Data Driven Classification of Hand Postures for Myoelectric Control

A Thesis Submitted

In Partial Fulfilment of the Requirements for

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Master of Technology

Submitted by

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Certificate

This is to certify that the project report entitled "Data Driven Classification of Hand Postures for Myoelectric Control" being submitted to the Indian Institute of Technology Guwahati, India, by Mr. Harshit Paramhans (Regn. No. 234103420) for the fulfilment of the requirement for the degree of Master of Technology is a record of Bonafide research work carried out by him under my supervision. He fulfils the requirements of the regulations of the same. The results embodied in this report have not been submitted to any other University or Institute for the award of any degree.

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Abstract

Surface electromyography (sEMG) offers a non-invasive window into muscle activity and serves as a critical modality for decoding human motor intentions, particularly in the control of assistive devices such as hand exoskeletons. Myoelectric control is a sophisticated method that involves capturing and analysing electrical signals generated by muscles, then interpreting them to operate assistive robots or devices used in rehabilitation. This thesis explores two complementary approaches of feature evaluation for the classification of 15 distinct hand gestures from multi-channel sEMG signals collected from 8 human subjects.

In the first approach, the raw sEMG signals were first subjected to a standard preprocessing pipeline comprising amplification, bandpass filtering (20–450 Hz), and notch filtering at 50 Hz to remove noise and power line interference. The cleaned signals were then segmented into overlapping windows of 128 milliseconds. From each window, 16 time-domain features were extracted, capturing the statistical and morphological characteristics of the EMG waveform. These features were organized into structured feature matrices and fed into three machine learning classifiers: Random Forest (RF), Support Vector Machine (SVM), and Extra Trees Classifier (ETC). All three models demonstrated strong performance, achieving high classification accuracies in identifying the 15 hand gestures.

Subsequently, an approach which includes dimensionality reduction was employed, centered around the concept of muscle synergies. Non-negative Matrix Factorization (NMF) was applied to the processed EMG data to uncover low-dimensional representations of muscle activation patterns. The optimal number of synergies was determined using Variance Accounted For (VAF) analysis, which identified three dominant synergies that could effectively reconstruct the original signal space. These synergies were then used as features for classification. Despite the dimensionality reduction, the synergy-based features preserved sufficient discriminatory power, enabling accurate classification of hand gestures.

The results from both approaches validate the feasibility of decoding complex hand gestures using structured features and biologically inspired muscle synergy representations. This work contributes toward the development of intuitive, data-driven control strategies for intelligent hand exoskeletons and other assistive technologies

Contents

Nomenclature

EMG	Electromyography
sEMG	Surface Electromyography
MES	Myoelectric Signals
MCS	Myoelectric Control System
RF	Random Forest
ETC	Extra Tree Classifier
SVM	Support Vector Machine
NMF	Non-Negative Matrix Factorization
MAV	Mean Absolute Value
WL	Waveform Length
PSD	Power Spectral Density
PCA	Principal Component Analysis
RL	Reinforcement Learning

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Chapter 1

Introduction

1.1 Background and Motivation

The human hand is a marvel of biological engineering, capable of performing a vast array of intricate movements with precision and dexterity. However, injuries, neurological disorders, and age-related conditions often impair hand functionality, significantly affecting an individual's ability to perform daily tasks. To address these challenges, hand exoskeletons have emerged as a promising solution in rehabilitation and assistive technologies. These devices are designed to aid in restoring motor functions, assisting with movement, and enabling users to regain independence.

A critical aspect of hand exoskeleton development lies in understanding and replicating the complex neuromuscular signals that govern hand movements. Electromyography (EMG) signals, which capture the electrical activity of muscles during contraction, offer a direct interface for controlling exoskeletons. By analysing EMG signals, it is possible to infer user intent and translate it into specific hand gestures or movements. This capability makes EMG based systems particularly valuable for creating intuitive and responsive control mechanisms.

Machine learning has emerged as a powerful tool for addressing these challenges by enabling the classification of EMG signals into distinct hand gestures. However, traditional approaches often rely on complex models with extensive computational requirements, limiting their real time applicability. Furthermore, identifying the most relevant features from raw EMG data to improve classification accuracy is an ongoing area of research

The motivation for this study stems from the need to develop a data-driven approach that balances accuracy, robustness, and computational efficiency. By leveraging machine learning techniques this research aims to classify hand gestures based on EMG signals effectively.

1.2 Introduction to Machine Learning

Machine learning (ML) is a branch of artificial intelligence research that focuses on the creation and analysis of statistical algorithms that can effectively generalize and complete jobs without explicit instructions.

Mitchell [1] describes ML as "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E".

The great flexibility of machine learning algorithms enables them to process a variety of data types such as text, image, audio, numerical, and time series data. Machine learning is therefore finding use in many different domains. From the study of medicine to speech and picture recognition to problem-solving in engineering.

There are three broad categories into which machine learning can be divided which are as the following:

1. **Supervised Learning**: In supervised learning, models are trained on labelled datasets, where each input is paired with an output label. The model learns to map inputs to the correct outputs by finding patterns in the data. This approach is commonly used for tasks like classification (e.g., identifying images) and regression (e.g., predicting prices).
2. **Unsupervised Learning**: Unsupervised learning deals with unlabelled data, where the model is not given specific output labels. Instead, it learns to identify patterns and relationships within the data itself. This is useful for tasks like clustering (e.g., customer segmentation) and dimensionality reduction (e.g., feature extraction).
3. **Reinforcement Learning**: In reinforcement learning, an agent learns by interacting with an environment, receiving feedback through rewards or penalties for its actions. The goal is to maximize the cumulative reward by developing a policy that selects optimal actions over time. Reinforcement learning is widely used in applications requiring sequential decision-making, such as robotics, game playing, and autonomous driving.

The basic functioning of a machine learning algorithm is depicted in Figure 1.1. The training set, validation set, and test set are separated from the original data set.

The training data set is used to train the model. The validation set is used to verify the outcomes of the training process. Various model parameters are fine-tuned based on the validation data set results. Using the revised set of parameters, training is repeated on the training data set.

The purpose of the test data set is to evaluate the model's performance after the complete training.

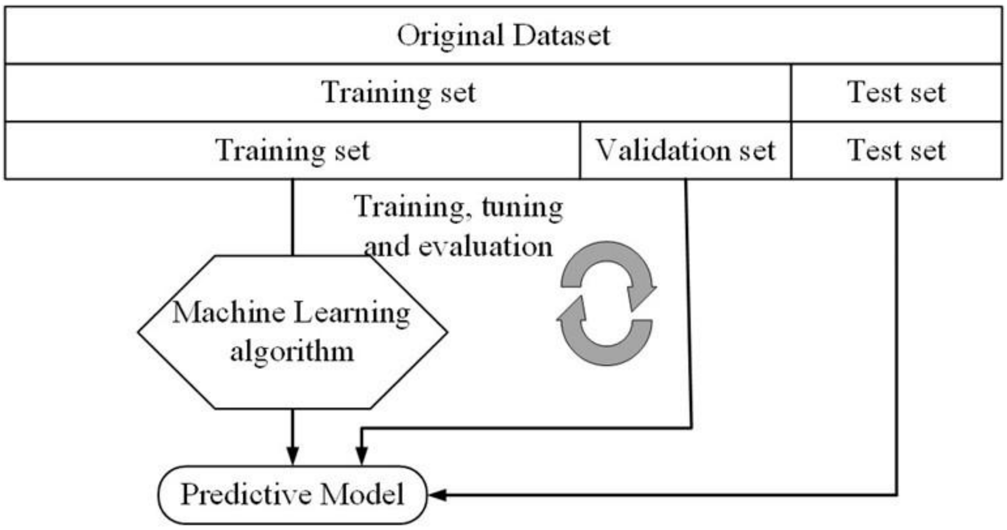

Figure 1.1 Overall working of an ML model

Through advanced algorithms, machine learning models can analyse signals from electromyography (EMG) or other sensors, allowing prosthetic hands to better interpret user intentions and provide more natural and precise movements. This adaptability helps in restoring motor function, improving user comfort, and enhancing the quality of life for amputees. Additionally, machine learning enables continuous learning and customization of prosthetic devices, ensuring they evolve with the user's needs over time, which is essential for long-term rehabilitation.

1.3 Myoelectric Control

Surface electrodes can detect myoelectric signals (MES), which carry valuable information about a person's muscle activity and intent. These signals, produced during muscle contractions, are especially useful for individuals with limb loss or physical impairments, as they can consistently generate identifiable MES patterns, even as those patterns shift slightly with different muscle efforts or limb movements. These signal patterns serve as input to a system called a myoelectric control system (MCS), which enables the operation of robotic aids or rehabilitation tools.

A key benefit of this approach, when compared to traditional systems like body-powered mechanical controls, is that it allows for intuitive, hands-free operation guided by the user's intent. MES can be recorded non-invasively from the skin's surface and tailored to control the force or speed of a device. Moreover, the level of muscular effort needed to generate a control signal is minimal, similar to what a natural limb would require. As a result, myoelectric control has emerged as a strong, commercially viable alternative to mechanical body-powered prosthetic systems.

Figure 1.2 illustrates the fundamental elements of a standard myoelectric control system that uses pattern recognition. Surface electrodes placed over muscle groups capture the myoelectric signals (MES). These electrodes are often paired with small pre-amplifiers to better isolate the weak electrical signals of interest. After acquisition, the signals are amplified, filtered, digitized using conventional EMG tools, and forwarded to a controller that processes them through four key modules:

Data Segmentation: This step involves applying specific methods to structure the raw data before extracting features. Proper segmentation helps enhance both the accuracy and responsiveness of the control system.

Feature Extraction: In this stage, selected characteristics or metrics are calculated from the segmented signals. Instead of using raw EMG data directly, these extracted features are passed to the classifier, increasing the effectiveness and speed of classification. Choosing the right features is critical to building a reliable and efficient myoelectric control setup.

Classification: This module identifies patterns within the processed signals and assigns them to predefined categories. Given the complexity and variability of biological signals, especially under changing physical or physiological conditions, the classifier must be adaptive and intelligent. It should be capable of learning and adjusting, whether through offline or real-time training.

Controller: The final stage translates the recognized signal patterns into actionable control commands. This module may also include post-processing strategies like majority voting to smooth out the output and reduce erratic behaviour. Incorporating high-level feedback (e.g., visual cues or sensory inputs) or combining MES with other sensor data can significantly improve control precision and device responsiveness (Oskoei et. al.).

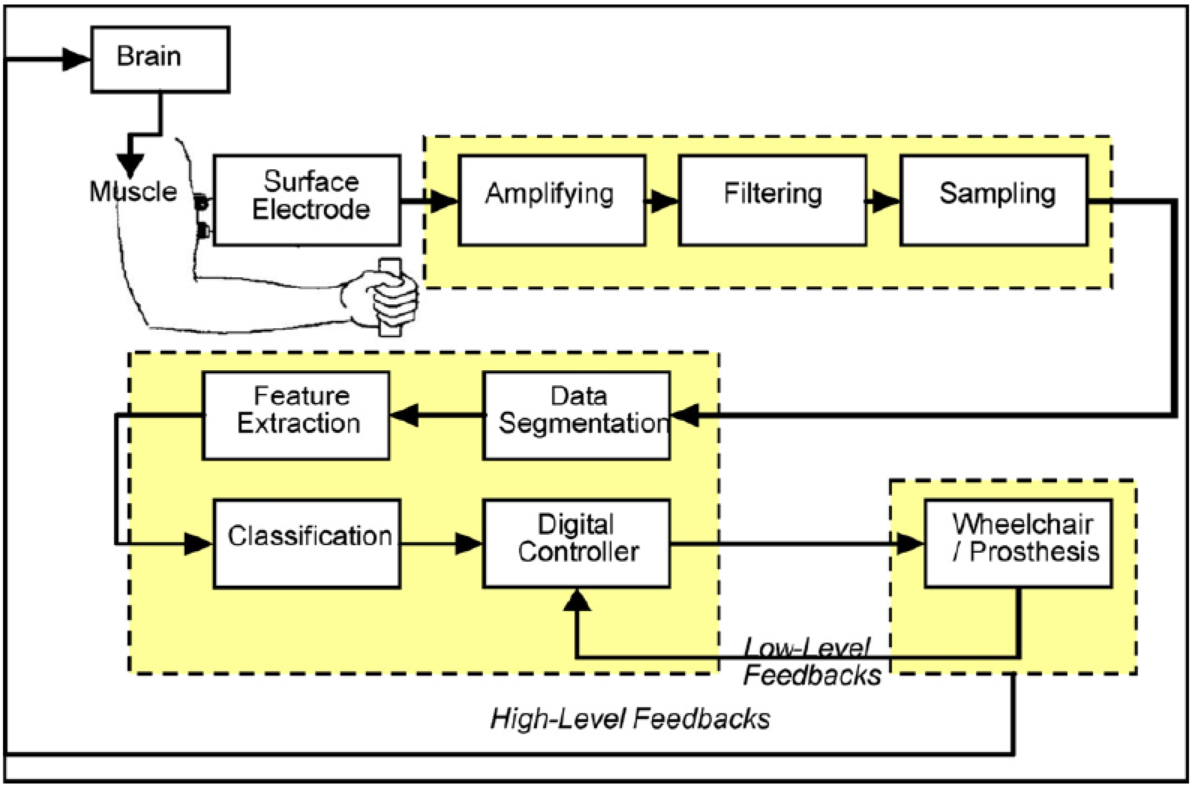

Figure 1.2 A myoelectric control system based on pattern recognition [29]

1.4 Supervised Classification in ML

One of the main areas of machine learning is supervised learning, which allows models to predict future outcomes after they have been trained using historical data. In supervised learning, input-output pairs or labelled data are used to train the model in order to generate a function that is sufficiently approximate to predict outputs for new inputs when they are introduced.

A classification algorithm is one that learns from the training set and then assigns new data point to a particular class. A classification model concludes some valid mapping function from training dataset and predicts the class label with the help of the map- ping function for the new data entry. A classification model can be built by following steps [3]:

1. Collect and clean the dataset or data preprocessing.
2. Make the classifier model initialized.
3. Split the dataset using cross-validation and feed the classifier model with training data. Python-based scikit-learn package has inbuilt methods named fit-transform (*X*,

Y)/fit (X, Y) that map the input data member set X and corresponding label set Y to prepare the classifier model.

4. Predict the label for a new observation data. There is also a method predict (X) that returns the mapped label Y for the input instance X.
5. Evaluate error rate of the classifier model on the test dataset

1.5 Objectives

The primary objective of this study is to develop a data-driven framework for the classification of hand gestures using electromyography (EMG) signals, with a focus on enabling precise and reliable control of an intelligent hand exoskeleton. By leveraging

Rami Khushaba's publicly available dataset, which contains EMG data from eight channels for 15 different hand gestures, this research seeks to bridge the gap between raw EMG signal acquisition and gesture recognition. A critical component of this study is the systematic extraction and evaluation of features from the raw EMG signals. The features are selected to capture both the temporal and spectral characteristics of the signals, along with statistical measures to enhance the differentiation between gestures. Specifically, three time-domain features two frequency-domain features and two statistical features are extracted and integrated into a feature matrix.

To achieve the classification of these gestures, the study employs three different machine learning algorithms namely Random Forest classifier, Support Vector Machines and Extra Tree Classifier, all of them known for their ability to handle high-dimensional data, robustness to overfitting, and effectiveness in capturing complex nonlinear relationships. The classifiers are trained and evaluated to determine their accuracy in distinguishing between the fifteen gestures.

The study envisions leveraging Non-Negative Matrix Factorization (NMF) to derive muscle synergies from the EMG data, simplifying the control strategy by reducing the dimensionality of the input space.

In summary, the objective of this study is to design and validate a feature-based machine learning approach for accurately classifying hand gestures from EMG signals.

1.6 Organization of the Thesis

This thesis is structured into five chapters.

Chapter 1 provides an introduction to the core concepts, including machine learning (ML), particularly supervised classification, and outlines the primary goal and motivations behind the work.

Chapter 2 offers a review of related literature, focusing on prior studies in EMG signal analysis, techniques for extracting relevant features, and the application of machine learning algorithms for recognizing hand gestures.

Chapter 3 details the methodology, describing the dataset used, characteristics of the EMG signals, and associated hand gestures. It elaborates on the steps involved in data preprocessing, the feature extraction process, and the deployment of a machine learning algorithms to perform gesture classification.

Chapter 4 showcases the classification results, assesses the performance of the ML models, and interprets the findings. This chapter concludes with a summary of contributions made by the research.

Chapter 5, the concluding chapter, discusses potential future work, such as enhancing the synergy-based classification models and incorporating control strategies to enable adaptive, real-time control of a hand exoskeleton system.

Chapter 2

Literature Review

This literature review seeks to present the current state of research relevant to the topic of myoelectric control and gesture recognition using surface electromyographic (sEMG) signals. It explores foundational and recent advancements in EMG signal acquisition, preprocessing techniques, feature extraction methods, and machine learning approaches applied to classify hand gestures. By examining existing methodologies, this review aims to identify the strengths, limitations, and research gaps within the field, laying the groundwork for the development of more efficient and adaptive control systems for assistive technologies such as hand exoskeletons.

2.1 Rehabilitation and Hand Exoskeletons

The field of hand exoskeletons, particularly for rehabilitation, has gathered significant attention due to the increasing need for effective assistive devices. These exoskeletons are designed to restore motor functionality, assist with daily tasks, and improve the quality of life for individuals with motor impairments. The design and development of active hand exoskeletons face significant challenges due to the intricate anatomy of the human hand and the constraints imposed by ergonomics, size, and weight. A decade-long review of technological advancements in this field highlights four principal application areas: rehabilitation, assistance, augmentation, and haptics. Across these domains, the integration of intelligent control systems, particularly those leveraging electromyography (EMG) has emerged as a key enabler for decoding user intent and enabling responsive robotic assistance (Du Plessis et al. [4]). Such systems are essential to bridge the gap between human intention and robotic execution, especially in clinical and assistive contexts.

Complementing these insights, a large-scale analysis of 97 active hand exoskeletons has revealed evolving design trends, including a clear preference for underactuated mechanisms due to their simplicity, reduced weight, and mechanical robustness. Soft robotics has also gained traction as a promising approach to enhance flexibility and safety in human-machine interaction. Despite these advancements, the translation of prototypes into practical, deployable solutions remains limited. The majority of systems are still confined to laboratory environments or early-stage clinical trials, with few achieving full commercialization (Noronha et al. [5]). These findings underscore the need for interdisciplinary collaboration, user-centered design, and rigorous long-term validation to facilitate the real-world adoption of hand exoskeleton technologies.

2.2 EMG-Driven Control Systems for Hand Exoskeletons

Electromyography (EMG)-based control systems have become a cornerstone of modern hand exoskeletons, enabling intuitive interaction and precise control. These systems leverage electrical signals generated by muscle activity to drive robotic mechanisms, making them particularly useful for rehabilitation and assistive purposes. Oskoei et al. [29] reviewed recent advancements in the field of myoelectric control systems, focusing on their role in developing sophisticated human–machine interfaces for rehabilitation purposes. They highlighted the importance of biomedical signals, particularly myoelectric signals, in enabling such interfaces. The study discussed both pattern recognition-based and non-pattern recognition-based approaches to myoelectric control, outlining their structures, classifications, and practical applications. Their work offers an overview of current technologies and identifies key developments shaping the future of assistive robotic systems.

Farfán et al. [26] proposed two evaluation methods grounded in information theory to assess the effectiveness of EMG signal processing techniques for use in biomedical and rehabilitation applications, particularly in the control of prosthetic and orthotic devices. They emphasized the importance of digital processing in accurately capturing the physiological changes associated with muscle contractions. The study examined four common signal processing methods, absolute mean value (AMV), root mean square (RMS), variance (VAR), and difference absolute mean value (DAMV), using EMG data collected from the middle deltoid muscle during arm abduction and adduction in the scapular plane, under both static and dynamic conditions. They also analysed factors such as optimal segmentation window length, movement type, and inter-electrode distance. Their findings indicated that RMS, AMV, and VAR were most effective during static contractions, while RMS alone performed best under dynamic conditions. The study also noted measurable differences in information content between abduction and adduction movements when using RMS.

A novel approach has been proposed for enhancing the recognition of hand and finger gestures using surface electromyographic (sEMG) signals, with a focus on improving both recognition accuracy and computational efficiency through optimized feature extraction.

Unlike earlier methods that predominantly utilized full-waveform data and the entire set of extracted features, recent strategies emphasize the importance of segmentation and selective processing to address limitations in feature redundancy and time complexity. One such method integrates a sliding window technique with the Median Absolute Deviation (MAD) for identifying significant motion segments across multiple EMG channels. From each channel, a comprehensive set of eighteen time-domain and frequency-domain features is extracted, leading to 144 features for the MA21 dataset and 360 for the UC8 dataset. To enhance efficiency, Logistic Regression (LR) is employed for feature selection, effectively reducing dimensionality while retaining informative components. The resulting feature set is evaluated using four machine learning classifiers, Extra Trees Classifier (ETC), Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbours (KNN),on both segmented and full-length signals. ETC consistently delivers the highest classification accuracy across both datasets. As demonstrated in comparative analyses, this method outperforms existing techniques by over 5%, highlighting its robustness and effectiveness in EMG-based gesture recognition (Miah et al. [27])

Bilateral EMG-driven exoskeletons have shown significant promise in the rehabilitation of stroke patients, particularly through designs that preserve tactile sensation and proprioceptive feedback. One innovative approach utilizes the non-paretic limb to generate control signals that drive the movement of the paretic hand, thereby promoting symmetrical and naturalistic motion. Real-time control strategies in such systems are designed to closely replicate voluntary motor patterns, enhancing neuroplastic recovery. Importantly, devices that feature a free-palm and free-fingertip configuration support residual sensory perception, which is critical for motor relearning and user comfort (Leonardis et al. [5]). Clinical evaluations have demonstrated that these systems can lead to measurable improvements in motor function, reinforcing the role of bilateral control paradigms in post-stroke therapy. Other EMG-based hand exoskeletons have focused on improving user safety and feedback responsiveness to meet the specific needs of patients with impaired mobility. Incorporating force sensors and safety interlocks ensures that device movement remains within safe thresholds, reducing the risk of injury during use. Such designs enable patients to gradually regain motor control by facilitating muscle activation training and guided trajectory learning. These systems underscore the importance of adaptive feedback and mechanical safety in the design of rehabilitation-focused EMG-driven exoskeletons (Wege et al., [6]). By integrating these elements, the user experience is significantly improved, promoting consistent and confidence-building use during therapy sessions.

In EMG-based gesture recognition, a segment refers to a specific time window of signal data used for extracting features. The choice of segment length plays a critical role in balancing system responsiveness and classification accuracy. For real-time applications, the duration of a segment, combined with the time required to process and classify the signal must generally remain under 300 milliseconds to ensure timely control responses. Shorter segments enable quicker response times but tend to introduce higher variability and bias in the computed features, which can negatively impact the accuracy of classification. On the other hand, longer segments may improve feature stability but reduce the system's responsiveness. Hence, an optimal trade-off between response time and accuracy must be established. It has been shown that if segmentation is applied continuously on a steady-state EMG signal, the segment duration can be safely reduced to 128 ms or even 32 ms with minimal loss in classification performance. Thanks to advancements in real-time computation and high-speed processors, where processing delays are often below 50 ms, modern systems can effectively operate with segment lengths ranging from 32 to 250 ms (Oskoei et al. [29]).

Advancements in EMG signal processing have significantly contributed to the development of these systems. Accurate and reliable EMG signal analysis is fundamental to the development of effective control systems for prosthetics and human-computer interaction. Robust signal processing techniques encompassing decomposition, feature extraction, and classification are essential to address challenges such as inter-subject variability, muscle crosstalk, and noise contamination. A comprehensive review of EMG analysis methodologies has highlighted the critical need for adaptive algorithms that can maintain performance across varying signal conditions and user profiles (Reaz et al. [7]). These insights form the groundwork for designing systems that are both responsive and generalizable across diverse rehabilitation and assistive applications.

Feature selection also plays a pivotal role in improving classification accuracy while reducing computational load in EMG-driven systems. An extensive evaluation of time-domain and frequency-domain features has identified a subset that consistently enhances discriminability among different motor intentions. This work has been instrumental in simplifying the design of real-time classification algorithms by prioritizing features that balance performance with efficiency (Phinyomark et al., [10]). The resulting frameworks enable more streamlined and scalable implementations of EMG-based control systems in wearable robotics and neurorehabilitation devices.

Despite these advancements, challenges remain in improving the robustness and adaptability of EMG-driven systems. Factors such as muscle fatigue, signal interference, and variations in electrode placement can affect performance. Addressing these issues requires the integration of adaptive algorithms and machine learning techniques to enhance real-time signal interpretation.

2.3 ML techniques for EMG Signal Classification

Machine learning (ML) has significantly advanced the classification of electromyographic (EMG) signals, offering robust frameworks for interpreting neuromuscular activity and converting it into accurate control commands for assistive technologies such as hand exoskeletons. These techniques are particularly well-suited for modeling the complex, high-dimensional, and often noisy nature of EMG data, enabling the extraction of underlying patterns that may not be easily distinguishable through conventional signal processing methods. Ensemble learning models, such as Bagged Trees, have shown exceptional promise in this domain; in one notable study, a Bagged Tree classifier achieved a classification accuracy of 98.55%, underscoring its effectiveness in handling the variability and non-linearity intrinsic to EMG signals.

Random Forest (RF) algorithms have also emerged as a preferred choice in EMG-based classification due to their ability to balance accuracy and interpretability while mitigating the risk of overfitting. RF methods not only excel in classification but also contribute meaningfully to feature selection by ranking the importance of individual features—thereby streamlining model complexity and improving performance. This dual capability is particularly beneficial in applications involving high-dimensional datasets with redundant or irrelevant variables. Further enhancements to the RF framework, such as incorporating attribute evaluation and instance filtering, have enabled even higher accuracy levels in multi-class gesture recognition tasks. These advancements illustrate the growing synergy between signal processing and intelligent algorithms, pointing toward the development of real-time, adaptive myoelectric control systems that are both computationally efficient and functionally robust. (Seyidbayli et al. [12], Jaiswal et al. [13], Chaudhary et al. [15]) Beyond traditional ML algorithms, researchers have explored advanced ensemble methods for EMG signal processing. Ren et al. [16] reviewed various ensemble techniques, including bagging, boosting, and deep learning-based approaches. Their findings underscored the versatility of ensemble methods in addressing diverse classification challenges, from motion recognition to clinical diagnosis.

Support Vector Machines (SVMs) are powerful supervised learning algorithms widely used for classification tasks due to their ability to handle both linear and non-linear data. SVMs work by finding an optimal hyperplane that maximizes the margin between data points of different classes, ensuring a robust separation with minimal classification error. When data is not linearly separable, SVMs use kernel functions to project it into a higher-dimensional space where a linear separation becomes possible. This flexibility makes SVMs highly effective in complex pattern recognition problems such as image recognition, bioinformatics, and EMG-based gesture classification. Their ability to generalize well, even with high-dimensional data and limited samples, highlights their importance in scenarios where accuracy and reliability are critical. Samrah et al. [28] conducted an evaluation of classification accuracy after extracting muscle synergies from EMG signals and reported strong results. A Support Vector Machine (SVM) classifier with a Radial Basis Function (RBF) kernel was employed, and its hyperparameters were carefully optimized to enhance performance. The use of SVM proved to be highly effective in classifying finger movements, achieving an impressive accuracy of $97.5 \pm 1.67\%$. The model performed particularly well when configured with the optimal number of synergies. Additionally, it was noted that using four or more EMG channels consistently led to classification accuracies above 95.61% across all subjects in the dataset. This highlights the significance of SVMs in accurately interpreting neuromuscular signals for gesture recognition tasks. While these methods have significantly improved classification performance, challenges such as overfitting, computational efficiency, and scalability persist. Future research should focus on developing hybrid models that combine the strengths of multiple algorithms to achieve greater robustness and adaptability.

2.4 Synergy Based Analysis Using Non-Negative Matrix Factorization (NMF)

Non-Negative Matrix Factorization (NMF) has emerged as a powerful tool for analyzing muscle synergies, offering insights into the underlying coordination patterns of human motor control. By decomposing EMG signals into non-negative components, NMF provides a biologically interpretable representation of muscle activation patterns. Non-negative Matrix Factorization (NMF) has shown considerable promise in predicting untrained static hand postures with minimal training data, achieving classification accuracies exceeding 90%. This performance is attributed to its ability to uncover underlying muscle synergies, which simplify the control of high-dimensional neuromuscular systems. Two distinct types of synergies have been identified through such analyses: subject-specific synergies that involve coordinated activation of multiple muscles, and population synergies dominated by the activation of single muscles. These insights highlight the capacity of NMF to enable more intuitive and streamlined control strategies for assistive devices such as prosthetic hands and robotic exoskeletons (Ajiboye et al. [18]).

In addition to its predictive capabilities, NMF has demonstrated superior robustness in extracting physiologically meaningful muscle activation patterns compared to traditional dimensionality reduction techniques like Principal Component Analysis (PCA). Unlike PCA, which may yield negative component values that lack direct biological interpretability, NMF ensures non-negative components that align more closely with actual muscular behavior. This makes it particularly well-suited for applications in rehabilitation robotics and prosthetics, where interpretability and alignment with human motor control principles are critical (Tresch et al. [19]).

NMF has also been applied to other domains, such as facial image recognition and semantic text analysis. Lee et al. [17] demonstrated the versatility of NMF in providing parts-based representations, contrasting it with holistic approaches like PCA. These applications underscore the adaptability of NMF as a dimensionality reduction technique.

Synergy analysis relies on evaluating the amplitude of EMG signals, which can be assessed using either averaged activity or various measures of the EMG envelope. Although EMG amplitude represents spinal motoneuron output, their relationship is not straightforward making the choice of EMG acquisition and processing methods critical. Preprocessing is a critical step in EMG signal analysis, as it directly influences the accuracy and reliability of extracted muscle synergies. Standard procedures typically include signal rectification followed by low pass filtering to generate a smooth signal envelope. Although various filtering approaches such as moving averages, root mean square (RMS) calculations, and wavelet transforms can be employed, the differences in their outcomes are often marginal. However, the level of smoothing and the choice of cut-off frequency can substantially affect the composition and clarity of the identified synergies. Lower cut-off frequencies, for instance, may cause increased signal overlap, which can distort the spatial characteristics of synergy structures. A cut-off range between 9–12 Hz is generally considered optimal, offering a trade-off between effective noise suppression and the retention of meaningful signal patterns. Further refinements, such as demeaning or baseline correction, can eliminate constant background interference or amplifier bias, thereby improving signal quality. While not universally applied, these enhancements can significantly boost the signal-to-noise ratio and facilitate more accurate synergy extraction (Turpin et al. [21]).

2.5 Summary

This literature review consolidates key research developments in the field of myoelectric control and gesture recognition using surface electromyographic (sEMG) signals, with a focus on applications in rehabilitation and assistive technologies such as hand exoskeletons.

The review begins by discussing the evolution of hand exoskeletons for rehabilitation, emphasizing their potential to restore motor function in individuals with neuromuscular impairments. Design challenges, such as anatomical complexity and user safety, are addressed through underactuated mechanisms, soft robotics, and user-centered approaches. However, despite technological advancements, the transition from laboratory prototypes to real-world deployment remains limited.

In the domain of EMG-driven control systems, multiple signal acquisition and preprocessing strategies are explored to decode user intent effectively. Studies highlight the importance of robust signal segmentation, adaptive feedback, and precise motion tracking. Techniques such as RMS and variance-based feature extraction, bilateral control architectures, and integrated safety mechanisms are shown to enhance usability and therapeutic efficacy.

The section on machine learning techniques demonstrates the growing reliance on intelligent algorithms for classifying EMG signals. Ensemble methods, particularly Random Forests and

Bagged Trees, exhibit high classification accuracy and feature selection capabilities. Support Vector Machines (SVMs), especially with RBF kernels, also prove highly effective, particularly in synergy-driven classification of hand gestures.

Finally, Non-Negative Matrix Factorization (NMF) is presented as a biologically meaningful tool for synergy analysis. NMF outperforms conventional dimensionality reduction methods by preserving physiological interpretability and simplifying control strategies. It reveals both subject-specific and population-level synergies, enabling accurate classification of hand postures with minimal training data.

Overall, this review identifies critical gaps in generalizability and robustness of EMG-driven systems. It suggests that future research should prioritize hybrid machine learning models, adaptive control strategies, and physiologically grounded dimensionality reduction methods to enhance the practicality and effectiveness of human-machine interfaces in rehabilitation.

Chapter 3

Methodology

This study seeks to develop an accurate and efficient classification system for recognizing hand gestures using surface electromyography (sEMG) signals, forming a foundational step toward the larger goal of intuitive control for a hand exoskeleton. The work completed so far focuses on building a robust pipeline for EMG signal preprocessing, feature extraction, and classification, using a publicly available dataset. Emphasis is given on accurate gesture recognition through machine learning techniques.

3.1 Description of the Dataset

The raw EMG signal data is taken from the online bio signals repository provided by Dr. Rami N. Khushaba. In the experiment he conducted for his paper [20], eight subjects, six males and two females, aged between 20-35 years were recruited to perform the required finger movements. The subjects were all normally limbed with no neurological or muscular disorders. All participants provided informed consent prior to participating in the study. Subjects were seated on an armchair, with their arm supported and fixed at one position. The datasets were recorded using eight EMG channels (DE 2.x series EMG sensors) mounted across the circumference of the forearm and processed by the Bagnoli desktop EMG system from Delsys Inc. A 2-slot adhesive skin interface was applied on each of the sensors to firmly stick them to the skin. A conductive adhesive reference electrode, dermatrode reference electrode, was placed on the wrist of each of the subjects during the experiments.

The collected EMG signals were amplified using a Delsys Bagnoli-8 amplifier to a total gain of 1000. A 12-bit analog-to-digital converter (National Instruments, BNC-2090) was used to sample the signal at 4000 Hz; the signal data were then acquired using Delsys EMGWorks Acquisition software. The EMG signals were then bandpass filtered between 20-450 Hz with a notch filter implemented to remove the 50 Hz line interference. Fifteen classes of movements were collected during this experiment including: the flexion of each of the individual fingers, i.e., Thumb (T), Index (I), Middle (M), Ring (R), Little (L), and the combined Thumb-Index (T-I), Thumb-Middle (T-M), Thumb-Ring (T-R), Thumb-Little (TL), Index-Middle (I-M), Middle-Ring (M-R), Ring-Little (RL), Index-Middle-Ring (I-M-

R), Middle-Ring-Little (M-RL), and finally, the hand close class (HC) as shown in Fig.3.1. These were labelled from number 1 to 15 in the same order as above.

The subjects were asked to perform each of the aforementioned fifteen movements and hold that movement for a period of 20 seconds in each trial. So, in summary, the raw data consists of EMG signals for fifteen hand gestures for eight subjects conducted over three trials.

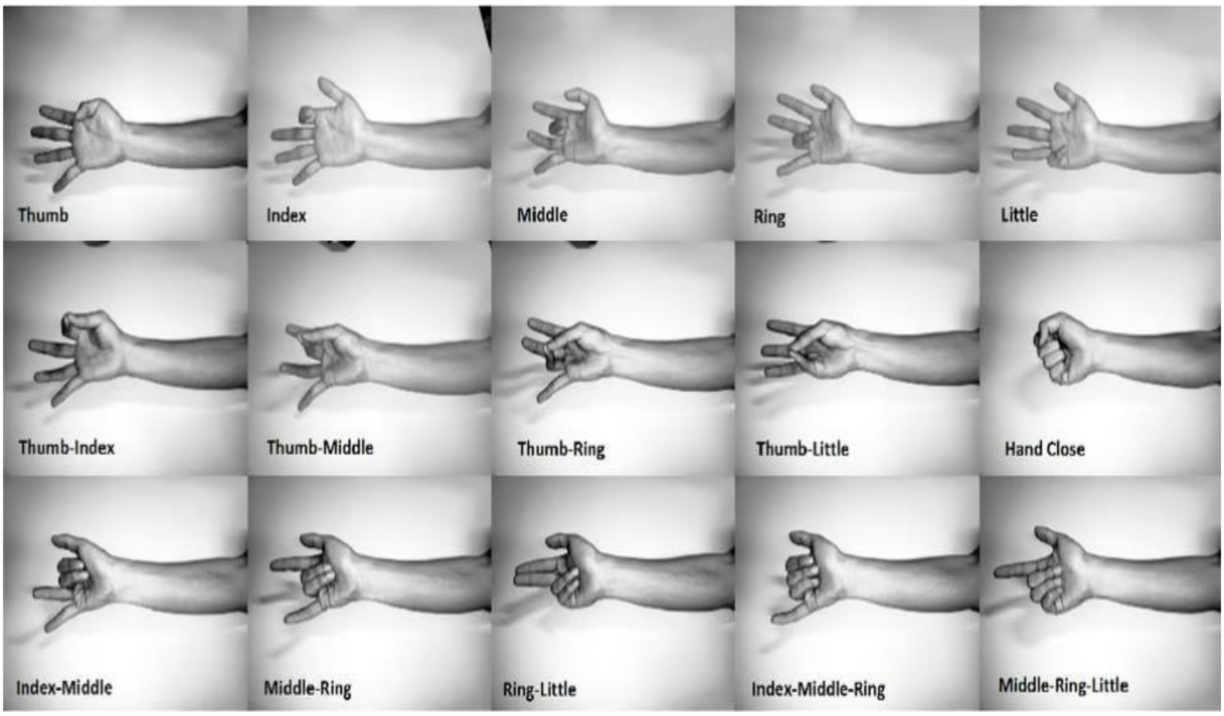

Figure 3.1 Different classes of individual and combined fingers movement [20]

3.2 Visualising the raw EMG data

To gain an initial understanding of the characteristics and structure of the recorded EMG signals, visual inspection was carried out. Plotting the raw EMG data provides insights into the signal amplitude, periodicity, and potential artifacts or noise. This step is crucial for identifying the typical features of muscle activation patterns across different hand gestures and subjects before applying any preprocessing or analysis techniques.

To understand the temporal behaviour of the EMG signals, the amplitude of all eight muscle channels was plotted over a one second window for a single trial corresponding to the thumb flexion posture of subject 1. The time series plot shown in Figure 3.2 illustrates the natural variability and burst-like structure typical of EMG signals during voluntary muscle contractions. Each colored line represents the EMG signal from one of the eight forearm muscles. The plot reveals distinct peaks in signal amplitude, especially in certain muscle channels, which suggests varying levels of muscle activation during the gesture.

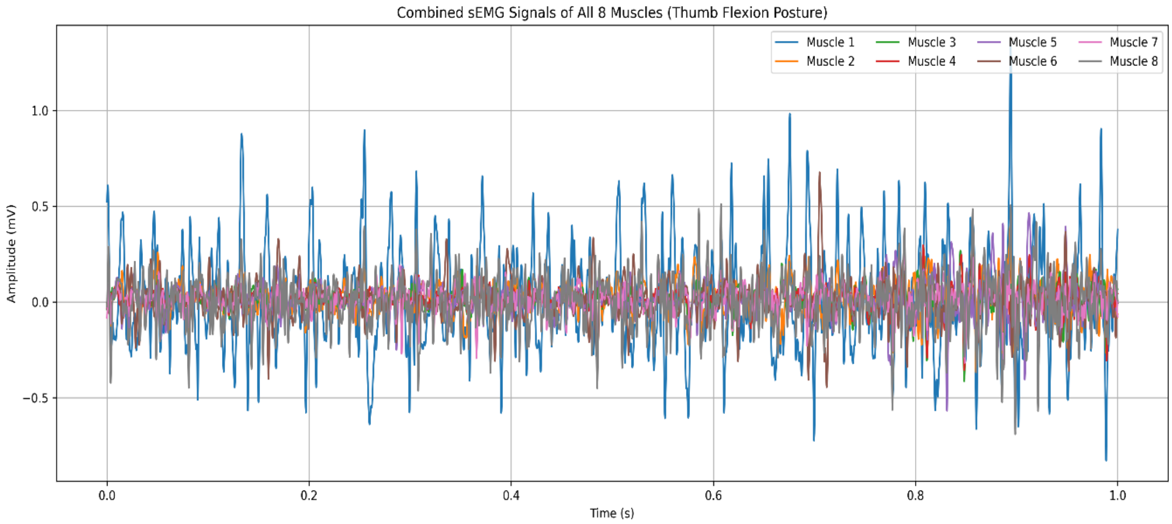

Figure 3.2 Combined signals from all 8 forearm muscles for the thumb flexion posture (S1)

To further analyse the activity patterns of individual muscles, the sEMG signals from each of the eight channels were plotted separately over a 20-second duration for the same posture. As shown in Figure 3.3, this visualization helps identify distinct signal characteristics, such as amplitude ranges, baseline drift, and potential artifacts in each muscle's signal. Notably, some muscles exhibit higher peak amplitudes compared to others, indicating stronger involvement during that gesture.

3.3 Analysis using raw data

An initial attempt was made to analyse and classify hand gestures using raw surface electromyography signals. The goal was to explore the viability of direct feature extraction from unprocessed data for gesture recognition.

3.3.1 Extracting Features from raw data

For each trial (total of 360 across all subjects and postures), four time-domain features were extracted from the raw EMG signals corresponding to each of the 8 forearm muscles. The features selected for this preliminary analysis were:

Root Mean Square (RMS): It represents the square root of the average of the squared values of the signal. It reflects the power content of the EMG signal and correlates with the contraction level of muscles.

Mean Absolute Value (MAV): MAV calculates the average of the absolute values of the EMG signal. It provides an estimation of the signal's overall activity level and is computationally simple to implement.

Waveform Length (WL**):** WL is the cumulative length of the waveform over the analysis window. It measures the complexity and variability of the signal.

Simple Squared Integral (SSI): It is time-domain feature that quantifies the total energy of the EMG signal over a given time window by summing the squares of all signal values. It provides insight into the intensity and power of muscle activation during movement.

The raw EMG signals were processed and analysed using Python, which served as the primary tool for data handling, signal processing, and classification tasks throughout the study. Python's open-source ecosystem offers a rich collection of libraries such as NumPy, Pandas, SciPy, and scikit-learn, which were instrumental in efficiently manipulating large datasets, extracting meaningful features, and building machine learning models. Signal processing techniques including feature computation like RMS, MAV, WL, and SSI were implemented using NumPy and SciPy, while data organization and transformation were handled using Pandas. The classification of hand gestures was performed using Random Forest Classifier from scikit-learn, benefiting from Python's simplicity, readability, and robust scientific computing capabilities.

3.3.2 Organising the extracted features

The four features (Root Mean Square, Mean Absolute Value, Waveform Length, Simple Square Integral) were calculated for all eight muscles for a given hand gesture, resulting in a feature matrix of size 8×4 for each hand gesture. Since there were eight subjects, each performing fifteen hand gestures for three trials, therefore the total number of trials were 360 (8×15×3). To prepare the data for compatibility with machine learning algorithms requiring a vectorized input, the 8×4 matrix of features for each gesture was flattened into a one-dimensional vector of size 32 (8×4). This transformation ensured that the feature data for each hand gesture was represented as a single feature vector. The above process was repeated for all hand gestures in the dataset, resulting in a set of feature vectors corresponding to each hand gesture.

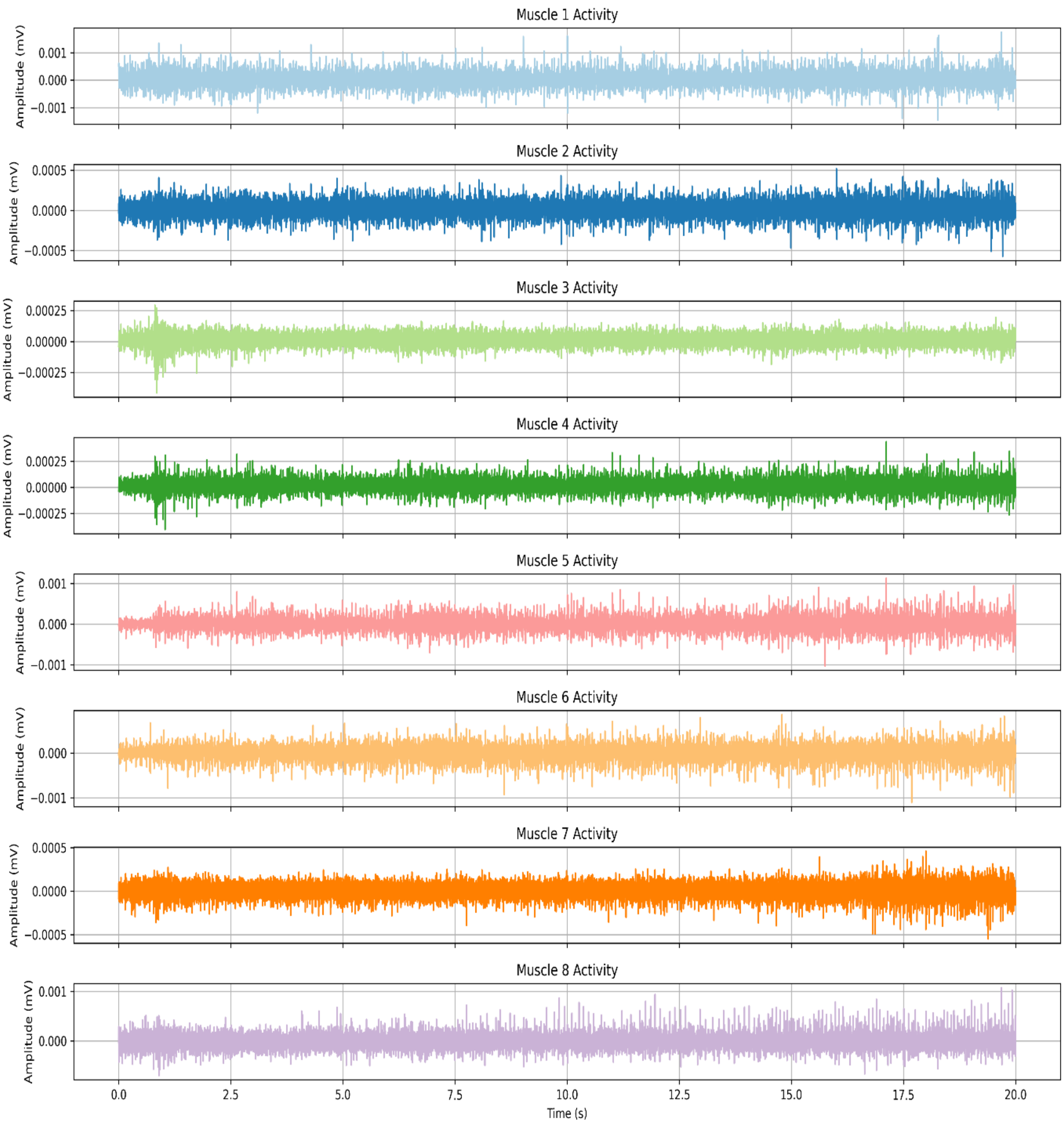

Figure 3.3 Individual sEMG activity plots of all muscles for thumb flexion posture of subject 1

The flattening step allowed for seamless integration of the feature data into the machine learning pipeline while preserving the contribution of features from all muscles. Lastly, to complete the feature matrix, a label column was added corresponding to each hand gesture. This preparation enabled consistent analysis and classification of hand gestures based on their EMG signal patterns.

3.3.3 Classification using Random Forest Classifier

A single decision tree often is not effective, as it learns specific patterns from the training data and fails to generalize well to unseen data. To overcome this limitation, the Random Forest (RF) algorithm is employed, which builds an ensemble of decision trees rather than relying on a single model. This ensemble approach introduces controlled randomness by selecting subsets of features and data samples through Breiman's bagging method. Each decision tree in the forest is trained on a randomly drawn subset of the training data, with replacement, which helps to increase diversity among the trees. Additionally, at each node, only a random subset of features is considered for splitting, encouraging varied decision paths across the forest. Each tree acts as a weak learner, and their collective predictions are aggregated using majority voting to produce the final output. This ensemble strategy enhances classification robustness, reduces overfitting, and effectively filters out noise from the input data, making Random Forest a reliable choice for the classification task.

The extracted feature matrix X of size 360×32, containing features for all eight muscles across all hand gestures, along with the corresponding labels vector y of size 360×1 was used for classification. A Random Forest (RF) classifier was implemented to classify hand gestures based on the extracted features. The implementation was performed using Python and the Scikit-learn library. To ensure the classifier performs optimally, the dataset was split into training and testing subsets using a stratified train-test split with 80% of the data allocated for training i.e. 252 out of 360 data points and 20% for testing i.e. 108 out of 360 data points. This stratification preserved the proportion of labels in both subsets. The features were then standardized using the StandardScaler function from Scikit-learn to normalize their values, which is critical for algorithms sensitive to feature scaling. To identify the optimal number of decision trees (estimators) for the Random Forest classifier, a hyperparameter tuning procedure was conducted, the Random Forest model was trained iteratively with the number of estimators (n_estimators) varying from 50 to 300 in steps of 50.

For each configuration, the model was trained on the standardized training set and evaluated on the test set using classification accuracy as the performance metric. The resulting accuracy scores were recorded across all tested values of n_estimators.

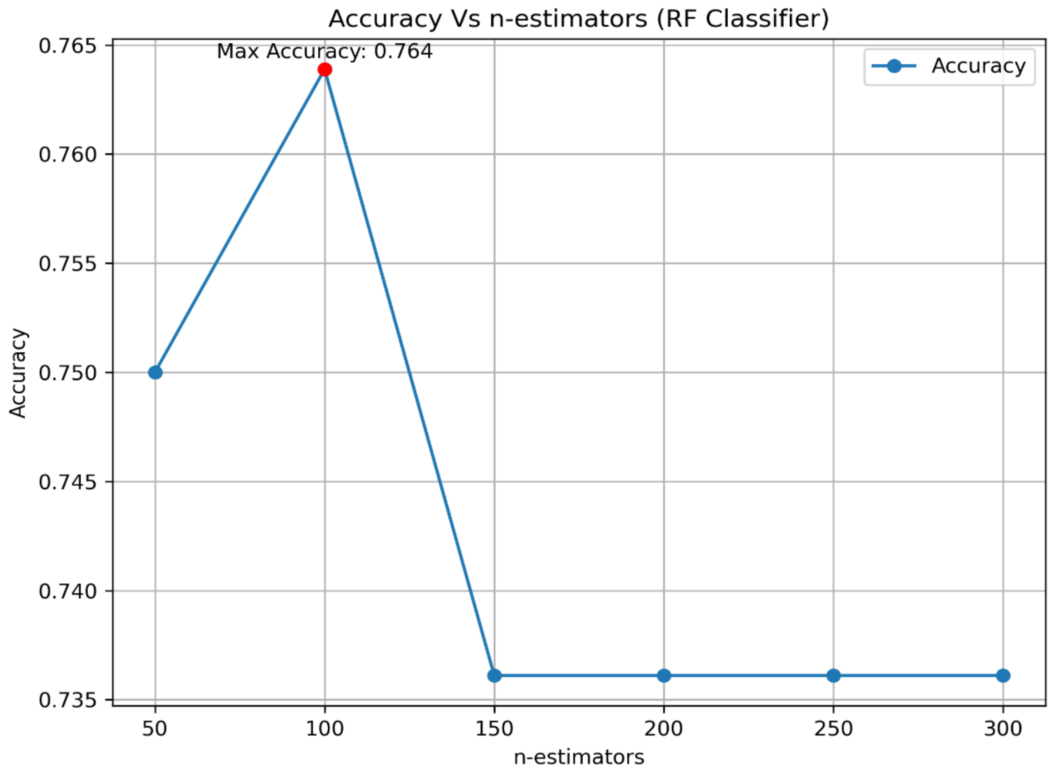

Figure 3.4 Accuracy vs Number of Estimators for Random Forest Classifier.

3.4 Processing the raw data

In the previous section, hand gesture classification was performed using features directly extracted from unprocessed raw EMG signals, which resulted in a classification accuracy of 76.3%. While this provided a useful preliminary benchmark, raw EMG data is inherently noisy due to factors such as motion artifacts and powerline interference, which can adversely affect the quality of extracted features and reduce classification performance.

To improve signal quality, a systematic preprocessing pipeline was implemented. The EMG signals were first amplified using a gain of 1000, mimicking the amplification typically applied during EMG acquisition. This step ensured that the signals had sufficient amplitude for reliable analysis. Next, a bandpass filter with a passband of 20–450 Hz was applied to retain the physiological frequency range of EMG activity, effectively suppressing both low-frequency motion artifacts and high-frequency noise. Following this, a notch filter centered at 50 Hz was used to remove powerline interference, which is a common source of noise in biomedical recordings. These filtering steps significantly improved the clarity of the EMG signals and prepared the data for accurate segmentation and feature extraction in the subsequent stages of the methodology.

3.5 Data Segmentation and Feature Extraction

After preprocessing, the continuous EMG data was segmented into smaller windows to facilitate meaningful feature extraction and improve classification performance. As a first step, the duration of each trial was trimmed from 20 seconds to 5 seconds. This reduction offered multiple advantages: it ensured a more manageable dataset size, minimized redundant or low-activity periods from the signal, and significantly reduced computational overhead without sacrificing the quality of information captured during the gesture execution window.

For the segmentation process, each 5-second EMG signal was divided into overlapping windows of 128 milliseconds equivalent to 512 samples at a 4000 Hz sampling rate, with a sliding increment of 64 milliseconds (256 samples). This overlap ensures a dense representation of temporal dynamics while still enabling real-time applicability. The choice of a 128 ms window strikes a balance between achieving fast system responsiveness and preserving sufficient signal content for robust feature extraction, aligning well with existing literature on real-time EMG-based control systems.

From each 128 ms segment, a set of sixteen time domain and statistical features were extracted. These features capture diverse signal characteristics such as amplitude, power, shape, and complexity, and are widely recognized for their effectiveness in EMG-based pattern recognition tasks. The extracted features and their mathematical formulae are shown in Table 3.1.

Feature Name	**Formula**
Mean Absolute Value (MAV)	$MAV = \frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert$
Variance (VAR)	$\sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)^2$
Standard Deviation (STD)	$\sigma = \sqrt{\left\{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2\right\}}$
Minimum Amplitude (MA)	$x_{min} = min(x)$

Maximum Amplitude (MxA)	$x_{max} = max(x)$
Peak to peak (PTP)	$PTP = x_{min} - x_{max}$
Root Mean Square (RMS)	$RMS = \sqrt{\left\{\frac{1}{N}\sum_{i=1}^{N} x_i^2\right\}}$
Sum of Absolute Difference (SAM)	$SAM = \sum_{i=0}^{N-1}(X_{i+1} - X_i)$
Skewness	$G_1 = \frac{m_3}{m_2^{3/2}}\,; m_3 = E[(x_i - \mu)^3];$ $m_2 = E[(x_i - \mu)^2]\,; m_4 = E[(x_i - \mu)^{4]}$
Kurtosis	$G_2 = \frac{m_4}{m_2^2}$
Zero-Crossing (ZC)	$ZC = \sum_{n=1}^{N-1}[\mathrm{sign}(x_n \times x_{n+1}) \cap \lvert x_n - x_{n+1}\rvert \geq 0]$
Energy	$Ene = \frac{1}{N}\sum_{i=1}^{N} x_i^2$
Hjort parameter activity (HPA)	$HPA = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$
Inter Quartile Range (IQR)	$IQR = UQ - LQ \;\; ; \;\; UQ = (3/4)[(N+1)^{th}$ term] $LQ = (1/4)[(N+1)^{th}$ term]
Slope Sign Change (SSC)	$SSC = \sum_{i=2}^{N-1} f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]\,;$ $f(x) = \{1, x \geq 0;\; 0, x < 0\}$
Willison Amplitude (WAMP)	$WAMP = \sum_{i=1}^{N-1} f(\lvert x_i - x_{i+1}\rvert);$ $f(x) = \{1, x \geq 0;\; 0, x < 0\}$

Table 3.1 All Feature names and formula

3.6 Organisation of the Features

Following the segmentation of the EMG signals, a structured feature matrix was generated to facilitate classification of hand gestures. From each 128 ms window, a total of 16 features were extracted per muscle. Given that signals were recorded from 8 forearm muscles, this resulted in a feature vector of length 128 (i.e., 16 features × 8 muscles) for each window.

The 5-second trimmed EMG signal for each gesture was segmented using a window length of 128 ms and an overlap of 64 ms. The number of segments N generated from a 5-second signal can be calculated using the formula:

$$N = \left[\frac{Total\ Samples - Window\ Length}{StepSize}\right] + 1 \tag{3.1}$$

For our case, the total samples for 5 seconds at a sampling frequency of 4000 hertz come out to be 20,000 samples. The window length is 128 ms which is equivalent to 512 samples, and the step size is 64 ms which is equivalent to 256 samples. Hence, number of segments for our case comes out to be 77. Thus, for each trial of a given hand gesture, 77 feature vectors of size 128 were obtained, resulting in a feature matrix of size 77×128 per trial.

Each subject performed 15 distinct hand gestures, with 3 trials per gesture. Therefore, for a single subject, the total number of feature vectors was 3465. Consequently, for each subject, the final organized feature matrix had a shape of 3465×128, where each row represented a segmented window of EMG data flattened into 128 features, and each row was labelled with the corresponding hand gesture class. This structured dataset served as the input for three classification models namely Random Forest, Support Vector Machines and Extra Tree Classifier.

3.7 Classification of Hand Gestures

To accurately classify hand gestures from sEMG signals, it is essential to select an appropriate machine learning algorithm capable of handling the variability in feature values. The choice of classifier plays a crucial role in determining the overall efficiency, reliability, and accuracy of the gesture recognition system. Factors such as computational speed, adaptability to feature distributions, and classification precision are taken into account while identifying the most effective model. In this study, three machine learning classifiers were evaluated for their performance in classifying sEMG-based hand gestures: Random Forest (RF), Extra Trees Classifier (ETC), and Support Vector Machine (SVM). The working mechanism of RF is discussed in section 3.3.3, the working procedure of SVM and ETC are discussed below.

3.7.1 Support Vector Machine

Support Vector Machine (SVM) is a supervised learning algorithm that constructs an optimal hyperplane to classify data points in an N-dimensional feature space. While SVMs are inherently designed for binary classification, they can be effectively extended to multi-class problems using the One-vs-Rest strategy. By using kernel functions, SVMs can effectively handle non-linear classification problems by projecting the data into higher dimensions where a linear separation is feasible. The algorithm maximizes the margin between classes, ensuring robustness against overfitting, especially in high-dimensional spaces like EMG feature vectors. In this study, SVM was used to classify hand gestures based on muscle activation patterns with a focus on achieving high accuracy and generalization. In this approach, separate classifiers are trained for each class, distinguishing one class from all others, and the final class prediction is determined based on the classifier with the highest confidence score [30].

3.7.2 Extra Tree Classifier

The Extra Trees Classifier (ETC) is an ensemble learning method that constructs multiple unpruned decision trees using a conventional top-down approach. While its structure is similar to that of the Random Forest algorithm relying on an ensemble of decision trees and randomly selected feature subsets for node splitting, it differs in two fundamental ways: ETC does not employ bootstrapped sampling of the training data, and it selects split points at random rather than choosing the optimal split based on a criterion such as information gain. In ETC, both the cut-points and the features used for splitting are chosen randomly, which often results in fully random tree structures that are less sensitive to the initial training sample. Each decision tree contributes an individual prediction, and the final output is determined by aggregating these predictions through majority voting. The algorithm's design specifically its use of original training samples and random split selection helps reduce variance while maintaining computational efficiency [31]. This makes ETC particularly advantageous for handling high dimensional data with minimal training overhead.

Each model was trained and validated using five-fold cross validation to ensure robustness and generalizability. The best-performing classifier was selected based on its classification accuracy and consistency across validation folds.

3.8 Dimensionality Reduction

Surface electromyography (sEMG) signals are inherently high-dimensional due to multiple recording channels and feature extraction across time. While this rich information is valuable, it can also lead to computational inefficiency and overfitting in classification models. To address this, dimensionality reduction techniques were explored to identify compact, yet physiologically meaningful representations of muscle activity. Specifically, this study focusses on extracting muscle synergies, coordinated activations of groups of muscles, which are hypothesized to underlie motor control. This approach allows for a reduction in the number of input features while preserving the essential structure of the data.

3.8.1 Muscle Synergy

A simple definition of a muscle synergy given by Lee et. al [31] is "a set of muscles which act together to produce a desired effect". Muscle synergy analysis is a tool used in various domains such as neurosciences, robotics, sport sciences or rehabilitation to gain insights about basic motor control science, motor coordination strategies or to quantify functional deficits in pathologies. The core of the method is to reduce the number of dimensions of the electromyographic (EMG) data, i.e., the number of muscles, to a limited set of meaningful variables, referred to as synergies. Muscle synergies can be conceptualized as vectors in the multidimensional muscle activation space. The EMG activity of m muscles for T number of time samples can be written in a matrix form as:

$$E = W \times C + residual \tag{3.2}$$

with E, W, C and residual, matrices of dimensions, $m \times T, m \times s, s \times T$ and $m \times T$ respectively. This representation allows to separate the spatial (W) and temporal (C) components.

Synergy analysis is based on the examination of the amplitude of EMG signals, using either averaged activity or different measures of its envelope and The most commonly accepted method to obtain the envelope is to low-pass filter the rectified EMG (using a zero-lag, Butterworth filter in most cases): the EMG envelope is obtained by smoothing the EMG signal after rectification.[21]

3.8.2 Creating EMG envelopes

To extract meaningful patterns of muscle activation from the raw surface EMG signals, a series of signal processing steps were applied to generate the EMG envelopes for each gesture, subject, and trial. These envelopes serve as smooth, amplitude-modulated representations of muscle activity over time, and are essential for subsequent muscle synergy analysis.

The raw EMG signals were first subjected to baseline drift removal by subtracting the mean value of the signal. This step ensures that any low frequency offset or DC component is eliminated. Following this, a band-pass filter (Butterworth, 4th order) with cut-off frequencies of 20 Hz and 450 Hz was applied to isolate the relevant frequency components of the EMG signal while removing motion artifacts and high-frequency noise. To address power-line interference commonly present in biomedical recordings, a notch filter was applied at 50 Hz using an infinite impulse response (IIR) notch filter with a quality factor of 80. The filtered signal was then rectified by taking the absolute value of each sample, converting the signal into a unipolar form that emphasizes the magnitude of muscle activity. Finally, the rectified signal was passed through a low-pass filter (Butterworth, 1st order) with a cutoff frequency of 10 Hz to produce the smoothed EMG envelope. Previous studies suggest that a cut-off frequency of approximately 9–12 Hz may preserve subject-specific information while reducing the amount of noise [21]. This envelope captures the gradual changes in muscle activation intensity while discarding rapid fluctuations.

This complete preprocessing pipeline was uniformly applied across all trials, gestures, and subjects to generate consistent and noise-suppressed EMG envelopes for muscle synergy extraction and further analysis.

3.8.3 Application of VAF to Obtain Optimal Number of Synergies

To determine the appropriate number of muscle synergies, Variance Accounted For (VAF) analysis was conducted. VAF measures how well the synergies reconstructed the original EMG data. Non-negative Matrix Factorization (NMF) was applied iteratively, increasing the number of synergies from 1 to 8. For each configuration, VAF was calculated using the formula:

$$VAF = \left(1 - \frac{(E - WH)^2}{E^2}\right) \tag{3.3}$$

The optimal number of muscle synergies was the minimum number of synergies when the mean of the VAFs was > 0.95 with the mean VAFs increase < 0.01 upon addition of muscle synergy [22]. Figure 3.5 shows the relationship between the mean VAF and the number of muscle synergies of subject 1. The mean VAF of the 15 for subject 1 for the first trial was 98.67% when the number of muscle synergies was 2 (s = 2) and 99.3% when s = 3. According to the rule for determining the number of muscle synergies above, the optimal number of synergies for the study is 2.

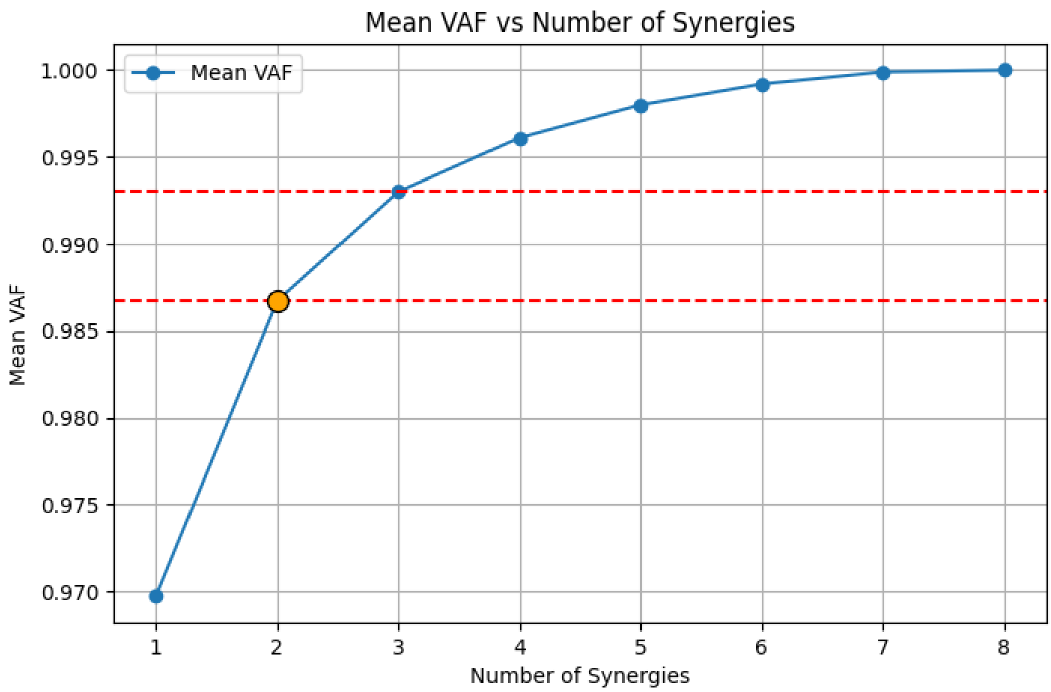

Figure 3.5 Relationship between mean VAF and the number of muscle synergies (Subject 1)

3.8.4 Classification using Muscle synergies

After extracting muscle synergies through Non-Negative Matrix Factorization (NMF), the spatial synergy matrix W, which encodes the invariant muscle activation patterns, was utilized as the feature set for classification. Each column of W represents a muscle synergy, these spatial components provide a compact, physiologically interpretable representation of muscle coordination. The synergy matrix was derived from the EMG envelope across the 8 muscles for all gestures for subject 1. Given that the number of synergies was determined using Variance Accounted For (VAF) analysis, the resulting W matrix had a shape of 8×2, where 2is the optimal number of synergies. This matrix was flattened into a 16-dimensional feature vector for each gesture-trial combination. Consequently, a feature matrix of size 45×16 (15 gestures × 3 trials) was constructed. This matrix was then used to train and evaluate the ETC using 5-fold cross-validation. Figure 3.6 shows the muscle activations with respect to each posture of the first trial of subject 1.

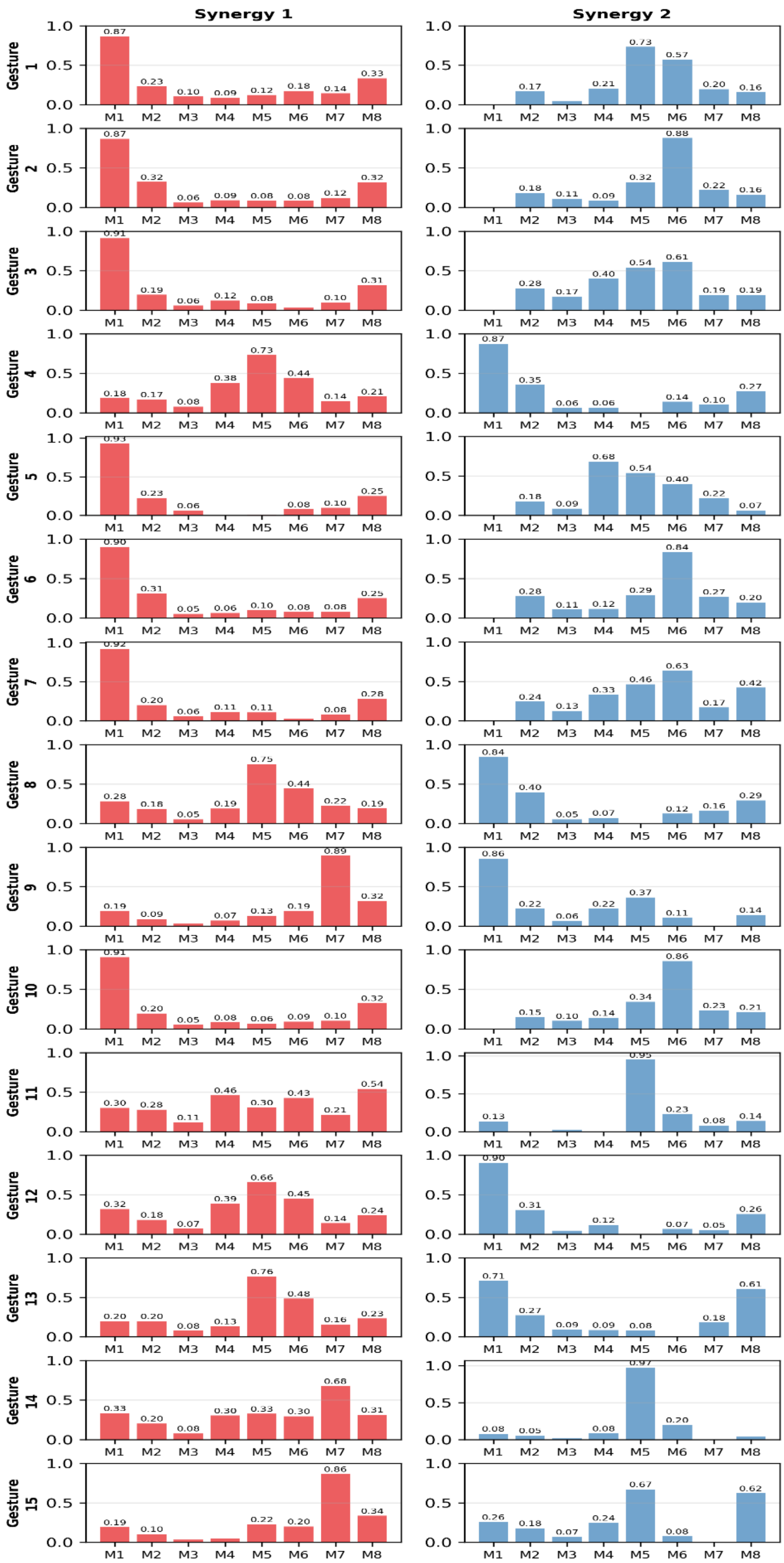

Figure 3.6 Normalized Synergy Vectors for first trial of Subject 1

Chapter 4

Results and Discussions

4.1 Model Performance for Unprocessed Data

4.1.1 Classification Report

The Random Forest Classifier achieved an accuracy of **76.39%** indicating its effectiveness in classifying hand gestures based on the extracted EMG features. The model's performance was evaluated using several metrics, including precision, recall, F1-score, and support for each gesture class, as detailed in Table 4.1.

Label	precision	recall	f1-score	support
1	1.000	0.750	0.857	4.000
2	0.667	0.800	0.727	5.000
3	0.571	0.800	0.667	5.000
4	0.714	1.000	0.833	5.000
5	1.000	0.800	0.889	5.000
6	1.000	1.000	1.000	5.000
7	1.000	1.000	1.000	5.000
8	0.667	0.400	0.500	5.000
9	0.714	1.000	0.833	5.000
10	0.667	0.500	0.571	4.000
11	1.000	0.200	0.333	5.000
12	0.500	0.500	0.500	4.000
13	0.667	0.800	0.727	5.000
14	0.833	1.000	0.909	5.000
15	0.800	0.800	0.800	5.000
accuracy	0.764	0.764	0.764	0.764
macro avg	0.787	0.757	0.743	72.000
weighted avg	0.789	0.764	0.747	72.000

Table 4.1 Classification report of RF classifier (without preprocessing)

The classifier achieved an overall accuracy of 76.39%, indicating moderate performance in recognizing hand gestures based on unprocessed EMG data. Notably, several classes such as gesture 6 and 7 were classified with perfect precision and recall, suggesting clear separability in the feature space. However, others like gesture 11 and 8 showed significantly lower F1-scores (0.33 and 0.50 respectively), likely due to noise and inter-class overlap in the raw signals. This initial evaluation serves as a baseline and underscores the necessity for robust preprocessing methods to enhance signal quality and improve classification accuracy.

4.1.2 Confusion matrix

The confusion matrix (Fig 4.2) provides a visual representation of the classifier's predictions compared to the true labels. It highlights the correctly classified instances along the diagonal and the misclassified instances elsewhere.

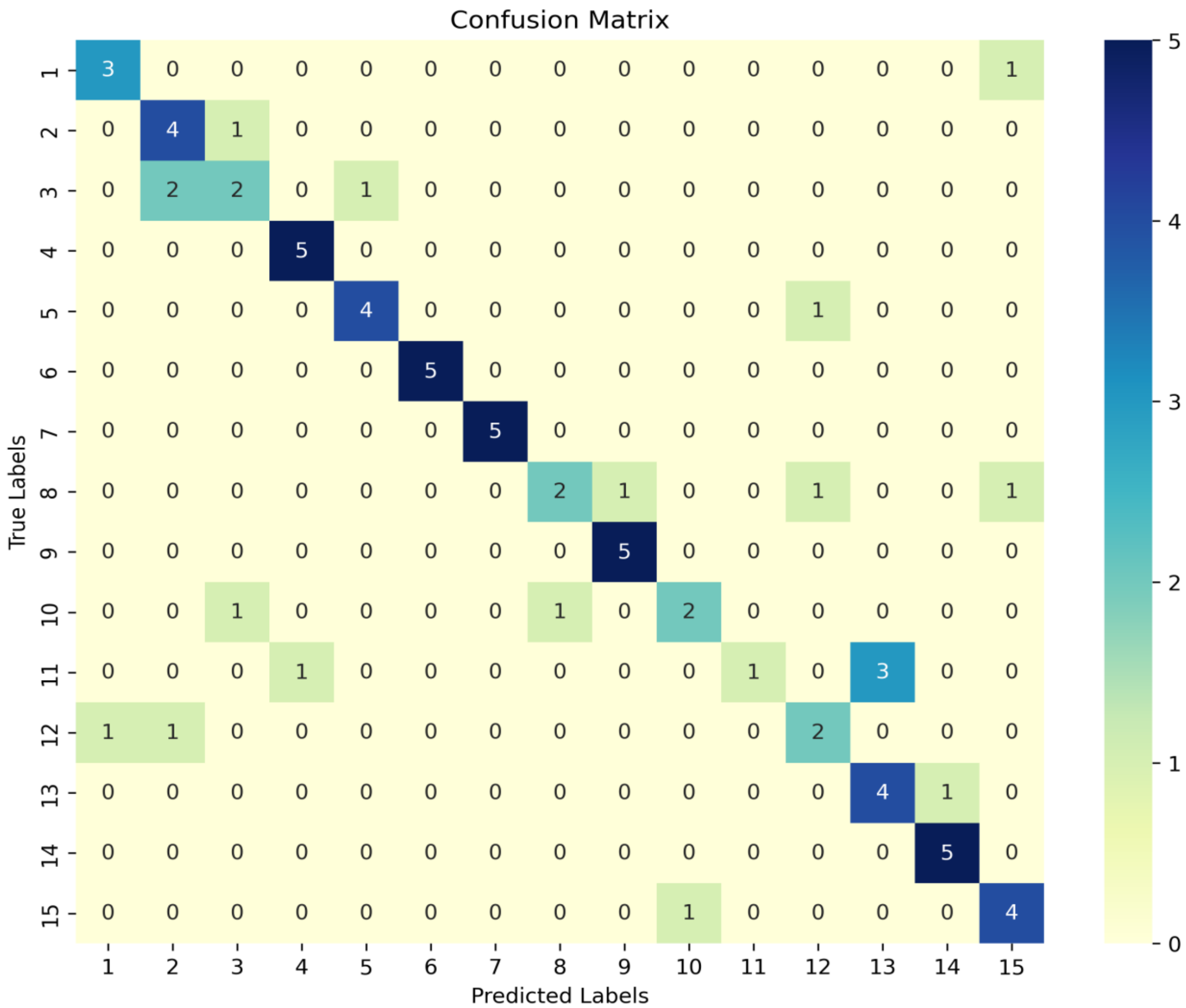

Figure 4.1 Confusion matrix of RF classifier (without preprocessing)

The confusion matrix corresponding to the Random Forest classifier trained on raw EMG features reveals that certain hand gestures, such as classes 6 and 7, were classified perfectly with no misclassifications, indicating clear feature separability. Gestures like classes 4 and 9 showed high recall but slightly lower precision, suggesting that while all true instances were correctly identified, some other classes were misclassified as these. Moderate performance was observed for gestures such as classes 2, 3, 8, and 10, with several instances being confused with other gestures. Notably, class 11 exhibited poor performance with only one out of five instances correctly predicted, despite a high precision that indicates predictions for this class were rare but accurate. Overall, the confusion matrix highlights the classifier's tendency to favour certain well-separated gestures while struggling with others, underscoring the need for preprocessing to enhance signal quality and improve classification consistency.

4.2 Impact of Preprocessing on Model Performance

To evaluate the classification performance on the preprocessed and segmented dataset, three classifiers Random Forest (RF), Support Vector Machine (SVM) with a linear kernel, and Extra Trees Classifier (ETC) were trained using a 5-fold cross-validation strategy. For SVM classifier, hyperparameter tuning using gridsearchCV was done to find the best parameters. Each classifier was embedded in a pipeline with a StandardScaler to normalize feature distributions. The classification accuracies obtained across all eight subjects are summarized in Table 4.2.

Subject	RF	SVM	ETC
S1	97.922	98.788	98.413
S2	97.431	98.297	98.470
S3	93.045	94.690	94.488
S4	97.316	97.605	98.124
S5	98.788	98.990	99.336
S6	98.297	98.615	99.048
S7	99.134	99.048	99.481
S8	96.075	97.662	97.345
Average Accuracy	**97.251**	**97.962**	**98.088**

Table 4.2 Classification Accuracy after Preprocessing (5-fold Cross-Validation)

The results clearly demonstrate a substantial improvement in classification performance after preprocessing. All classifiers achieved consistently high accuracy across subjects, with the Extra Trees Classifier (ETC) slightly outperforming others in most cases. The SVM classifier, although slightly behind ETC, showed remarkable consistency and strong generalization, especially for subjects S1, S2, S5, and S7. Notably, the lowest accuracy observed (93.04% for S3 with RF) still significantly exceeds the baseline performance achieved on unprocessed data.

The bar plot in figure 4.2 demonstrates that all three classifiers performed consistently well across subjects, with accuracies generally above 94%. Notably, the ETC achieved the highest accuracy for most subjects, closely followed by SVM. The y-axis, starting at 0.90, highlights subtle differences in performance, making it easier to distinguish classifier effectiveness at a higher accuracy range.

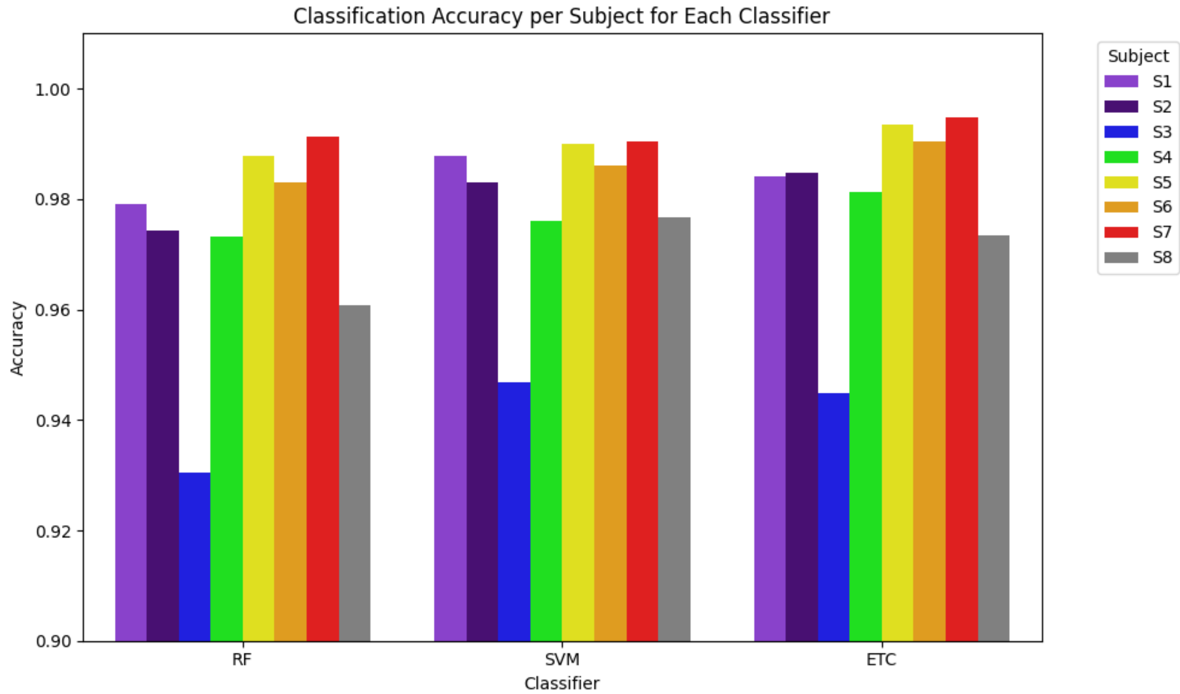

Figure 4.2 classification accuracy of classifiers over 8 subjects

This significant enhancement validates the importance of preprocessing and data segmentation in EMG-based gesture recognition. By reducing noise, stabilizing signal amplitude, and segmenting the data into analysis windows, the features became more discriminative and robust, enabling more effective learning by the classifiers.

To comprehensively evaluate the classification performance of the Extra Trees Classifier (ETC) across all subjects, additional metrics including macro-averaged precision, recall, and F1-score were computed using 5-fold cross-validation. The results, as presented in Table 4.3, show consistently high values for all three metrics across the eight subjects. Notably, subjects S5, S6, and S7 exhibited the highest performance, with F1-scores of 0.9933, 0.9904, and 0.9948 respectively, indicating excellent classification consistency. Even the lowest-performing subject, S3, achieved a respectable F1-score of 0.9448, highlighting the robustness of the ETC model on preprocessed EMG features. These metrics further validate the model's ability to generalize well across multiple subjects and maintain high predictive reliability for classifying complex hand gestures.

Subject	Precision	Recall	F1-Score
S1	0.9843	0.9841	0.9841
S2	0.9850	0.9847	0.9848
S3	0.9460	0.9449	0.9448
S4	0.9815	0.9812	0.9813
S5	0.9934	0.9934	0.9933
S6	0.9905	0.9905	0.9904
S7	0.9948	0.9948	0.9948
S8	0.9734	0.9734	0.9734

Table 4.3 Macro-Averaged Precision, Recall, and F1-Score for each subject using ETC

Figure 4.3 shows the confusion matrix of the Extra Trees Classifier (ETC) for Subject 7, generated using 5-fold cross-validation. The matrix provides a detailed view of the classifier's performance across all 15 hand gesture classes by displaying the number of correct and incorrect predictions for each class. As observed, the diagonal elements of the matrix are prominently populated, indicating a high rate of correct predictions.

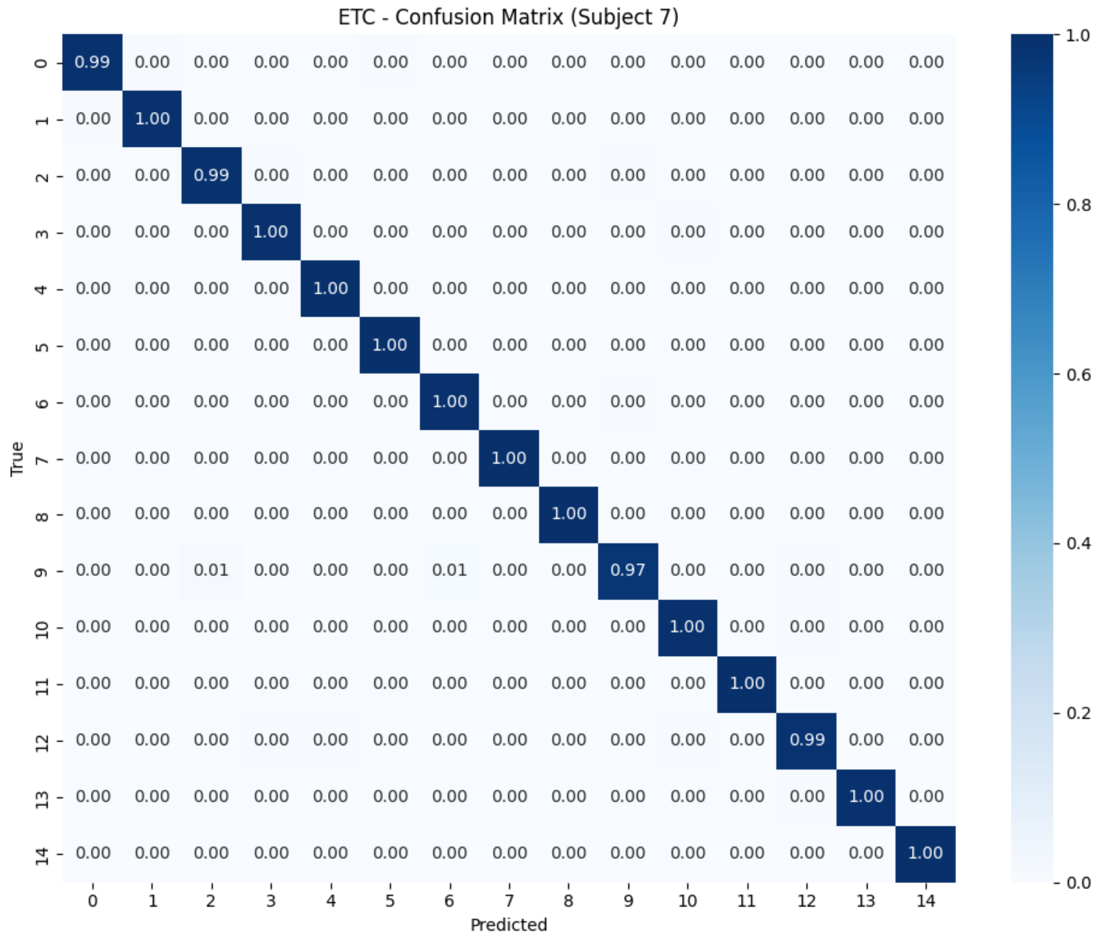

Figure 4.3 Confusion matrix of subject-7 for ETC

4.3 Evaluation of model based on Muscle Synergies

The classification performance of the Extra Trees Classifier (ETC) was evaluated using muscle synergy-based features extracted from Subject 1. Unlike the previous approaches that relied on conventional time-domain and statistical features from pre-processed EMG signals, this analysis aimed to explore the utility of dimensionality-reduced representations derived via Non-Negative Matrix Factorization (NMF). The mean classification accuracy over the 5 folds achieved was 93.33%. The results demonstrate that muscle synergy-based features, despite their reduced dimensionality, retain a substantial amount of discriminative information necessary for gesture classification. Although the performance is slightly lower and more variable compared to feature-rich, pre-processed input methods, this approach shows promise for real-time control applications where computational efficiency and feature compactness are critical.

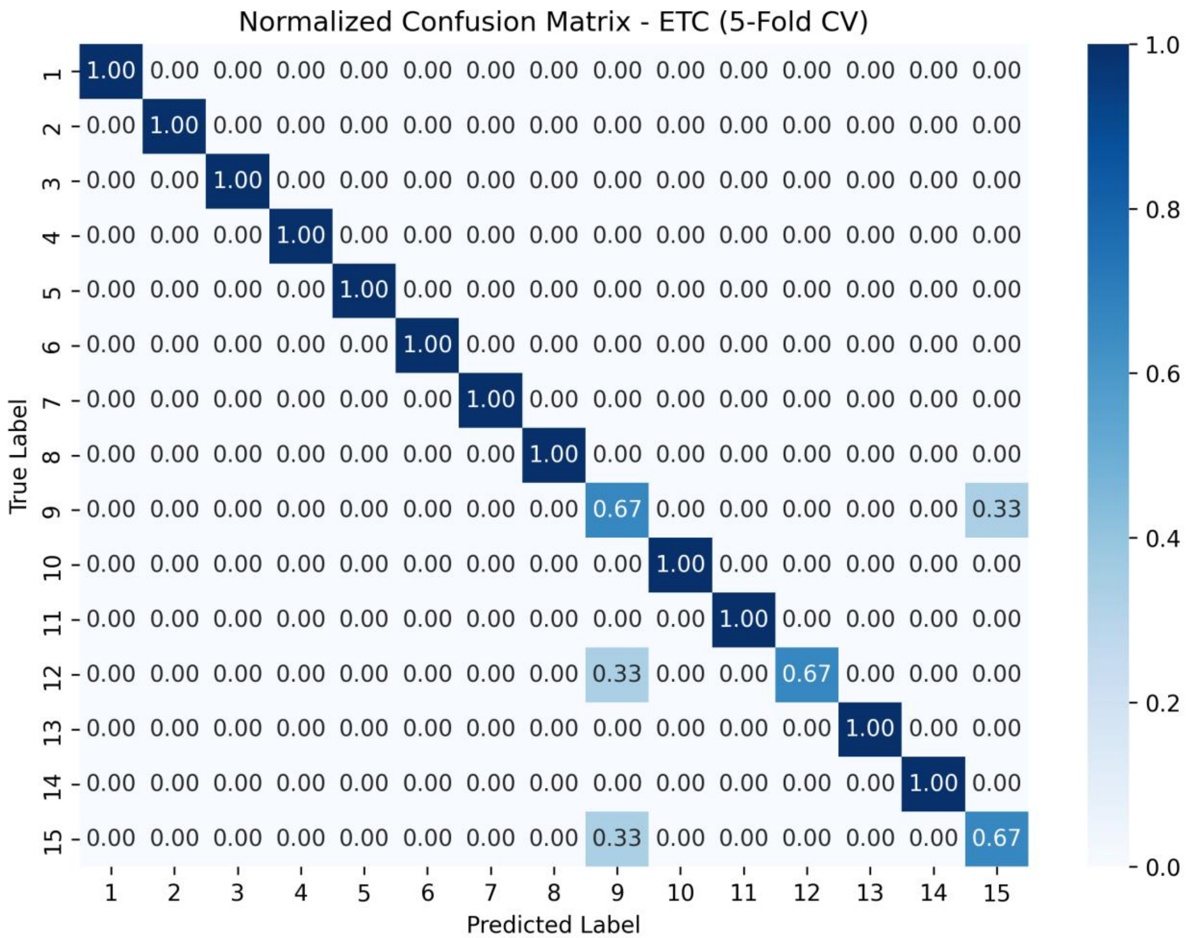

Figure 4.4 Confusion matrix for ETC with synergies as input

The normalized confusion matrix for the Extra Trees Classifier (ETC) using 5-fold cross-validation, as shown in Figure 4.4, demonstrates excellent classification performance across most gesture classes. Perfect accuracy (1.00) was observed for the majority of classes, including classes 1 through 8, and 10, 11, 13, and 14, indicating that the model is highly effective at distinguishing these gestures based on the extracted muscle synergy features. These results highlight the strong discriminative capability of synergy-based representations for these postures.

However, the matrix also reveals some degree of misclassification among a few classes, particularly involving classes 9, 12, and 15. For instance, class 9 was predicted correctly 67% of the time but showed confusion with class 15 (33%), while class 12 was partially misclassified as class 11. Similarly, class 15 exhibited confusion with class 9, with 33% of its samples predicted incorrectly. These off-diagonal entries suggest overlapping muscle activation patterns or insufficient discriminatory information in the synergy space for these gestures. Overall, the confusion matrix confirms the robustness of the ETC model in classifying most gestures while pinpointing specific pairs that warrant further investigation for improved accuracy.

This work validates the feasibility of decoding complex hand gestures from multi-channel sEMG signals using data-driven methods, bridging the gap between bio signal acquisition and intuitive, high-performance control interfaces for rehabilitation and assistive technologies.

Chapter 5

Conclusion and Future Scope

5.1 Conclusion

This chapter brings together the key findings and implications of the research, highlighting how the objectives of the study have been addressed and what new contributions have been made to the field of myoelectric control and gesture recognition using surface electromyography (sEMG) signals. The following points summarise the main results, discuss their significance in the context of current literature, and outline potential directions for future research and practical applications:

- Machine learning classifiers such as Random Forest (RF), Support Vector Machine (SVM), and Extra Trees Classifier (ETC) achieve high accuracy **97.25%, 97.96%, 98.09%** respectively in classifying hand gestures from surface electromyography (sEMG) signals when provided with well pre-processed and structured features.
- Preprocessing steps including amplification, filtering, and segmentation significantly enhance the discriminative power of EMG features, leading to improved classification performance compared to models trained on raw data.
- Dimensionality reduction using Non-Negative Matrix Factorization (NMF) to extract muscle synergies enables compact and physiologically meaningful feature representations, preserving sufficient information for accurate gesture classification despite reduced dimensionality.
- The ETC model, when trained on muscle synergy features, demonstrates perfect or near-perfect classification for several hand gesture classes, while also identifying specific class pairs prone to misclassification due to overlapping muscle activation patterns. ETC also slightly outperformed SVM and RF in the classification task.
- The synergy-based framework provides valuable insights into neuromuscular coordination strategies, contributing to both scientific understanding and practical advancements in intelligent prosthetic and exoskeleton devices.

5.2 Future Scope

5.2.1 Improvement in Synergy Based Classification Models

The synergy-based classification framework, utilizing the spatial components extracted through Non-Negative Matrix Factorization (NMF), has demonstrated notable success in reducing feature dimensionality while preserving the essential structure of coordinated muscle activity. However, there are several opportunities for further improving the accuracy and robustness of this model. While the current approach effectively leverages the spatial synergies for classification, further improvements can be explored by incorporating temporal synergies or combining both spatial and temporal components for a more holistic representation of muscle activity.

5.2.2 Development of Control Strategies

While classification of hand gestures using EMG signals provides a strong foundation for recognizing intended user movements, translating these classifications into real-time, responsive control signals for assistive devices remains a critical challenge. Bridging this gap requires the development of effective control strategies that can map the identified muscle synergies or classified gestures to proportional and continuous control actions. One promising approach is to employ regression models that can infer control signals such as joint angles or actuation torques directly from the synergy activations or their temporal evolution. To achieve adaptive and goal directed control, Reinforcement Learning (RL) can be integrated into the framework. RL algorithms can learn optimal control policies through interaction with a simulated or real environment, enabling the system to adapt to dynamic tasks and subject-specific variability.

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