

Slope Sign Change (SSC) counts the times the slope of a signal changes within a set interval, aiding in detecting transitions in signal dynamics.

$$SSC = \sum_{i=2}^{L-1} f(x_i)$$
$$where\ f(x_i) = \begin{cases} 1,\ if\{(x_i > x_{i-1}\ \&\ x_i > x_{i+1})|\ (x_i < x_{i-1}\ \&\ x_i < x_{i+1})\} \ldots \\ \&\ \{(|x_i - x_{i+1}| \geq T)\ |\ (|x_i - x_{i-1}| \geq T)\} \\ 0,\ otherwise \end{cases} \tag{6}$$

Root Mean Square (RMS) calculates the average power of a signal by taking the square root of the average of the squares of all signal values, offering insight into signal intensity, and finding application in noise analysis, signal characterization, and power estimation.

$$RMS = \sqrt{\frac{1}{L}\sum_{i=1}^{L}(x_i)^2} \tag{7}$$

Energy of Wavelet Coefficients (EWLs) quantifies the energy distribution across frequency bands in wavelet-transformed signals, aiding tasks like signal classification and denoising.

$$EWL = \sum_{i=2}^{L} \left|(x_i - x_{i-1})^p\right|$$
$$where\ p = \begin{cases} 0.75,\ if\ (i > 0.2L\ \&\ i < 0.8L) \\ 0.50,\ otherwise \end{cases} \tag{8}$$

Enhanced Mean Absolute Value (EMAV) enhances traditional Mean Absolute Value (MAV) by incorporating weighting factors to emphasize higher amplitude signal components, improving the accuracy of muscle activity representation in EMG signal processing.

$$EMAV = \frac{1}{L}\sum_{i=1}^{L} \left|(x_i)^p\right|$$
$$where\ p = \begin{cases} 0.75,\ if\ (i \geq 0.2L\ \&\ i \leq 0.8L) \\ 0.50,\ otherwise \end{cases} \tag{9}$$

4.6. Dimensionality Reduction Methods

Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) are essential dimensionality reduction techniques in machine learning, serving multiple purposes such as feature dimension reduction, visualization, and noise reduction. They transform high-dimensional data into lower-dimensional representations, simplifying computational tasks and aiding in understanding complex data structures. By focusing on the most informative features or directions of variance, LDA and PCA enhance model interpretability, mitigate collinearity issues, and improve overall model performance, making them valuable tools in data preprocessing for machine learning applications.

4.6.1. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is a statistical method used for dimensionality reduction and classification tasks. It aims to find a linear combination of features that effectively distinguishes between multiple classes in a dataset by reducing within-class variability and maximizing between-class variability. LDA is widely applied in machine learning, pattern recognition, and data analysis, especially in classification challenges involving multiple classes. Figure 20 provides a simple illustration of how LDA works to classify the classes.

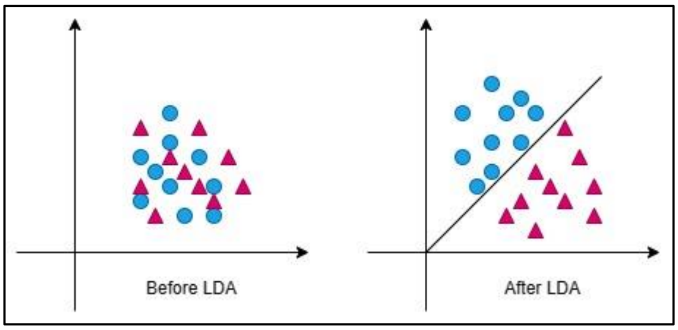


Figure 20. Comparison of signal distribution before and after Linear Discriminant Analysis (LDA) for 2 classes.

4.6.2. Principle Component Analysis (PCA)

Principal Component Analysis (PCA) is a statistical technique used for dimensionality reduction and data visualization. It identifies principal components, which are orthogonal vectors that capture the maximum variance within the dataset. By mapping data onto these components, PCA transforms high-dimensional data into a lower-dimensional representation while retaining essential variability.

5. Overview of Machine Learning Methods

Machine learning refers to mathematical algorithms that, when applied, produce desired outputs based on given inputs. These algorithms are designed to generate accurate outputs under specific conditions. Machine learning is the result of combining principles from both science and engineering, enabling systems to perform various tasks without explicit programming. It involves solving problems using datasets and mathematical algorithms to construct statistical models based on the data. Machine learning encompasses four main types of learning: supervised, semi-supervised, unsupervised, and reinforcement learning.

5.1. Machine Learning Classifiers

The research will focus on three popular and effective learning algorithms that are not only used on their own, but also as building blocks for advanced learning algorithms.

5.1.1. K-Nearest Neighbor Classifiers

K-Nearest Neighbor (KNN) is a non-parametric supervised learning algorithm. As depicted in Figure 21, the classification of an individual or new data point is determined by the proximity to a specified number of neighbors. Common distance functions used in KNN include Euclidean distance or negative cosine similarity.

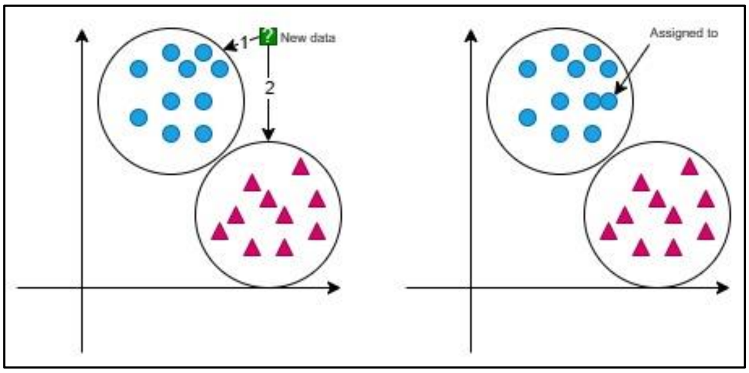


Figure 21. Visualization of K-Nearest Neighbor classes and classification method.

5.1.2. Naïve Bayes Classifier

The Naïve Bayes classifier, rooted in Bayes' theorem, simplifies classification by assuming that features are conditionally independent given the class label. Despite its simplicity and the assumption of feature independence, Naïve Bayes is valued for its efficiency and effectiveness, especially with high-dimensional data. It calculates the probability of each class for a given data point and selects the class with the highest probability.

$$Naive\ Bayes\ Theorem \rightarrow P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{10}$$

$$Posterior\ probability = \frac{Likelihood \cdot Class\ prior\ probability}{Predictor\ prior\ probability} \tag{11}$$

5.1.3. Support Vector Machine (SVM)

The Support Vector Machine (SVM) is advantageous in scenarios involving noise or outliers, where perfect data separation using a plane may not be feasible. Additionally, the SVM is suitable when the data can only be separated by employing a high-order polynomial. Figure 22 provides visualizations of SVM techniques for graphs with higher dimensions. The SVM utilizes a method called the kernel trick, which maps the original data into a higher-dimensional space where it becomes linearly separable. In this higher-dimensional space, SVM can effectively find a hyperplane that separates the data [11].

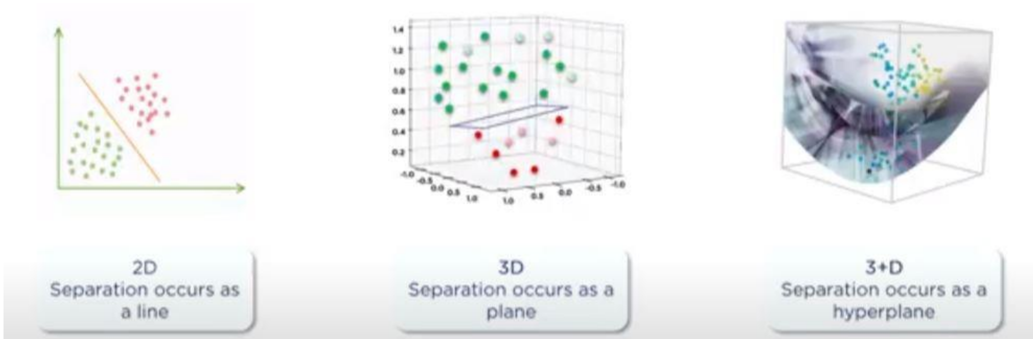


Figure 22. Visualization of Support Vector Machine classification methods [11].

6. Results and Discussion

The outcomes of this research are based on a focused scope, utilizing the GRABMyo dataset containing signals for 16 gestures collected across three sessions. However, the results presented here are specifically derived from data corresponding to five gestures from one session. Initially, a smaller dataset was employed to evaluate the model's performance using the process illustrated in Figure 9. This was followed by a comprehensive assessment using the full dataset, as highlighted in the final process diagram shown in Figure 23. Section 6.3 showcases the results from one session of the dataset, while Section 6.4 delves into the model's performance on the complete dataset. Various novel methods were explored during signal processing and machine learning stages. Through rigorous testing, certain key concepts and methods displayed the most favorable performance metrics. Consequently, for the final evaluation, Linear Discriminant Analysis (LDA) was selected for dimensionality reduction, while the Support Vector Machine (SVM) was chosen as the classification method for machine learning.

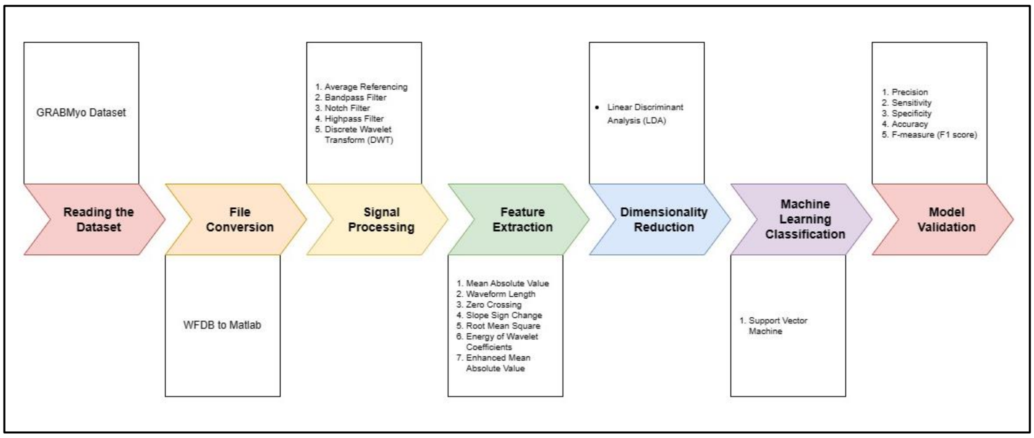


Figure 23. Final process diagram illustrating the results of the research.

6.1. Overview of Analytical Process

This research examines the performance of the dimensionality reduction techniques PCA and LDA, followed by the machine learning [4,5] classification methods KNN, NB, and the SVM. In the first part of our comparative analysis, LDA outperformed PCA across various evaluation metrics. While both methods aim to reduce dimensionality and extract essential features from the data, LDA demonstrated better discriminatory power by explicitly considering class information during dimensionality reduction. This allows LDA to more effectively capture the underlying structure of the data, resulting in enhanced separability between different classes. Conversely, PCA, despite its effectiveness in preserving overall variance, may not prioritize features that are discriminative for classification tasks. LDA was chosen as the dimensionality reduction technique based on the objectives and characteristics of the dataset. Figure 24 provides a visualization of the dataset after the application of PCA, while Figure 25 shows the dataset after the application of LDA.

In the second part of our comparative analysis among the machine learning classifier techniques KNN, NB, and the SVM, the SVM provided better performance across various evaluation metrics. While KNN relies on proximity-based classification and NB assumes feature independence, SVM harnesses the concept of maximum margin hyperplanes to achieve robust classification boundaries, particularly in high-dimensional spaces. This enables SVM to optimize decision boundaries based on the data distribution and maximize the margin between different classes, resulting in better prediction and performance. Therefore, SVM proves to be the preferred choice for our specific application, underscoring the importance of selecting a classifier that aligns with the dataset's characteristics of supporting multiple classes.

6.2. Overview of Performance Measurement

The model's performance is evaluated based on precision, sensitivity, accuracy, and F-measure. These parameters are essential for assessing the model's effectiveness and predictive capability. The calculated values of these parameters are derived from the predicted outcomes, including true positives, true negatives, false positives, and false negatives.

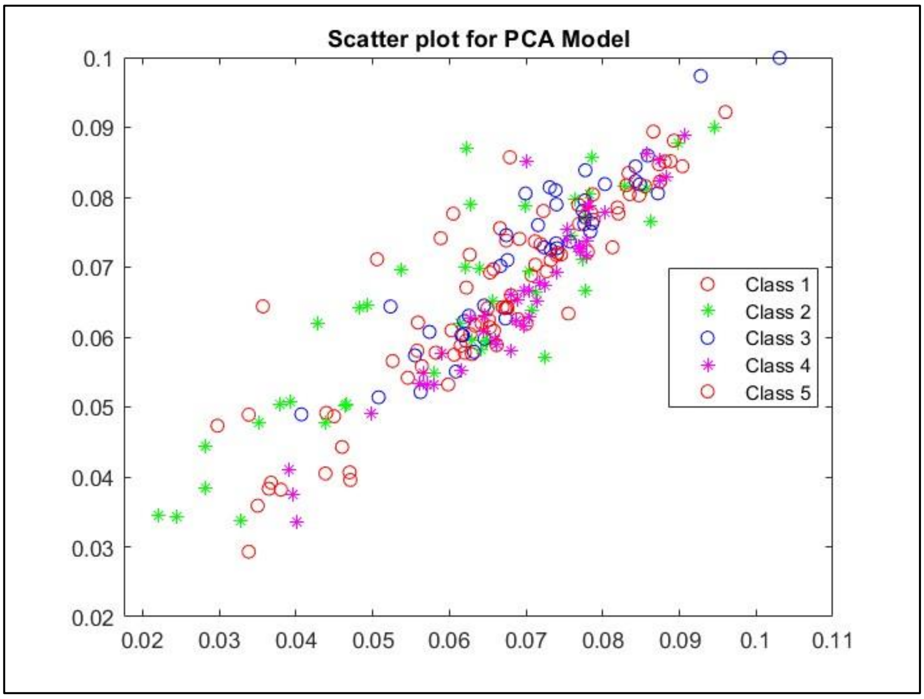


Figure 24. Scatter plot illustrating the classification of 215 EMG samples using the PCA–SVM model.

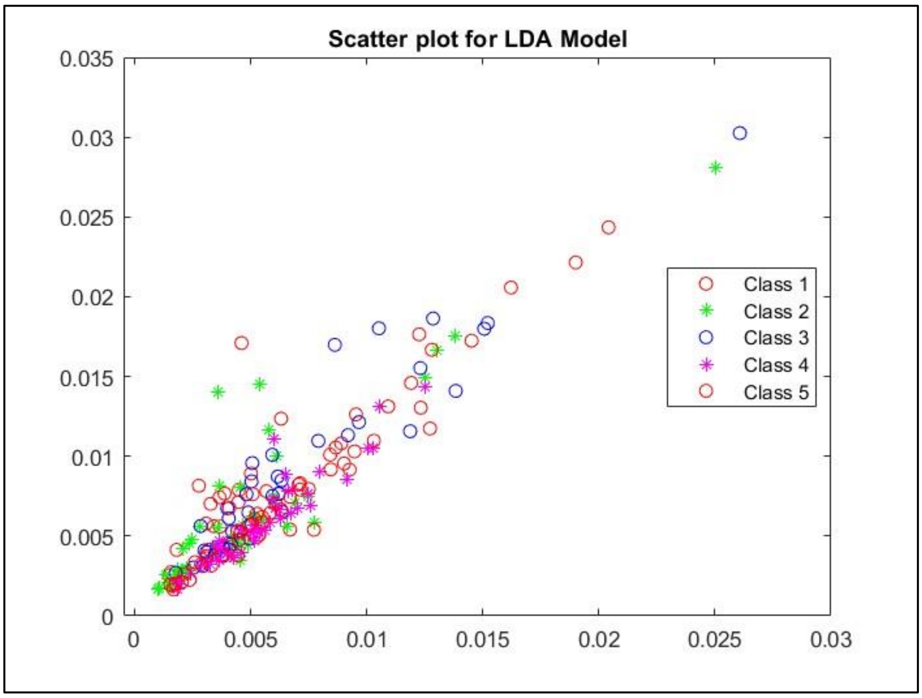


Figure 25. Scatter plot illustrating the classification of 215 EMG samples using the LDA–SVM model.

6.2.1. Precision

Precision calculates the ratio of true positive predictions to the total number of positive predictions, including both true positives and false positives. It assesses the model's ability to avoid misclassifying negative instances as positive. The formula for precision can be expressed as follows:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

6.2.2. Sensitivity

Sensitivity calculates the ratio of true positive predictions (TP) to the total number of actual positive instances, including both true positives and false negatives (FN). It measures the model's ability to avoid missing positive instances.

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

6.2.3. Accuracy

Accuracy calculates the ratio of correctly predicted instances (true positives and true negatives, TN) to the total number of instances in the dataset. It provides a general overview of the model's performance but may be misleading on imbalanced datasets where one class dominates.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + True\ Negatives + False\ Positves + False\ Negatives}$$

6.2.4. F-Measure (F1-Score)

The F1-score combines precision and sensitivity into a single metric, providing a balanced assessment of the model's performance. It considers both false positives and false negatives and is particularly useful for evaluating models on imbalanced datasets.

$$F\text{-}measure = \frac{2 \times (Precision \times Sensitivity)}{Precision + Sensitivity}$$

6.3. Performance Metrics for One Session

The performance metrics provide a comprehensive assessment of the models' efficacy in accurately classifying gestures within the GRABMyo dataset. Key evaluation criteria such as accuracy, precision, recall, and F1-score were computed to gauge the models' performance across various classification tasks. The computed values for the model employing the PCA method for dimensionality reduction are presented in Table 3, while those for the model utilizing the LDA method are presented in Table 4. The following tables compare the performance metrics obtained for the three machine learning models: KNN, NB, and the SVM. The model utilizing PCA has an average accuracy across the five classes of 76.55% for KNN, 75.44% for NB, and 81.76% for the SVM. Meanwhile, the model utilizing LDA has an average accuracy across the five classes of 83.25% for KNN, 76.55% for NB, and 86.97% for SVM, as shown in Tables 3 and 4.

The analysis reveals that the LDA–SVM model yields the highest accuracy for the processed signals. Based on this preliminary assessment, the subsequent Section 6.4 will present the outcomes of processing the complete GRABMyo dataset of 645 samples and its corresponding results.

6.4. Performance Metrics for Three Sessions

Building upon our initial exploration utilizing data from one session of the GRABMyo dataset, this section delves into the outcomes derived from employing data spanning three sessions. Notably, our preliminary analysis revealed that the LDA–SVM model achieved the highest accuracy when trained and evaluated on data from a single session. Leveraging these insights, we aim to ascertain whether employing the entire dataset, encompassing multiple sessions, will yield superior results, thus harnessing the potential benefits of a larger and more comprehensive database. Figure 26 illustrates the methodology for processing the three sessions and consolidating them to be utilized for machine learning.

Table 3. PCA performance metrics for machine learning models, KNN, NB, and the SVM, using data from one session.

Evaluation Metrics	Classes (Five Hand Gestures)					Macro Average
PCA–K-Nearest Neighbor						
True Positive	6	24	18	22	19	17.8
False Positive	13	23	40	29	21	25.2
False Negative	37	19	25	21	24	25.2
True Negative	159	149	132	143	151	146.8
Precision	0.31579	0.51064	0.31034	0.43137	0.475	0.40863
Sensitivity	0.13953	0.55814	0.4186	0.51163	0.44186	0.41395
Accuracy	0.76744	0.80465	0.69767	0.76744	0.7907	0.76558
F-measure	0.19355	0.53333	0.35644	0.46809	0.45783	0.40185
PCA–Naïve Bayes						
True Positive	12	15	12	26	18	16.6
False Positive	28	11	36	36	21	26.4
False Negative	31	28	31	17	25	26.4
True Negative	144	161	136	136	151	145.6
Precision	0.3	0.57692	0.25	0.41935	0.46154	0.40156
Sensitivity	0.27907	0.34884	0.27907	0.60465	0.4186	0.38605
Accuracy	0.72558	0.8186	0.68837	0.75349	0.78605	0.75442
F-measure	0.28916	0.43478	0.26374	0.49524	0.43902	0.38439
PCA–Support Vector Machine						
True Positive	18	28	20	28	23	23.4
False Positive	24	20	30	11	13	19.6
False Negative	25	15	23	15	20	19.6
True Negative	148	152	142	161	159	152.4
Precision	0.42857	0.58333	0.4	0.71795	0.63889	0.55375
Sensitivity	0.4186	0.65116	0.46512	0.65116	0.53488	0.54419
Accuracy	0.77209	0.83721	0.75349	0.87907	0.84651	0.81767
F-measure	0.42353	0.61538	0.43011	0.68293	0.58228	0.54685

Table 4. LDA performance metrics for machine learning models, KNN, NB, and the SVM, using data from one session.

Evaluation Metrics	Classes (Five Hand Gestures)					Macro Average
LDA–K-Nearest Neighbor						
True Positive	14	29	24	33	25	25
False Positive	10	14	24	20	22	18
False Negative	29	14	19	10	18	18
True Negative	162	158	148	152	150	154
Precision	0.58333	0.67442	0.5	0.62264	0.53191	0.58246
Sensitivity	0.32558	0.67442	0.55814	0.76744	0.5814	0.5814
Accuracy	0.8186	0.86977	0.8	0.86047	0.81395	0.83256
F-measure	0.41791	0.67442	0.52747	0.6875	0.55556	0.57257
LDA–Naïve Bayes						
True Positive	17	22	10	27	13	17.8
False Positive	44	12	25	34	11	25.2
False Negative	26	21	33	16	30	25.2
True Negative	128	160	147	138	161	146.8
Precision	0.27869	0.64706	0.28571	0.44262	0.54167	0.43915
Sensitivity	0.39535	0.51163	0.23256	0.62791	0.30233	0.41395
Accuracy	0.67442	0.84651	0.73023	0.76744	0.8093	0.76558
F-measure	0.32692	0.57143	0.25641	0.51923	0.38806	0.41241

Table 4. *Cont.*

Evaluation Metrics	Classes (Five Hand Gestures)					Macro Average
LDA–Support Vector Machine						
True Positive	26	28	29	30	32	29
False Positive	13	19	12	9	17	14
False Negative	17	15	14	13	11	14
True Negative	159	153	160	163	155	158
Precision	0.66667	0.59574	0.70732	0.76923	0.65306	0.6784
Sensitivity	0.60465	0.65116	0.67442	0.69767	0.74419	0.67442
Accuracy	0.86047	0.84186	0.87907	0.89767	0.86977	0.86977
F-measure	0.63415	0.62222	0.69048	0.73171	0.69565	0.67484

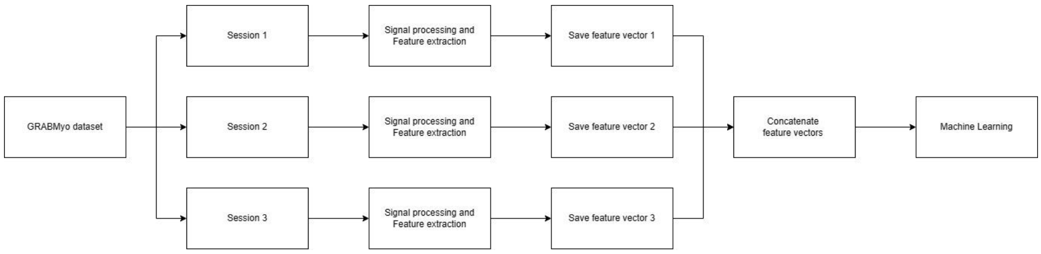


Figure 26. Methodology for processing the three sessions from the GRABMyo dataset.

The scatter plot in Figure 27 provides a visual comparison of the data that have undergone dimensional reduction, illustrating the clustering differences as the dataset increases from one session to the complete dataset of three sessions.

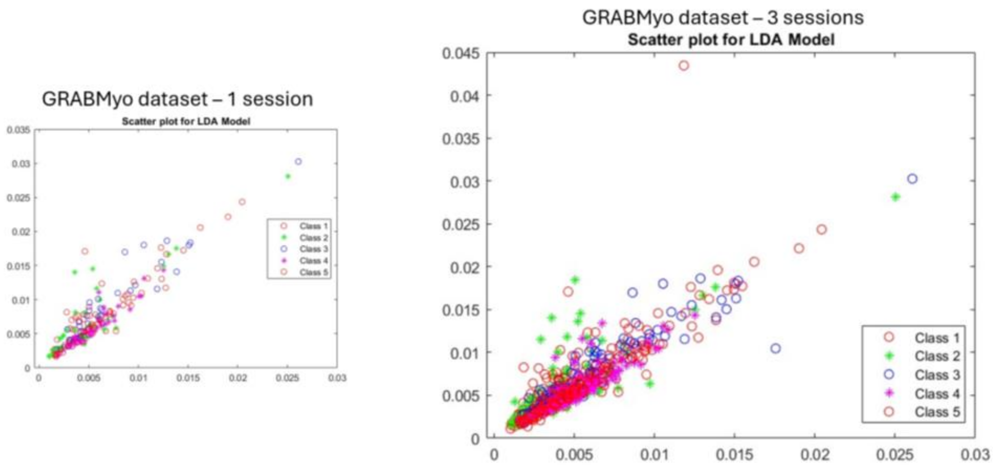


Figure 27. Comparison of scatter plots between one session and the complete dataset of three sessions of data.

A confusion matrix is a tool used to assess the performance of a classification model by comparing its predictions to the actual outcomes across various classes. Rows correspond to true classes and columns to predicted classes, with diagonal elements indicating correct predictions and off-diagonal elements representing misclassifications. It offers valuable insights into the model's accuracy, precision, recall, and other performance metrics. The confusion matrix for the full GRABMyo dataset is shown in Figure 28. It is a 5×5 matrix that compares the data with those predicted by the machine learning model. Please note that only five gestures were selected to represent the five classes for prediction.

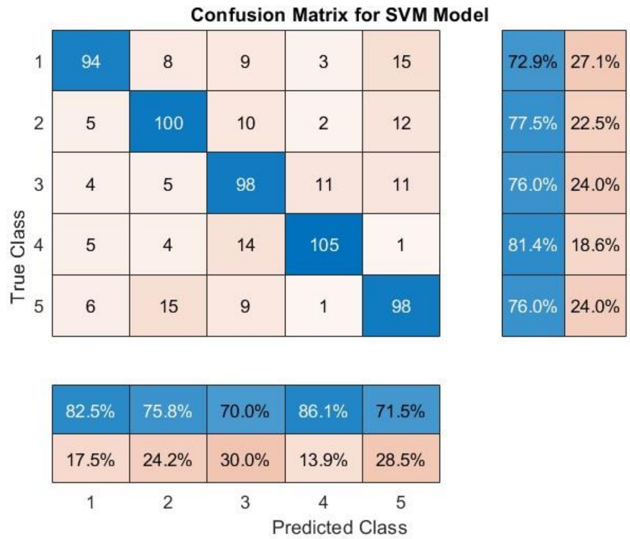


Figure 28. Confusion matrix for the SVM model using data from the complete dataset of three sessions of data.

The outcomes presented in Table 5 demonstrate an improvement in accuracy compared to the previous single session. Specifically, the LDA–SVM model's performance increased from 86.98% accuracy to 90.69% when considering data from three sessions.

Table 5. Performance metrics of the LDA for machine learning models, KNN, NB, and the SVM, using the full dataset comprising data from three sessions.

Evaluation Metrics	Classes (Five Hand Gestures)					Macro Average
			Support Vector Machine (Three Sessions)			
True Positive	94	100	98	105	98	99
False Positive	20	32	42	17	39	30
False Negative	35	29	31	24	31	30
True Negative	496	484	474	499	477	486
Precision	0.82456	0.75758	0.7	0.86066	0.71533	0.77162
Sensitivity	0.72868	0.77519	0.75969	0.81395	0.75969	0.76744
Accuracy	0.91473	0.90543	0.88682	0.93643	0.89147	0.90698
F-measure	0.77366	0.76628	0.72862	0.83665	0.73684	0.76841

6.5. Interpretation of Results

The bar plots depicted in Figure 29 provide a concise overview of the findings discussed in Section 6.3. Notably, SVM demonstrated the highest accuracy when employing LDA for dimensionality reduction, achieving an accuracy rate of 86.98% across 215 samples.

The GRABMyo dataset presents several distinctive features and applications compared to other surface EMG datasets, which significantly contribute to the current state of the art in EMG analysis. One of the main differences lies in the variety and complexity of gestures included in the GRABMyo dataset. The dataset encompasses a wide range of gestures with varying degrees of complexity, enabling the development of models that generalize better across different types of movements. In contrast, other EMG datasets may focus on a limited set of gestures, which can be sufficient for specific applications but less effective for creating general-purpose models. Another notable difference is the diversity of participants in the GRABMyo dataset. It includes data from many participants with diverse backgrounds, providing a robust training set for machine learning models. Other EMG datasets might have fewer participants or lack diversity, which can limit the models' applicability to broader populations. Additionally, the recording conditions in the GRABMyo dataset are varied, encompassing different muscle contraction levels, speeds, and environments. This variety helps in developing more resilient models, whereas other EMG datasets might be recorded under more controlled conditions, making their models less adaptable to real-world variations. The quality and annotation detail of the GRABMyo dataset also stand out, emphasizing high-quality signal recordings and detailed annotations that are crucial for precise machine learning training and validation. In contrast, the quality and annotation detail in other EMG datasets can vary, impacting the ease of use and accuracy of the models trained on them. In terms of applications, the GRABMyo dataset is highly suitable for developing advanced prosthetic control systems that need to recognize a wide range of gestures and adapt to different users. It is also useful for designing rehabilitation protocols that require detailed monitoring of various muscle activities and for creating human–computer interfaces requiring complex gesture recognition and adaptability to different users. Other EMG datasets might be more appropriate for specific types of prosthetics, simpler control systems, targeted rehabilitation exercises, or interfaces requiring fewer gestures.

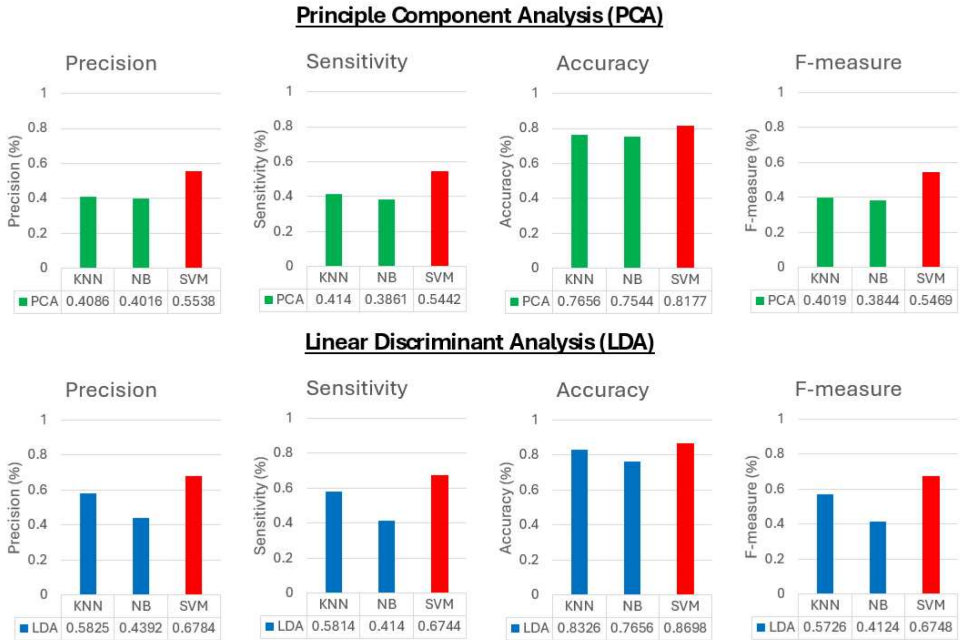


Figure 29. Performance metrics for KNN, NB, and SVM classifiers using data from one session.

Figure 30 bar plots illustrate a comparison between the results obtained from the LDA–SVM model for a single session and three sessions. The model exhibited an enhancement in accuracy by 3.72%, rising from 86.97% to 90.69% as the sample size increased to 645.

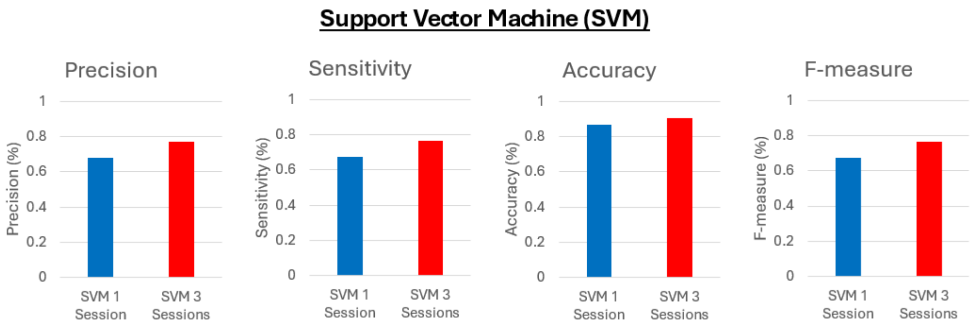


Figure 30. Comparing performance metrics for SVM classifiers utilizing data from one session and the complete dataset of three sessions of data.

Our findings in this proposed work, based on the GRABMyo dataset, contribute significantly to the current state of the art by improving generalization across different types of gestures and users due to the dataset's diversity. Our models achieve higher accuracy and robustness in gesture recognition, which is a notable improvement over models trained on more limited datasets. Additionally, this proposed work introduces new or improved methods for feature extraction and signal processing capable of handling the complexity of the GRABMyo dataset, thereby advancing current methodologies. The real-world applicability of the models developed using the GRABMyo dataset is also enhanced due to its realistic recording conditions and participant diversity, making a significant impact on practical implementations in prosthetics, rehabilitation, and human–computer interaction. This study employs the GRABMyo dataset, consisting of EMG signals from the forearm of 43 participants performing 16 gestures, each repeated seven times per gesture across three sessions. EMG signals are captured using surface electrodes placed on the forearm muscles and sampled at a high frequency to ensure detailed capture of muscle activity. The raw EMG signals undergo preprocessing, including bandpass filtering (20–450 Hz) to remove noise and motion artifacts, normalization to ensure uniformity across participants and gestures, and segmentation into fixed-length windows (200 ms) with a 50% overlap to enhance temporal resolution. Various time-domain and frequency-domain features are extracted from each signal segment, including Mean Absolute Value (MAV), Waveform Length (WL), Zero Crossing (ZC), Slope Sign Change (SSC), Root Mean Square (RMS), Energy of Wavelet Coefficients (EWLs), and Enhanced Mean Absolute Value (EMAV). Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are employed for dimensionality reduction: PCA is selected for its ability to retain 95% of the variance by transforming features into orthogonal components, while LDA is chosen to maximize class separation, retaining the most discriminative features.

Three machine learning classifiers—K-Nearest Neighbor (KNN), the Support Vector Machine (SVM), and Naïve Bayes (NB)—are evaluated to determine the most effective model for EMG signal classification. KNN is included due to its simplicity and effectiveness in classification tasks with small datasets; the number of neighbors (k = 5) is selected via cross-validation using the Euclidean distance metric and uniform weighting scheme. The SVM is chosen for its robustness in high-dimensional spaces and effectiveness with small to medium-sized datasets, employing a Radial Basis Function (RBF) kernel with a regularization parameter (C = 1.0), kernel coefficient (gamma = 1/n_features), and a stopping criterion tolerance (tol = 1×10^{-3}), with balanced class weights to handle class imbalance. The Naïve Bayes classifier is selected for its simplicity and efficiency, using a Gaussian model with priors estimated from the training data.

The dataset is split into training (70%), validation (15%), and test (15%) sets, with five-fold cross-validation employed during training to tune hyperparameters and prevent overfitting. Performance metrics include accuracy, precision, recall, and F1-score to ensure a comprehensive evaluation of model performance. Implementation is conducted using Python, leveraging Scikit-Learn for machine learning, SciPy for signal processing, and NumPy for numerical computations, on a workstation with an Intel i7 processor, 16 GB RAM, and an NVIDIA GPU for accelerated computation. This detailed methodology ensures the transparency and reproducibility of the study's results, providing a clear rationale for the selection of specific methods and parameter settings to optimize the decoding of EMG signals for controlling arm movements.

7. Discussion

The results of this study indicate that the model combining Linear Discriminant Analysis with the Support Vector Machine (LDA–SVM) exhibits superior accuracy in classifying EMG signals for prosthetic control, achieving 90.69% accuracy with a comprehensive dataset spanning three sessions [25]. This performance surpasses that of the K-Nearest Neighbor (KNN) and Naïve Bayes (NB) models, which is consistent with findings in the existing literature where the SVM often outperforms other classifiers in high-dimensional and complex data scenarios [26,27]. The effectiveness of LDA in dimensionality reduction and enhancing class separability aligns with prior studies highlighting its utility in EMG signal processing [28]. The use of a detailed dataset like GRABMyo, encompassing diverse gestures and participants, underscores the importance of comprehensive data in developing robust machine learning models [29]. These findings have significant implications for prosthetic control systems and rehabilitation technologies, suggesting that advanced machine learning models can improve the intuitiveness and responsiveness of robotic arm movements, ultimately enhancing user experience and quality of life. Future research should explore integrating deep learning approaches, such as convolutional neural networks (CNNs), which have shown promise in EMG signal classification [7]. Additionally, addressing limitations related to inter-subject variability and real-time implementation could further advance the practical applications of these methodologies in clinical settings. Expanding the dataset to include more varied and complex gestures, as well as real-world usage scenarios, could also help in developing more generalized and adaptable prosthetic control systems.

8. Conclusions

8.1. Summary of Key Findings

The results indicate that the model combining Linear Discriminant Analysis with the Support Vector Machine (LDA–SVM) exhibited the highest accuracy in classifying EMG signals for prosthetic control. Initially, with data from a single session, the LDA–SVM model achieved an accuracy of 86.98%. When the dataset was expanded to include three sessions, accuracy improved to 90.69%, demonstrating the benefits of a larger, more comprehensive dataset. This enhancement underscores the model's robustness and its ability to generalize across different sessions and participants. The confusion matrix and performance metrics, such as precision, sensitivity, and F-measure, provided deeper insights into the classification effectiveness. For instance, the precision and sensitivity metrics indicated that the model not only accurately predicted the correct class but also had a high true positive rate across various hand gestures. Comparing the results with other machine learning models like K-Nearest Neighbor (KNN) and Naïve Bayes (NB), the SVM consistently outperformed these classifiers, particularly in handling high-dimensional data and maximizing the margin between classes. This highlights the importance of choosing appropriate dimensionality reduction and classification techniques tailored to the dataset's characteristics. The analysis also demonstrated the impact of using a diverse and detailed dataset like GRABMyo, which includes a wide range of gestures and diverse participants, on improving model performance and applicability in real-world scenarios. These findings suggest that advanced machine learning models, particularly those using SVM with LDA, can significantly enhance the functionality and intuitiveness of prosthetic control systems, paving the way for more adaptable and user-friendly prosthetic devices. Furthermore, it introduces innovative methodologies for processing EMG signals, with the goal of creating artificial intelligence systems capable of decoding brain activity to control arm movements. The research entails a comprehensive investigation into signal processing techniques and machine learning classification algorithms, all implemented on the GRABMyo dataset. The findings indicate that the employed range of techniques, signal filtering and discrete wavelet transform (DWT), alongside a composite feature set (MAV + WL + ZC + SSC + RMS + EWLs + EMAV) followed by LDA dimensionality reduction and SVM classification, yielded optimal performance. In summary, each stage of EMG signal processing is crucial for determining accuracy, highlighting the importance of careful methods selection and processing.

8.2. Recommendations for Future Work

The first limitation is that the research examines only five specific hand gestures, whereas the GRABMyo dataset offers data on 16 different hand gestures. In reality, the variety of hand gestures is virtually limitless, restricted only by an individual's creativity.

The second limitation is that the GRABMyo dataset only captures EMG signals from the forearm, while human signals originate from the brain as EEG signals before being converted by alpha motor neurons into EMG signals as illustrated in Figure 31. Future research could explore the relationship between brain activity and muscle activity to enhance artificial intelligence for controlling arm movements. The next limitation is that this research demonstrates communication with the arm operating on a half-duplex network, meaning that it only allows for a one-way transmission. Investigation can be done into the signals that are generated by the neurons, providing feedback to the senses that provide sensory information. Further exploration into incorporating bidirectional communication capabilities would enhance the system's functionality, enabling more comprehensive interaction and feedback between the user and the prosthetic device.

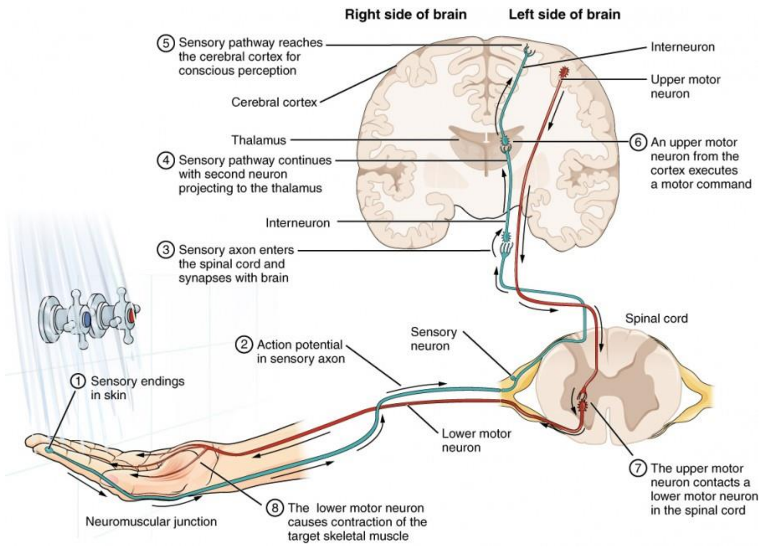


Figure 31. Diagram depicting the schematic pathway of nerves extending from the brain to the hand [30–33].

The primary focus of our analysis was on electromyographic (EMG) data, with the objective of enhancing the control systems for prosthetic devices through improved EMG signal processing and machine learning techniques. While EMG data provide valuable insights into muscle activity, it is important to acknowledge that this study does not include electroencephalographic (EEG) data analysis or the combination of EEG and EMG data for a more comprehensive analysis of motor activation patterns. The decision to concentrate exclusively on EMG data was driven by several factors. EMG signals are directly associated with muscle activity, making them particularly relevant for applications in prosthetic control. Additionally, the complexity and computational requirements of EEG signal processing were beyond the scope of this study, which aimed to develop efficient and practical solutions for prosthetic device control based on muscle activity alone. Incorporating EEG data and combining it with EMG data could offer a more detailed understanding of the neural and muscular coordination during motor tasks. EEG signals reflect brain activity and can provide insights into the intention behind motor actions, which, when combined with EMG signals, could enhance the precision and responsiveness of prosthetic control systems. Previous studies have demonstrated the feasibility and benefits of integrating EEG and EMG data. These studies utilized various methodologies to successfully integrate and analyze EEG and EMG data. Our future research work will explore the integration of EEG and EMG data to develop more advanced control systems for prosthetic devices. Proposed methodologies could include the simultaneous recording and synchronization of EEG and EMG signals, advanced signal processing techniques to extract relevant features from both data types, and machine learning algorithms designed to handle multimodal inputs. Potential challenges include managing the increased complexity of data processing and ensuring the real-time responsiveness of the control systems.

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