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Classification of EMG Signals of Eye Movement using Machine Learning Techniques

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CANDIDATE'S DECLARATION

I, Akshansh Srivastava, Roll No. 2K21/SPD/02 student of MTech (Signal Processing and Digital Design), hereby declare that the project Dissertation titled "**Classification of EMG Signals of Eye Movement using Machine Learning Techniques**" which is submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological university, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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CERTIFICATE

I hereby certify that the project Dissertation titled "**Classification of EMG Signals of Eye Movement using Machine Learning Techniques**" which is submitted by Akshansh Srivastava, Roll No. 2K21/SPD/02, Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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ABSTRACT

This approach aims to classify electromyography (EMG) signals from the extraocular muscles into six distinct eye movement classes: Blink, Normal Behavior, Left, Right, Downward, and Upward Movement and to apply in medical applications. The dataset used in this study consisted of two types of signal values: one obtained from horizontally connected electrodes and the other from vertically connected electrodes. We explored both signal types individually but found that the classification accuracy was lower when using the vertically connected electrodes, and determined by correlation between variables and scattering plot. To process the data, windowing technique was employed. This technique involves dividing the preprocessed data stream into smaller segments, or windows, to analyze and extract features. A total of 28 features were calculated from the preprocessed dataset, forming a feature matrix that also included the corresponding class labels. To ensure that the training process did not lead to overfitting, the rows of the feature matrix were randomized. We compared this approach to existing works in the literature and found that it outperformed previous methods in terms of accuracy. The evaluation of classification accuracies was performed using various classifier algorithms. Among them, the best accuracy achieved was 96.8% using the Cubic Support Vector Machine (SVM) algorithm.

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CHAPTER-1
INRODUCTION

1.1 Background

Electromyography (EMG) is a valuable tool in the field of neuroscience and medicine, providing insight into the function of the neuromuscular system. The neuromuscular system is responsible for the control of voluntary and involuntary muscle movement, and EMG signals can provide information about the electrical activity of muscle tissue during contractions. The EMG signals are used in various fields, such as clinical diagnosis, rehabilitation, sports medicine, ergonomics, and the development of prosthetics and exoskeletons [1]. One of the primary applications of EMG is in the clinical diagnosis of neuromuscular disorders. These disorders can affect the structure, function, or metabolism of muscles and nerves, resulting in a range of symptoms such as muscle weakness, pain, and atrophy. The EMG can be used to detect abnormalities in the electrical activity of muscle tissue, which can help diagnose the underlying condition. For example, the EMG can be used to diagnose conditions such as carpal tunnel syndrome, myopathy, or peripheral neuropathy. The EMG signals are also used in rehabilitation to monitor progress and evaluate treatment efficacy [2]. During rehabilitation, EMG signals can be used to assess muscle function, activation patterns, and strength, which can be used to develop individualized treatment plans. The EMG biofeedback can also be used to train patients to activate specific muscle groups and improve muscle control. Additionally, the EMG signals can be used to evaluate the efficacy of interventions such as electrical stimulation, massage, or stretching. In sports medicine, the EMG signals can be used to analyze athletic performance and identify potential areas for improvement [3]. The EMG can be used to assess muscle activation patterns during different types of movement, such as running, jumping, or throwing. This information can be used to identify muscle imbalances or weaknesses, which can be targeted through specific exercises or training programs. By identifying these imbalances early, athletes and coaches can modify training programs or techniques to reduce injury risk and improve performance. Ergonomics is another field that utilizes EMG signals to evaluate the impact of workplace design on muscle activity and fatigue. Ergonomics is the study of designing equipment, devices, and processes that fit the human body, its movements, and its cognitive abilities. By measuring the EMG activity of muscles during different work tasks, researchers can identify ergonomic risk factors and recommend changes to improve worker safety and comfort [4]. For example, the EMG can be used to assess the impact of workstation design on neck and shoulder muscle activity in office workers or the impact of tool design on hand and wrist muscle activity in assembly line workers.

Lastly, EMG signals can be used in the development of prosthetics and exoskeletons. By measuring the EMG activity of muscles, researchers can develop control algorithms that allow users to control prosthetic limbs or exoskeletons using their own muscle activity. This technology has the potential to greatly improve the quality of life for individuals with limb loss or weakness [5]. The EMG signals can also be used to improve the performance of assistive devices such as wheelchairs or orthotics. There are different types of EMG signals, their measurement and analysis, and their applications in various fields. EMG signals can be divided into two types: surface EMG (sEMG) and intramuscular EMG (iEMG). sEMG measures the electrical activity of muscles by placing electrodes on the skin surface, while iEMG measures the electrical activity of muscles by placing electrodes directly into the muscle tissue. Both types of EMG signals have advantages and disadvantages. The Electromyography (EMG) is a technique that records the electrical activity generated by muscle fibers during muscle contraction. Surface EMG (sEMG) and intramuscular EMG (iEMG) are two types of EMG signals that are used for different purposes in various fields. sEMG is a non-invasive method that is commonly used in clinical diagnosis, rehabilitation, and sports medicine. It involves placing electrodes on the skin surface overlying the muscle of interest, which can measure the electrical activity of multiple muscles simultaneously [1] [4]. This method is easy to apply and does not require specialized equipment, making it a widely used technique in clinical settings. However, sEMG signals are affected by several factors, including the thickness of the subcutaneous fat layer, skin impedance, and the presence of adjacent muscles. The thickness of the subcutaneous fat layer can cause a decrease in the amplitude of the EMG signal, which can lead to inaccurate readings. Skin impedance, which varies from person to person, can also affect the quality of the signal recorded [6]. Finally, sEMG signals can be contaminated by electrical activity from neighboring muscles, which can make it challenging to isolate the activity of the muscle of interest [7]. On the other hand, iEMG is an invasive technique that involves inserting a needle electrode directly into the muscle of interest. This method provides a more accurate measure of muscle activity since it is less susceptible to interference from surrounding muscles. iEMG can also record the electrical activity from deeper muscle fibers that are not accessible with sEMG. However, iEMG requires specialized equipment and expertise and can only measure activity from a single muscle at a time. In clinical settings, iEMG is typically used for more specific and focused diagnoses or when sEMG is not providing sufficient information. iEMG can provide detailed information about the activity of a single muscle, which can help diagnose muscle disorders, such as myopathies, dystrophies, and neuropathies. iEMG can also provide valuable information during surgery, allowing surgeons to locate and avoid nerves or muscles during an operation. In sports medicine, iEMG is used to analyze the performance of athletes and evaluate muscle imbalances that can lead to injuries or decreased performance. iEMG can provide a more accurate measure of muscle activation during specific movements, allowing coaches and trainers to tailor training programs to target specific muscles or movement patterns. Both sEMG and iEMG have their advantages and disadvantages, and their use depends on the specific needs of the study or clinical application. sEMG is non-invasive, easy to apply, and can measure activity from multiple muscles simultaneously. iEMG is more invasive, requires specialized equipment, and can only measure activity from a single muscle [4]. However, iEMG signals are less susceptible to interference from surrounding muscles and provide a more accurate measure of muscle activity. Understanding the differences between sEMG and iEMG can help researchers and clinicians choose the appropriate method for their specific application.

The measurement of EMG signals is a fundamental process in the study of muscle function, neurophysiology, and the diagnosis of neuromuscular disorders. EMG signals are electrical signals generated by the contraction and relaxation of muscles, and their measurement provides valuable information about the neuromuscular system. The first step in measuring EMG signals is to place electrodes on or into the muscle tissue of interest [2] [8]. The choice of electrode depends on the type of signal being measured and the application. Surface electrodes are the most commonly used type of electrode for surface EMG (sEMG) measurements. These electrodes are placed on the skin surface over the muscle belly, and they detect the electrical activity of the muscle fibers directly beneath the skin. In contrast, intramuscular EMG (iEMG) measurements require electrodes to be inserted directly into the muscle tissue using a needle or a wire. These electrodes are more invasive and require more skill to use, but they provide a more accurate measurement of the electrical activity of the muscle fibers. Once the electrodes are in place, the EMG signal is amplified, filtered, and digitized by an EMG amplifier. The amplifier amplifies the signal detected by the electrodes to a level that can be analyzed by the software [9]. The filter removes unwanted noise and interference from the signal, such as electrical noise from other sources or movement artifacts. The digitized signal is then analyzed using specialized software that calculates various signal features, such as amplitude, frequency, and duration. The analysis of the EMG signal can provide insight into various aspects of muscle function, such as muscle activation patterns, recruitment strategies, and fatigue [7] [9]. The resulting data can be displayed as a waveform or a frequency spectrum, depending on the type of analysis being performed. Waveform analysis provides a visual representation of the electrical activity of the muscle over time, while frequency analysis provides information about the frequency content of the signal [10]. The measurement of EMG signals involves placing electrodes on or into muscle tissue, amplifying and filtering the signal, and analyzing the signal using specialized software. This process provides valuable information about muscle function and is widely used in research and clinical settings.

1.2 Thesis Objectives

The work done in the thesis is primarily focused on providing a suitable method for eye movement classification to get applied in application of driver monitoring systems, Eye movement classification in driver monitoring systems is an incredibly useful application with significant benefits for road safety. Here's why:

1. Accident Prevention: Drowsiness and distraction are major causes of accidents on the road. By accurately monitoring and classifying eye movements, the driver monitoring system can detect signs of drowsiness, inattention, or distraction in real-time. This enables timely interventions, such as alerting the driver or triggering safety mechanisms, helping prevent potential accidents before they occur.

2. Early Warning System: The eye movement classification system serves as an early warning system, providing crucial insights into driver attention and engagement levels. By continuously monitoring eye movements, the system can detect subtle changes that may indicate a decrease in attention, allowing drivers to be alerted and take appropriate actions to stay focused on the road.

3. Personalized Assistance: Different drivers have varying levels of fatigue tolerance and

attention span. By analyzing individual eye movement patterns, the classification system can personalize the monitoring and alert thresholds. This ensures that drivers receive tailored alerts based on their specific behavior, optimizing the system's effectiveness and reducing unnecessary distractions.

4. Enhanced Autonomous Vehicles: Eye movement classification can significantly enhance the capabilities of autonomous vehicles. By integrating the classification system, the vehicle's control system can adapt its behavior based on the detected driver states. For example, if the system identifies signs of drowsiness, it can activate additional safety measures, adjust driving parameters, or even initiate a transition from autonomous to manual driving mode to ensure driver engagement.

5. Data Analysis and Insights: Eye movement data collected by the monitoring system can be analyzed to gain valuable insights into driver behavior and patterns. This data can contribute to research on driver attention, fatigue, and distraction, helping improve road safety measures, design better transportation systems, and inform policy decisions.

6. Driver Training and Feedback: Eye movement classification can be used as a tool for driver training and feedback. By providing real-time feedback on eye movements, drivers can become more aware of their attention levels and learn to adopt safer driving practices. The system can also generate post-analysis reports, offering valuable feedback to drivers, fleet managers, or insurance companies to identify areas for improvement and provide targeted training interventions.

Eye movement classification in driver monitoring systems offers immense utility in preventing accidents, providing early warnings, personalizing assistance, enhancing autonomous vehicles, generating valuable data insights, and facilitating driver training. By leveraging machine learning and eye tracking technologies, this application contributes significantly to road safety, ultimately saving lives and creating a safer driving environment for everyone.

1.3 Thesis Organization

In this thesis, work has been divided into seven sections. Chapter 1 includes brief introduction and application of the proposed work. Chapter 2 discusses the previous work and results achieved by previous works. The input dataset and methodology for classification of Eye Movement EMG signal is discussed in Chapter 3. In proposed work, different classifiers are used for those classifiers a brief explanation is given in Chapter 4.

In Chapter 5, results, applications and accuracies achievements are discussed. With Conclusion and future work, thesis is summarized in chapter 6.

CHAPTER-2

PREVIOUS WORK ON EYE MOVEMENT CLASSIFICATION

2.1 Discussion on Previous Work

Electromyogram (EMG) classification in machine learning plays a crucial role in various domains due to its significant importance. The EMG is a technique that captures the electrical signals produced by muscle movements. It has found widespread application in the treatment of neuromuscular disorders, including conditions like muscular dystrophy and carpal tunnel syndrome. Machine learning algorithms can be trained to accurately classify the EMG signals, which in turn facilitates the diagnosis of these disorders. By analyzing the patterns and characteristics of the EMG signals, machine learning models can differentiate between healthy muscle activity and abnormal patterns indicative of specific neuromuscular conditions. This capability can aid healthcare professionals in making accurate diagnoses and developing appropriate treatment plans. The EMG classification holds promise in the field of prosthetics. By leveraging machine learning techniques, the EMG signals from muscles can be analyzed to control prosthetic limbs [11]. This approach enables amputees to achieve more natural and intuitive control over their artificial limbs. By interpreting the EMG signals associated with desired movements, machine learning algorithms can translate them into corresponding actions of the prosthetic device, allowing users to perform a range of complex tasks with greater ease and precision.

The development of prosthetic devices that utilize the EMG classification empowers individuals with limb loss to regain functional capabilities and improve their quality of life. The integration of machine learning algorithms with the EMG technology enhances the adaptability and responsiveness of prosthetics, providing users with a more seamless and intuitive experience [11]. This advancement has the potential to revolutionize the field of prosthetics by bridging the gap between human intention and the actions performed by artificial limbs. The classification of EMG signals using machine learning algorithms has profound implications in several domains [12]. Its application in the diagnosis of neuromuscular disorders enables accurate identification and treatment of conditions, while its integration into prosthetic devices offers enhanced control and functionality for individuals with limb loss.

This intersection between EMG and machine learning showcases the power of combining technological advancements to improve healthcare and empower those in need. The EMG classification in machine learning extends its utility beyond medical applications and prosthetics [13]. It can be effectively utilized to analyze muscle activity during various physical activities, serving as a valuable tool in developing training programs for athletes and rehabilitation programs for individuals recovering from injuries. By applying machine learning algorithms to classify the EMG signals during activities like running, jumping, or weightlifting, researchers and trainers gain valuable insights into the patterns and intensities of muscle activation during specific tasks. The information derived from the EMG classification can be used to optimize training regimens for athletes. By analyzing muscle activity patterns, trainers can identify areas of strength and weakness, assess muscle fatigue levels, and tailor training programs to target specific muscle groups. This enables athletes to improve their performance, prevent injuries, and enhance overall physical conditioning [11]. Moreover, the EMG-based training programs can aid in the rehabilitation process by providing precise feedback on muscle activation and guiding individuals through targeted exercises to regain strength, coordination, and mobility after an injury.

In addition to sports and rehabilitation, the EMG classification in machine learning finds applications in human-computer interaction (HCI) [12]. By analyzing the EMG signals from muscles, machine learning algorithms can be trained to interpret specific muscle activations and translate them into control commands for computers or electronic devices. This enables the development of more natural and intuitive interfaces, where users can interact with technology through muscle movements, such as gestures or subtle muscle contractions. For example, using the EMG classification, a person could control a computer cursor or navigate through a menu simply by moving their hand or fingers in specific ways. This approach eliminates the need for traditional input devices like keyboards or mice and allows for a more seamless and immersive interaction between humans and machines. The EMG-based HCI holds great potential for individuals with limited mobility, providing them with alternative means of communication and control over electronic devices, thereby improving their accessibility and quality of life. Overall, the integration of EMG classification in machine learning has wide-ranging applications and offers valuable insights into muscle activity [14]. It enhances the development of tailored training and rehabilitation programs, facilitates more natural and intuitive human-machine interaction, and contributes to improved diagnosis, treatment, and overall understanding of muscle physiology.

This interdisciplinary approach has the potential to revolutionize various fields, including sports training, rehabilitation, and human-computer interaction [12]. The field of the EMG classification and its integration with machine learning holds vast unexplored potential and opportunities for further research. One such area of exploration involves the integration of the EMG data with other physiological signals, such as electroencephalography (EEG), electrocardiography (ECG), and respiration signals. By combining multiple streams of physiological data, researchers can gain a more comprehensive understanding of human movement, performance, and overall health. Integrating the EMG data with other signals can potentially improve the accuracy and effectiveness of machine learning models by capturing a broader range of information and patterns related to muscle activity [12]. Transfer learning is another avenue for enhancing the EMG classification models. By leveraging pre-trained models on similar tasks or datasets, transfer learning enables the transfer of knowledge and learned features from one task to another. This approach can improve the performance and efficiency of the EMG classification models, particularly when there is limited labeled data available. By utilizing knowledge gained from related tasks or datasets, transfer learning allows for more effective EMG analysis and classification, even in scenarios with sparse or imbalanced data.

While machine learning models have demonstrated impressive performance in the EMG classification, one notable challenge is the lack of interpretability [15]. Many models operate as black boxes, making it difficult to understand the underlying factors or features that contribute to their decision-making process. Addressing this challenge requires the development of explainable models in the EMG analysis. Explainable models aim to provide insights into the specific features or patterns that the model identifies as relevant for classification. By enhancing interpretability, researchers and healthcare professionals can gain a deeper understanding of the physiological mechanisms and factors that contribute to specific EMG patterns, leading to improved diagnosis, treatment, and rehabilitation strategies. Moreover, the field of EMG classification can benefit from exploring novel machine learning techniques and algorithms. Researchers can investigate the application of deep learning architectures, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), to further enhance the accuracy and robustness of the EMG classification models. Additionally, advancements in feature selection and dimensionality reduction techniques can help extract the most informative and discriminative features from raw the EMG signals, leading to more efficient and effective classification models.

There are numerous unexplored areas in the field of EMG classification and its integration with machine learning. Further research is needed to investigate the integration of EMG data with other physiological signals, explore transfer learning techniques, develop explainable models, and leverage advanced machine learning algorithms. By delving into these areas, researchers can unlock new insights, improve accuracy, and enhance the overall understanding and utilization of the EMG data for various applications in healthcare, sports, rehabilitation, and human-machine interaction [16].

The study implemented a methodology involving six participants who underwent simultaneous measurements of electroencephalography (EEG) and electromyography (EMG) while performing motor imagery tasks. Motor imagery tasks refer to mentally imagining specific movements without physically executing them. The objective was to develop a system that could classify motor imagery tasks based on integrated EEG and EMG data and utilize this classification to control the movement of a mobile robot [12]. The EEG and EMG data streams captured during the motor imagery tasks were subjected to processing and analysis using machine learning algorithms [14]. Researchers developed a proprietary classification algorithm specifically tailored to classify the motor imagery tasks based on the integrated EEG and EMG data. This algorithm enabled the recognition and classification of different motor imagery processes linked to specific movements of the mobile robot, including moving forward, turning left or right, and stopping.

The integrated EEG and EMG data streams were then utilized to control the movement of the robotic parts. By capturing the neural and muscular signals associated with motor imagery, the system translated these signals into control commands to guide the movement of the robotic limbs. This integration of EEG and EMG allowed for a more intuitive and efficient control interface between the participants and the mobile robot. The results of the study demonstrated the effectiveness of the integrated EEG and EMG signals in accurately classifying motor imagery tasks and controlling the movement of the robotic limbs. The average classification accuracy achieved for the motor imagery tasks was 88%, indicating the system's ability to discern different mental movements accurately. Moreover, the average accuracy of the robot's movement control based on the integrated signals was 89%, highlighting the system's reliability in translating the participants' intentions into robotic actions [12]. The proposed system, utilizing integrated EEG and EMG signals, holds promise as an efficient and intuitive control approach for mobile robots.

The successful classification of motor imagery tasks and the accurate control of the robotic movements demonstrate the potential for developing advanced control systems that can bridge the gap between human intention and robotic actions. Such systems could find applications in areas such as assistive robotics, prosthetics, and human-robot interaction, where intuitive and precise control is essential for enhanced functionality and user experience.

The presented study introduces a novel approach for sleep scoring, utilizing electrooculography (EOG) and electromyography (EMG) signals. The methodology involved the collection of sleep data from a large cohort of over 8000 subjects [17]. The signals were then processed using wavelet-based feature extraction techniques and machine learning algorithms for sleep stage classification. The study employed a five-stage sleep scoring system, categorizing sleep stages into wake, eye movement (REM), and non-eye movement (non-REM) stages. The proposed sleep scoring model demonstrated promising results in accurately classifying different sleep stages. For the wake stage, the model achieved an accuracy of 87.5%. Regarding REM sleep, the accuracy reached 89.5%, and for non-REM sleep stages, the accuracy obtained was 80.9%. These results highlight the effectiveness of the proposed approach in distinguishing between wakefulness, REM sleep, and non-REM sleep based on the EOG and EMG signals. To further validate the performance of the sleep scoring model, a separate dataset comprising 11 subjects was used. The results from this validation dataset exhibited high accuracy rates as well. Specifically, the model achieved an accuracy of 92.9% for wake, 85.2% for REM, and 79.7% for non-REM sleep stages. These findings reinforce the robustness and generalizability of the proposed sleep scoring model across different datasets.

The study concludes that the automated sleep scoring model, utilizing wavelet-based feature extraction and machine learning algorithms, presents a promising approach for sleep analysis. By accurately classifying sleep stages, the model has the potential to enhance the diagnosis and treatment of sleep disorders. Sleep scoring plays a crucial role in understanding sleep architecture, identifying abnormalities, and providing insights into various sleep disorders such as insomnia, sleep apnea, and narcolepsy. The utilization of EOG and EMG signals, in conjunction with machine learning techniques, offers a non-invasive and objective method for sleep analysis. By automating the sleep scoring process, the model provides a more efficient and standardized approach compared to manual scoring, which can be subjective and time-consuming. Moreover, the ability to accurately classify different sleep stages can aid in tailoring personalized treatment plans for individuals with sleep disorders, improving overall patient care and outcomes. The study's findings highlight the potential of the proposed automated sleep scoring model using wavelet-based feature extraction and machine learning algorithms.

This approach can contribute to advancements in sleep analysis, leading to improved understanding, diagnosis, and treatment of sleep disorders, ultimately promoting better sleep health and well-being for individuals. The research paper introduces an approach for utilizing electromyography (EMG) data in the classification of hand movements for myo-controlled prostheses. The methodology involved the collection of EMG data from eight healthy participants who performed seven distinct hand gestures. The collected data were then processed and analyzed using machine learning algorithms to develop a classification model. Notably, the study employed an Explainable Artificial Intelligence (XAI) approach to elucidate the decision-making process of the machine learning model and highlight the significance of EMG data features in accurately classifying hand gestures [11]. The XAI approach employed in the study aimed to provide explanations for the self-decisioning process of the machine learning model and shed light on the key features within the EMG data that contributed to the classification of hand gestures. By utilizing XAI techniques, researchers sought to create a transparent and interpretable model that could provide meaningful insights into how the machine learning algorithm arrived at its decisions. The results of the study demonstrated the effectiveness of the XAI approach in explaining the decision-making process of the machine learning model and identifying the important features within the EMG data for classifying hand gestures. The XAI explanations successfully revealed the underlying factors and patterns that influenced the model's classification decisions, offering valuable insights into the relationship between EMG data and hand movements.

To evaluate the performance and explanatory power of the XAI approach, the study compared it with other methods commonly used for feature importance analysis, such as LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (SHapley Additive exPlanations). The comparison showed that the XAI approach provided more meaningful and informative explanations compared to these alternative methods. This finding highlights the superiority of the XAI approach in elucidating the decision-making process of the machine learning model and providing comprehensive insights into the important features of the EMG data for hand movement classification. The study's results have significant implications for the field of myo-controlled prostheses. By utilizing the XAI approach, researchers can develop more interpretable and transparent models, enhancing the trust and acceptance of these systems by users and healthcare professionals. Moreover [11], the insights gained from the XAI explanations can contribute to the refinement and improvement of myo-controlled prostheses, enabling more accurate and intuitive control of artificial limbs based on EMG data. The research paper presents an approach for hand movement classification using EMG data in myo-controlled prostheses. The use of an XAI approach allows for the explanation of the machine learning model's decision-making process and identification of important features within the EMG data. The study demonstrates the efficacy of the XAI approach in providing meaningful explanations and highlights its superiority compared to other methods for feature importance analysis. The proposed approach has the potential to enhance the development and understanding of myo-controlled prostheses, facilitating more precise and intuitive control of artificial limbs based on the EMG data.

The research paper [18] introduces a novel approach for multi-class classification of electromyography (EMG) signals, specifically for hand gesture recognition. The study employed the Extreme Machine Learning (ELM) algorithm as the classification method. EMG data were collected from eight healthy participants who performed 10 different hand gestures [18]. To prepare the EMG signals for analysis, a bandpass filtration technique was applied to remove unwanted noise from the data stream. Additionally, the wavelet transform was used to calculate relevant features from the preprocessed signals. The extracted features were then used to train the ELM algorithm, which was responsible for classifying the hand gestures. The ELM algorithm is known for its efficiency and ability to handle large-scale data sets. In this study, it demonstrated its effectiveness in accurately classifying the 10 hand gestures based on the EMG signals. The reported results showed an impressive accuracy of 89.38% for the classification of the hand gestures using the proposed methodology. This high accuracy indicates that the ELM algorithm, combined with the preprocessing techniques and feature extraction using wavelet transform, can effectively distinguish between different hand gestures based on the EMG signals. The findings of this research highlight the potential of the ELM algorithm for multi-class hand gesture classification using the EMG signals. The ability to accurately recognize and classify hand gestures can have numerous practical applications, such as developing intuitive and efficient control interfaces for prosthetic devices and enhancing human-computer interaction. The research paper presents a multi-class classification approach utilizing the ELM algorithm for hand gesture recognition based on the EMG signals. The study demonstrates the effectiveness of the proposed method, achieving an impressive accuracy of 89.38% in classifying the 10 hand gestures. This research contributes to the advancement of gesture recognition technology, with potential applications in fields such as prosthetics, robotics, and human-computer interaction.

The research paper [13] introduces a multi-class classification approach that utilizes decision tree algorithms for the recognition of hand gestures based on electromyography (EMG) signals. In the study, the EMG data were collected from eight healthy participants who performed 12 distinct hand gestures. To prepare the EMG data for analysis, a bandpass filtration technique was applied to eliminate unwanted noise from the data stream. Additionally, the discrete wavelet transform was employed to extract relevant features from the preprocessed EMG signals. Three decision tree algorithms, namely C4.5, Random Forest, and AdaBoost, were utilized in the study for the classification task. These algorithms are known for their ability to handle complex and non-linear patterns in data. By training the decision tree algorithms on the extracted features, the study aimed to evaluate their effectiveness in accurately classifying the 12 hand gestures based on the EMG signals. The reported results demonstrated a remarkable accuracy of 92.38% in classifying the 12 hand gestures using the Random Forest algorithm. This finding indicates that decision tree algorithms, particularly Random Forest, can effectively classify the EMG signals for multi-class hand gesture recognition. The Random Forest algorithm, which leverages an ensemble of decision trees, outperformed both C4.5 and AdaBoost algorithms in terms of accuracy.

The outcomes of this research highlight the potential of decision tree algorithms, specifically Random Forest, in accurately recognizing and classifying hand gestures based on EMG signals. The high accuracy achieved suggests the feasibility of utilizing such algorithms for real-world applications, including gesture-controlled systems, rehabilitation devices, and human-computer interaction. The research paper proposes a multi-class classification approach using decision tree algorithms for hand gesture recognition based on EMG signals. The study demonstrates that decision tree algorithms, particularly Random Forest, can effectively classify the 12 hand gestures with an accuracy of 92.38%. These findings contribute to the advancement of hand gesture recognition technology, showcasing the potential of decision tree algorithms for accurately interpreting the EMG signals and enabling intuitive and efficient control of various applications [19].

The research paper [4] presents a novel deep learning approach for multi-class hand gesture identification using electromyography (EMG) signals. The study involved collecting the EMG data from 20 healthy participants who performed 20 distinct hand gestures. To prepare the EMG signals for analysis, a bandpass filtration technique was applied to remove noise, and the wavelet transform was employed for feature extraction. The deep learning architecture used in the study combined long short-term memory (LSTM) and convolutional neural network (CNN) layers. The LSTM layer, known for its ability to capture temporal dependencies, was integrated with the CNN layer, which excels at extracting spatial features. This combination aimed to leverage the strengths of both architectures and enhance the classification performance of the model. The proposed deep learning approach achieved an impressive accuracy of 94.8% in classifying the 20 hand gestures based on the EMG signals. The high accuracy demonstrated the effectiveness of the deep learning model in accurately recognizing and classifying the various hand gestures. The results of the study indicated that the proposed deep learning approach outperformed conventional machine learning algorithms previously used in similar studies. This finding highlights the superiority of deep learning techniques in handling complex patterns and extracting meaningful features from EMG signals for multi-class hand gesture recognition. The research paper's outcomes emphasize the potential of deep learning in improving the accuracy and performance of hand gesture recognition systems based on the EMG signals. The proposed approach offers a promising solution for applications such as prosthetics, virtual reality, and human-computer interaction, where precise and robust hand gesture recognition is crucial. The research paper introduces a novel deep learning approach for multi-class hand gesture identification using the EMG signals. The study demonstrates the effectiveness of the proposed approach, achieving an accuracy of 94.8% in classifying the 20 hand gestures. The deep learning model, combining LSTM and CNN layers, outperformed conventional machine learning algorithms, highlighting its potential for accurate and robust hand gesture recognition based on the EMG signals.

The research paper [20] presents a multi-class classification approach utilizing the Adaptive Neuro-Fuzzy Inference System (ANFIS) for hand gesture recognition based on the electromyography (EMG) data streams. The study involved collecting EMG data from eight healthy participants who performed 10 different hand gestures. To prepare the EMG data for analysis, a bandpass filtration technique was applied to eliminate unwanted noise, and the wavelet transform was used for feature extraction. The ANFIS technique, which combines the adaptive learning capabilities of neural networks with the interpretability of fuzzy logic, was employed in the study to classify the hand gestures. By training the ANFIS model on the extracted features, the researchers aimed to evaluate its effectiveness in accurately categorizing the 10 hand gestures based on the EMG signals. The reported results demonstrated an impressive accuracy of 95.42% in classifying the 10 hand gestures using the proposed ANFIS technique. This indicates that the ANFIS algorithm is highly effective in accurately recognizing and distinguishing different hand gestures based on the EMG signals.

The study revealed that the ANFIS approach outperformed some conventional machine learning algorithms previously used in similar studies. This finding underscores the superiority of the ANFIS algorithm in handling the complexities of EMG signals for multi-class hand gesture recognition tasks. The outcomes of this research highlight the potential of the ANFIS algorithm for accurate and robust classification of the EMG signals in multi-class hand gesture recognition. The high accuracy achieved with the proposed technique has implications for various applications, including assistive technologies, human-computer interaction, and rehabilitation devices. The research paper proposes a multi-class classification approach using the ANFIS algorithm for hand gesture recognition based on EMG signals. The study demonstrates the effectiveness of the proposed technique, achieving an accuracy of 95.42% in classifying the 10 hand gestures. The ANFIS algorithm proves its capability to accurately classify EMG signals for multi-class hand gesture recognition and outperforms some conventional machine learning algorithms used in prior studies. These findings contribute to the advancement of hand gesture recognition technology and pave the way for its application in real-world scenarios.

2.2 Comparison table of Previous work:

During the evaluation of various classification algorithms, the Cubic Support Vector Machine (SVM) algorithm emerged as the most successful one with a remarkable accuracy of 96.8%. This means that it correctly classified 96.8% of the instances in the dataset. The Cubic SVM is a variant of the SVM algorithm that uses a cubic kernel function to map the input data into a higher-dimensional feature space, enabling it to effectively separate different classes. Following closely behind, both the Quadratic SVM and the Wide Neural Network achieved an accuracy of 96.1%. The Quadratic SVM employs a quadratic kernel function, while the Wide Neural Network is a neural network architecture with a larger number of hidden units and layers, allowing it to capture complex patterns in the data.

Table 1: Comparison table of previous work

Authors	*Subjects*	*Classes*	*Subjects*
Zhang et al. [7]	11	4	94.20%
Cai et al. [9]	10	5	91.50%
Rana et al. [21]	12	3	93.30%
Liu et al. [5]	9	3	94.60%
Rana et al. [22]	10	6	94.60%
Chen et al. [7]	10	3	94.10%
Li et al. [23]	10	5	93.70%
Zou et al. [24]	10	3	92.50%
Zarei et al. [25]	8	4	90.50%
Srivastava et al. [26]	10	4	92.80%

CHAPTER 3
PROPOSED METHODOLOGY

3.1 Dataset

. The dataset used in our research is openly available on IEEE Dataport, providing transparency and accessibility to the research community [16]. To record the electromyography (EMG) signals from the extraocular muscles during eye movements, a specific methodology was followed. Four electrodes were strategically placed on the subject's face, consisting of two vertical electrodes and two horizontal electrodes. Additionally, an unbiased electrode was positioned at the center of the forehead. This electrode configuration allowed for the precise capture of the EMG signals related to vertical and horizontal eye movements. To ensure accurate signal acquisition, the electrical signals from the electrodes were first amplified using an AD620 differential amplifier. Subsequently, a bandpass filter with a pass band of 0-40 Hz was applied to remove any unwanted noise. The conditioned EMG signals were then acquired using an analog-to-digital converter (ADC) port of an FPGA card, with a sampling frequency of 120 Hertz. This high sampling rate ensured the capture of detailed information about the EMG signals. During the experiment, ten participants were instructed to perform ten random repetitions of specific eye movements. These movements included upward gaze, downward gaze, rightward gaze, leftward gaze, fixation in the center without movement, and blinking. By recording the EMG signals during these eye movements, a diverse and comprehensive dataset was obtained. The EMG data recorded during the experiment was stored in a format that consisted of two columns, C1 and C2. C1 contained the data readings from the horizontally placed electrodes, while C2 contained the data readings from the vertically placed electrodes. This organization of the data allowed for convenient analysis and classification of the EMG signals. The dataset used in our research was openly available on IEEE Dataport. The methodology involved precise placement of electrodes on the subject's face to record EMG signals from the extraocular muscles during various eye movements. The recorded signals were amplified, filtered, and acquired using an FPGA card with a high sampling frequency. The dataset included data columns corresponding to the horizontal and vertical electrode readings, providing valuable information for further analysis and classification of the EMG signals.

3.2 Methodology

. The raw dataset utilized in our study consisted of two columns, C1 and C2, representing the data collected from horizontally and vertically connected electrodes, respectively. However, upon analysis, we discovered that the accuracy achieved for column 2 (C2) was significantly lower compared to column 1 (C1), we verified it by calculating the Pearson's correlation between different classes. Classes of horizontally connected electrodes data stream were more correlated as compared to classes of vertically calculated electrodes data stream. Therefore, in this paper, we focused solely on presenting the accuracies obtained from column 1. To process the data, we initially obtained a vector of size 25000×1, representing the EMG signal samples. Subsequently, we calculated 28 features from this data vector. The process involved analyzing subsets of the data to extract the features. We started by examining the first 1 to 120 samples (1 second data) and computed all 28 features relevant to this subset. These features were then arranged in the first row of the feature matrix. Next, we proceeded to calculate the features for subsequent sample ranges, such as samples 60 to 180, 120 to 240, and so on. This iterative process continued until all the samples in the dataset were analyzed.

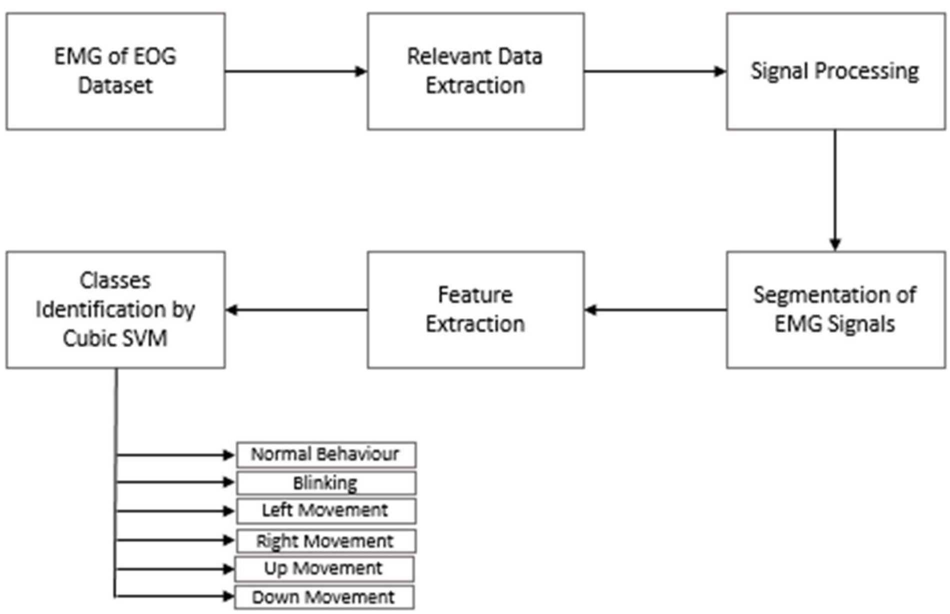

Figure 1: Flow Chart of Proposed Method

For each iteration, we selected a range of samples denoted by A and B. Initially, A and B were set to 1 and 150, respectively.

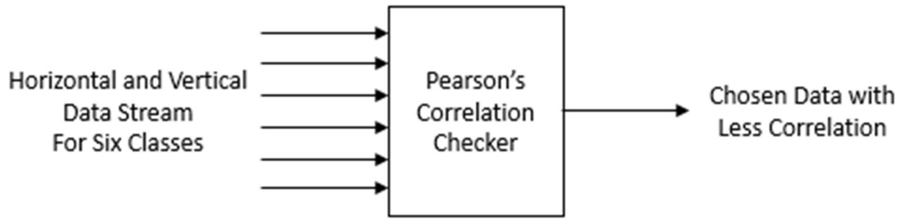

Figure 2:Relevant Data Selection

In each subsequent iteration, we increased both A and B by 60 Samples, allowing us to calculate the features for the next subset of samples.

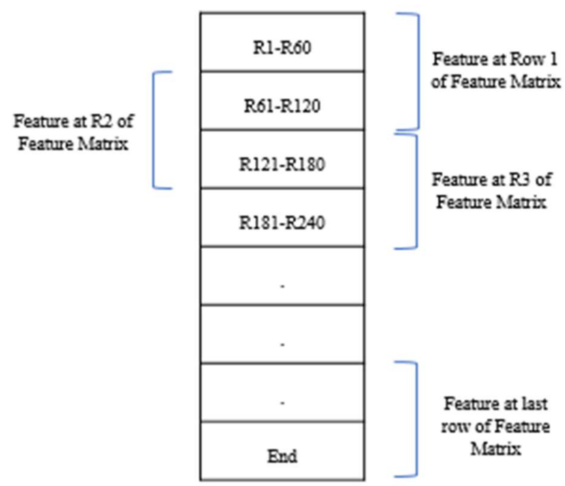

Figure 3: Time Windowing Approach

This approach enabled us to extract comprehensive features from the EMG data, capturing important characteristics and patterns within the signal. By segmenting the data into smaller subsets and calculating features iteratively, we ensured that the entire dataset was effectively analyzed and represented in the feature matrix. Our study focused on the accuracies achieved using the EMG data from column 1. We applied a methodology that involved segmenting the data and calculating 28 features iteratively, resulting in a comprehensive analysis of the EMG signals. By selecting subsets of samples and updating the range for feature calculation, we ensured a thorough examination of the data, leading to valuable insights into the characteristics and patterns of the EMG signals.

3.3 Feature Calculations and Feature Matrices:

Table 2: Calculated Features of EMG Data Segments

S.No	FEATURE	DESCRIPTION
1	Mean	Average value of the EMG signal
2	Median	Middle value of the EMG signal
3	Standard Deviation	Measure of the spread of the EMG signal
4	Variance	Measure of the variability of the EMG signal
5	Maximum	Highest value in the EMG signal
6	Minimum	Lowest value in the EMG signal
7	Mean Energy	Average energy of the EMG signal
8	Mean Curve Length	Average length of the curve in the EMG signal
9	Mean Teager Energy	Average energy based on Teager operator
10	Hjorth Mobility	Measure of signal mobility
11	Hjorth Complexity	Measure of signal complexity
12	Skewness	Measure of the asymmetry of the EMG signal
13	Kurtosis	Measure of the peakness of the EMG signal
14	First Difference	Absolute difference between consecutive samples
15	Normalized First Difference	First Difference normalized by the mean
16	Log Root Sum of Sequential Variation	Logarithm of the sum of sequential variations
17	Tsallis Entropy	Measure of signal complexity and irregularity
18	Band Power Alpha	Power in the alpha frequency band
19	Band Power Beta	Power in the beta frequency band
20	Band Power Delta	Power in the delta frequency band
21	Band Power Theta	Power in the theta frequency band
22	Band Power Gamma	Power in the gamma frequency band
23	Average Frequency	Average frequency content of the EMG signal
24	Frequency of Gravity	Dominant frequency in the EMG signal
25	RMS Frequency	Root Mean Square frequency of the EMG signal
26	Standard Deviation (Frequency)	Measure of the spread of frequencies in the EMG signal
27	Second Difference	Absolute difference between second consecutive samples
28	Normalized Second Difference	Second Difference normalized by the mean

The mean, denoted by the symbol μ for a population or $\bar{x}$ for a sample, is a fundamental statistical measure used to estimate the central tendency of a set of data points. It provides valuable insights into the average value of the data, serving as a summary statistic for researchers and practitioners alike. To compute the mean for a sample, one adds up all the individual data points $x_1, x_2, ..., x_n$ and divides the sum by the sample size n, resulting in the formula $\bar{x} = (x_1 + x_2 + ... + x_n) / n$. This calculation yields an estimate of the population mean based on the observed sample. For a population of size N, the population mean μ is determined in a similar manner, using the formula

$$\mu = \frac{X_1 + X_2 + \ldots + X_n}{N} \qquad (3.1)$$

The mean encapsulates the collective influence of all data points in the dataset, providing a central value that represents the typical nature of the data. However, caution should be exercised when interpreting the mean, particularly in the presence of extreme values or outliers, as they can unduly influence its magnitude. Therefore, it is advisable to supplement the mean with other statistical measures to gain a comprehensive understanding of the data distribution and variability.

The median, denoted as M or Med, is a statistical measure that represents the central value of a dataset. It is calculated by arranging the observations in ascending or descending order and identifying the middle value. The median is particularly useful when dealing with skewed or non-normal distributions, as it is less affected by extreme values compared to the mean.

Mathematically, let $X = \{x_1, x_2, ..., x_n\}$ be a dataset consisting of n observations. To compute the median, the dataset is first arranged in ascending order: $x(1) \leq x(2) \leq ... \leq x(n)$. The median is then determined as follows:

For an odd number of observations:

$$M = \frac{x(n+1)}{2} \qquad (3.2)$$

For an even number of observations:

$$M = \frac{x(n/2) + x((n/2)+1}{2} \qquad (3.3)$$

In the case of an odd-sized dataset, the median is simply the value at the center position, which divides the dataset into two equal halves. For even-sized datasets, the median is calculated as the average of the two middle values

The standard deviation, often denoted as σ (sigma), is a statistical measure that quantifies the dispersion or variability of a dataset. It provides a measure of how spread out the data points are from the mean. The standard deviation is widely used in research and data analysis to assess the consistency or variability within a dataset.

Mathematically, let $X = \{x1, x2, ..., xn\}$ be a dataset consisting of n observations. The standard deviation is calculated as follows:

1. Compute the mean (μ) of the dataset:

$$M = \frac{(x1 + x2 + \ldots + xn)}{n} \qquad (3.4)$$

2. Calculate the deviation of each observation from the mean:

$$\text{Deviation from the mean, } (d_i) = x_i - \mu \quad (3.5)$$

3. Square each deviation:

$$\text{Squared deviation, } (d_i^2) = (x_i - \mu)^2 \quad (3.6)$$

4. Calculate the sum of squared deviations:

$$\text{Sum of squared deviations } (\Sigma(d_i^2)) = (d_i^2 + d_i^2 + ... + d_i^2) \quad (3.7)$$

5. Compute the average of squared deviations:

$$\text{Average squared deviation} = \frac{1}{n}\Sigma(d_i^2) \quad (3.8)$$

6. Take the square root of the average squared deviation:

$$\text{Standard deviation } (\sigma) = \frac{\sqrt{\Sigma(di\text{^}2)}}{n} \quad (3.9)$$

The standard deviation represents the typical distance between each observation and the mean. A higher standard deviation indicates greater variability or dispersion within the dataset, while a lower standard deviation suggests that the data points are closer to the mean and exhibit less variability.

Variance, denoted as Var(X) or σ^2 (sigma squared), is a statistical measure that quantifies the spread or dispersion of a dataset. It provides a measure of the average squared deviation of data points from their mean. Variance is widely used in statistical analysis and research to assess the variability within a dataset.

Mathematically, let X = {x1, x2, ..., xn} be a dataset consisting of n observations. The variance is calculated as follows:

1. Compute the mean (μ) of the dataset:

$$\mu = \frac{x_1 + x_2 + x_3 + \cdots + x_n}{n} \quad (3.10)$$

2. Calculate the deviation of each observation from the mean:

$$\text{Deviation from the mean (di)} = x_i - \mu \quad (3.11)$$

3. Square each deviation:

$$\text{Squared deviation } (di^2) = (x_i - \mu)^2 \quad (3.12)$$

4. Calculate the sum of squared deviations:

$$\text{Sum of squared deviations } (\Sigma(d_i^2)) = (d_i^2 + d_i^2 + ... + d_i^2) \quad (3.13)$$

5. Compute the average of squared deviations:

$$\text{Variance } (\mathrm{Var}(X) \text{ or } \sigma^2) = \frac{1}{n}\Sigma(d_i^2) \tag{3.14}$$

The variance represents the average squared difference between each observation and the mean. It provides a measure of the spread or dispersion of the data points. A higher variance indicates greater variability within the dataset, while a lower variance suggests that the data points are closer to the mean and exhibit less dispersion.

The maximum, denoted as max(X), is a statistical measure that represents the largest value within a dataset. It provides a concise and definitive representation of the upper boundary or the highest observed value in the data. The maximum is a simple yet essential measure used in various fields to identify extreme values and assess the upper limit of a dataset.

Mathematically, let $X = \{x_1, x_2, ..., x_n\}$ be a dataset consisting of n observations. The maximum is calculated as follows:

$$max(X) = max(x_1, x_2, ..., x_n) \tag{3.15}$$

The maximum is determined by comparing each observation within the dataset and selecting the largest value as the maximum. It represents the upper limit of the values observed in the dataset and serves as a clear indicator of the highest value present.

The minimum, denoted as min(X), is a statistical measure that represents the smallest value within a dataset. It provides a concise and definitive representation of the lower boundary or the smallest observed value in the data. The minimum serves as a fundamental measure used in various fields to identify extreme values and assess the lower limit of a dataset.

Mathematically, let $X = \{x_1, x_2, ..., x_n\}$ be a dataset consisting of n observations. The minimum is calculated as follows:

$$min(X) = \min(x_1, x_2, ..., x_n) \tag{3.16}$$

The minimum is determined by comparing each observation within the dataset and selecting the smallest value as the minimum. It represents the lower limit of the values observed in the dataset and serves as a clear indicator of the smallest value present.

Mean energy, denoted as $\bar{E}$, is a statistical measure that represents the average energy of a system or a physical phenomenon. It provides a quantitative assessment of the typical or expected energy level within a given context. Mean energy is widely used in various fields, including physics, engineering, and signal processing, to analyze and characterize energy-related aspects of systems.

Mathematically, let $E = \{E_1, E_2, ..., E_n\}$ be a dataset consisting of n energy values. The mean energy is calculated as follows:

$$\bar{E} = \frac{E_1 + E_2 + E_3 + \cdots + E_n}{n} \tag{3.17}$$

The mean energy is obtained by summing up all the energy values in the dataset and dividing the sum by the total number of observations. It represents the central tendency or the average energy level within the dataset.

Mean curve length, denoted as $\bar{L}$, is a statistical measure that quantifies the average length or extent of a curve within a given context. It is used to assess the complexity or intricacy of a curve, providing a quantitative measure of its overall length. Mean curve length is widely utilized in fields such as image processing, computer vision, and geometry to analyze and characterize the shape and structure of curves.

Mathematically, let $C = \{c_1, c_2, ..., c_n\}$ be a set of n curves. Each curve is represented by a series of points or coordinates that define its path. The mean curve length is calculated as follows:

$$\bar{L} = \frac{L_1 + L_2 + L_3 + \cdots + \mathrm{Ln}}{n} \tag{3.18}$$

where Li represents the length of the i-th curve.

The length of a curve can be computed using various methods, such as the arc length formula or the Euclidean distance between consecutive points along the curve. The total length of a curve is obtained by summing the lengths of its individual segments or by integrating the arc length formula over the entire curve.

Mean Teager energy is a statistical measure that quantifies the average energy content of a signal or a time-varying phenomenon using the Teager energy operator. It provides a robust measure of signal energy by taking into account both the amplitude and the instantaneous frequency components of the signal. Mean Teager energy is widely used in fields such as signal processing, audio analysis, and vibration analysis to analyze and characterize the energy content of signals.

Mathematically, let x(t) be a continuous-time signal or a discrete-time sequence. The Teager energy operator, denoted as $TE[x(t)]$ or $TE[x[n]]$, is applied to the signal as follows:

$$TE[x(t)] = x^2(t) - x(t-1) * x(t+1) \tag{3.19}$$

$$TE[x[n]] = x^2[n] - x[n-1] * x[n+1] \tag{3.20}$$

where x(t) or x[n] represents the value of the signal at time t or index n.

The mean Teager energy is calculated by averaging the Teager energy values of the signal over a specified duration or length:

$$\bar{E}\_T = \frac{\mathrm{TE[x(t1)] + TE[x(t2)] + \ldots + TE[x(tN)}}{\mathrm{N}} \tag{3.21}$$

Or

$$\bar{E}\_T = \frac{\mathrm{TE[x[n2]] + TE[x[n2]] + \ldots + TE[x[nN]]}}{\mathrm{N}} \tag{3.22}$$

where $TE[x(t_1)]$ or $TE[x[n_1]]$, $TE[x(t_2)]$ or $TE[x[n_2]]$, ..., $TE[x(t_N)]$ or $TE[x[n_N]]$ are the Teager energy values at specific time instances or indices, and N is the total number of observations.

Hjorth mobility, developed by Bjorn Hjorth, is a mathematical measure that quantifies the mobility or activity level of a time series signal. It provides insight into the degree of signal variability or movement over time. Hjorth mobility is commonly used in fields such as biomedical signal processing, neuroscience, and movement analysis to assess the dynamic properties of signals.

Mathematically, let *x(t)* be a continuous-time signal or *x[n]* be a discrete-time sequence. Hjorth mobility, denoted as *HM[x(t)]* or *HM[x[n]]*, is calculated using the following formula:

$$HM[x(t)] = \sqrt{\frac{\mathrm{Var(dx(t))}}{\mathrm{Var(x(t))}}} \tag{3.23}$$

$$HM[x[n]] = \sqrt{\frac{\mathrm{Var(dx[n])}}{\mathrm{Var(x[n])}}} \tag{3.24}$$

where *dx(t)/dx[n]* represents the first-order derivative of the signal *x(t)/x[n]*, and Var denotes the variance.

Hjorth complexity [27], developed by Bjorn Hjorth, is a mathematical measure that quantifies the complexity or irregularity of a time series signal. It provides an assessment of the signal's waveform complexity based on its amplitude variations and changes over time. Hjorth complexity is widely used in fields such as biomedical signal processing, neuroscience, and pattern recognition to characterize the complexity of signals.

Mathematically, let *x(t)* be a continuous-time signal or *x[n]* be a discrete-time sequence. Hjorth complexity, denoted as *HC[x(t)]* or *HC[x[n]]*, is calculated using the following formula:

$$HC[x(t)] = \sqrt{\frac{Var(\mathrm{d}^2x(\mathrm{t}))}{Var(dx(\mathrm{t}))}} \tag{3.25}$$

$$HC[x[n]] = \sqrt{\frac{Var(\mathrm{d}^2x[\mathrm{n}])}{Var(dx[\mathrm{n}])}} \tag{3.26}$$

where dx(t)/dx[n] represents the first-order derivative of the signal x(t)/x[n], and $d^2x(t)/d^2x[n]$ represents the second-order derivative of the signal. Var denotes the variance.

Skewness is a statistical measure that quantifies the asymmetry or departure from symmetry in a probability distribution or a dataset. It provides insight into the shape of the distribution and the relative positioning of the data points. Skewness is widely used in various fields, including finance, economics, and data analysis, to assess the symmetry or skewness of data.

Mathematically, let $X = \{x_1, x_2, ..., x_n\}$ be a dataset consisting of n observations. The skewness, denoted as S, is calculated using the following formula:

$$\mathrm{S} = \frac{n}{(n-1)(n-2)} * \sum \frac{\mathrm{xi} - \bar{\mathrm{X}}^3}{\mathrm{s}^3} \tag{3.27}$$

where $\bar{X}$ is the mean of the dataset and s is the standard deviation.

Kurtosis is a statistical measure that quantifies the shape of a probability distribution or a dataset, specifically focusing on the degree of heaviness of the tails and the peakedness of the distribution. It provides insight into the presence of outliers or extreme values in the data. Kurtosis is widely used in various fields, including finance, economics, and data analysis, to assess the shape and distributional characteristics of data.

Mathematically, let $X = \{x_1, x_2, ..., x_n\}$ be a dataset consisting of n observations. The kurtosis, denoted as K, is calculated using the following formula:

$$K = \frac{\mathrm{n(n+1)}}{(n-1)(n-2)(n-3)} * \sum \frac{\mathrm{xi} - \bar{\mathrm{X}}^4}{\mathrm{s}^4} - \frac{3(\mathrm{n}-1)^2}{(n-2)(n-3)} \tag{3.28}$$

where $\bar{X}$ is the mean of the dataset and s is the standard deviation.

The first difference, also known as the discrete first derivative, is a mathematical operation used to analyze the rate of change or the incremental differences between consecutive data points in a sequence or time series. It provides insights into the local changes or trends within the data. The first difference is widely employed in fields such as economics, finance, and signal processing to study the dynamics and transformations of data.

Mathematically, let $X = \{x_1, x_2, ..., x_n\}$ be a sequence or time series consisting of n data points. The first difference of the sequence, denoted as $\Delta X = \{\Delta x1, \Delta x2, ..., \Delta xn\text{-}1\}$, is calculated as follows:

$$\Delta x_i = x_{i+1} - x_i \qquad \text{for } i = 1, 2, ..., n\text{-}1 \tag{3.29}$$

In other words, the first difference at index i represents the difference between the data point at index *(i+1)* and the data point at index i.

The normalized first difference, also known as the percentage change or relative change, is a mathematical measure used to analyze the proportional differences between consecutive data points in a sequence or time series. It provides insights into the relative rate of change or growth of the data, regardless of the scale or magnitude. The normalized first difference is commonly used in fields such as finance, economics, and statistics to compare the relative changes in variables.

Mathematically, let $X = \{x_1, x_2, ..., x_n\}$ be a sequence or time series consisting of n data points. The normalized first difference of the sequence, denoted as $\Delta X\% = \{\Delta x1\%, \Delta x2\%, ..., \Delta xn\text{-}1\%\}$, is calculated as follows:

$$\Delta x_i\% = ((x_{i+1} - x_i) * \frac{100}{x_i} \qquad \text{for i = 1, 2, ..., n-1} \tag{3.30}$$

The normalized first difference at index i represents the proportional difference between the data point at index *(i+1)* and the data point at index i, expressed as a percentage of the original value.

The log root sum of sequential variation (LRSV) is a statistical measure used to assess the volatility or fluctuation of a time series or sequence of data. It quantifies the cumulative effect of sequential variations or changes in the data over time. The LRSV is commonly used in finance, economics, and risk analysis to evaluate the stability and predictability of time series data.

Mathematically, let $X = \{x_1, x_2, ..., x_n\}$ be a sequence or time series consisting of n data points. The LRSV, denoted as *LRSV(X),* is calculated using the following formula:

$$LRSV(X) = \log\sqrt{\frac{\Sigma \ln\left(\frac{x_{i+1}}{x_i}\right)^2}{n-1}} \tag{3.31}$$

Here, ln represents the natural logarithm.

Tsallis entropy, named after Constantino Tsallis, is a generalization of Shannon entropy that provides an alternative measure of uncertainty or information content in a probability distribution. It is widely used in various fields, including physics, information theory, and complex systems, to capture the non-extensive properties of certain systems.

Mathematically, let *P = {p1, p2, ..., pn}* be a probability distribution consisting of n probabilities associated with n discrete events.

The Tsallis entropy, denoted as *Sq*, is calculated using the following formula:

$$Sq = \frac{\Sigma \frac{\left(p_i^q - p_i\right)}{q-1}}{1-q} \tag{3.32}$$

where q is a parameter that controls the degree of non-extensivity. It typically takes values in the range q > 0, and q = 1 corresponds to the Shannon entropy.

Band power refers to the measurement of the power or intensity of a signal within a specific frequency range. It is a common analysis technique used in various fields, including signal processing, neuroscience, and communication engineering. Band power analysis provides insights into the distribution of signal energy across different frequency bands, allowing for the examination of specific frequency components or bands of interest.

Mathematically, let *X(t)* represent a continuous-time signal or a discrete-time sequence, and let *X(f)* denote its Fourier transform or spectral representation. The band power *P_band* is calculated by integrating the squared magnitude of the signal spectrum within a specific frequency range of interest.

$$P\_band = \int [|X(f)|^2]\, df \tag{3.33}$$

Here, |X(f)|^2 represents the squared magnitude of the signal spectrum, and the integral is performed over the frequency range of the desired band.

Different types of band power

1. Alpha Band Power: Alpha band power typically refers to the power of brain signals within the alpha frequency range, which is typically around 8 to 13 Hz. It is widely studied in neuroscience and is associated with cognitive states such as relaxation, closed eyes, and reduced sensory input.

2. Beta Band Power: Beta band power represents the power of signals within the beta frequency range, typically ranging from 13 to 30 Hz. Beta oscillations are often associated with motor activities, cognitive processes, and focused attention.

3. Delta Band Power: Delta band power refers to the power of signals within the delta frequency range, typically below 4 Hz. Delta waves are prominent during deep sleep stages and are associated with restorative processes and physical recovery.

4. Theta Band Power: Theta band power represents the power of signals within the theta frequency range, typically ranging from 4 to 8 Hz. Theta waves are often observed during relaxation, meditation, and certain cognitive tasks, including memory and spatial navigation.

5. Gamma Band Power: Gamma band power refers to the power of signals within the gamma frequency range, typically above 30 Hz. Gamma oscillations are associated with higher cognitive functions, attention, and sensory processing.

Average frequency, also known as mean frequency, is a measure used to characterize the central tendency of frequency distribution in a signal or waveform. It provides information about the typical frequency content or the average spectral position of the signal.

Mathematically, let X(t) represent a continuous-time signal or a discrete-time sequence, and let X(f) denote its Fourier transform or spectral representation. The average frequency, denoted as *f_avg*, is calculated by integrating the product of frequency and the squared magnitude of the signal spectrum and then dividing it by the total power or energy of the signal.

$$F\_avg = \frac{\int f[|X(f)|^2]df}{\int [|X(f)|^2]\, df} \tag{3.34}$$

Here, f represents the frequency variable, |X(f)|^2 represents the squared magnitude of the signal spectrum, and the integrals are performed over the entire frequency range.

In physics, the concept of “frequency of gravity” does not have a direct interpretation. Gravity is described by the theory of general relativity, which defines gravity as the curvature of spacetime caused by mass and energy. It does not involve a specific frequency in the traditional sense.

However, in some theoretical frameworks, such as attempts to unify general relativity with quantum mechanics, certain speculative theories propose the existence of hypothetical particles called “gravitons” that could mediate the gravitational force. In these theories, it is possible to talk about a frequency associated with the gravitons.

Mathematically, if we consider a hypothetical graviton with frequency f, we can express its energy E using Planck’s relation:

$$E = hf \tag{3.35}$$

where h is the Planck constant. Here, the frequency f corresponds to the number of oscillations or cycles of the graviton per unit of time.

The second difference refers to the difference between consecutive differences in a sequence or function. It provides information about the rate of change or the curvature of the original sequence or function.

Mathematically, let $\{x_1, x_2, ..., x_n\}$ be a sequence of values. The first difference, denoted as Δx_i, is calculated as:

$$\Delta x_i = x_{i+1} - x_i \tag{3.36}$$

where x_{i+1} represents the value at the $(i+1)^{th}$ position and x_i represents the value at the i^{th} position.

The second difference, denoted as $\Delta^2 x_i$, is then calculated as:

$$\Delta^2 x_i = \Delta x_{i+1} - \Delta x_i \tag{3.37}$$

This equation represents the difference between consecutive differences in the sequence. It captures the change in the rate of change or the curvature of the original sequence.

Normalized second difference, also known as the centered second difference, is a variation of the second difference that provides a measure of the curvature of a sequence or function while accounting for the scale or magnitude of the data. It is commonly used in numerical analysis and signal processing.

Mathematically, let $\{x_1, x2, ..., x_n\}$ be a sequence of values. The first step is to compute the centered differences, denoted as δx_i, which are calculated as:

$$\delta x_i = x_{i+1} - x \tag{3.38}$$

where x_{i+1} represents the value at the $(i+1)^{th}$ position, and x_{i-1} represents the value at the $(i-1)^{th}$ position.

The normalized second difference, denoted as $\Delta^2 x_{i\_norm}$, is then obtained by dividing the centered second difference ($\Delta^2 x_i$) by the average of the squared centered differences:

$$\Delta^2 x_{i\_norm} = \Delta^2 x_i \, / \, \frac{1}{n} \Sigma \delta x_i^2 \tag{3.39}$$

Here, n represents the number of values in the sequence, Σ denotes the summation, and δx_i is the centered difference as defined earlier. analyzed.

These features were computed to capture different characteristics of the EMG signal, providing insights into its statistical properties, energy distribution, frequency content, and other relevant information. The feature matrix, consisting of all 28 calculated features, played a crucial role in our methodology. It had dimensions of 332 rows and 29 columns. Among these columns, 28 represented the features, while the 29th column was dedicated to the class label. As we had six classes, we created a total of six such feature matrices. These individual matrices were then combined to form a consolidated feature matrix with dimensions of 1992 rows and 29 columns. To address potential overfitting concerns and improve the accuracy of our model during training, we took steps to ensure the randomness and even representation of classes within the feature dataset. We accomplished this by shuffling or randomizing the rows of the feature matrix. By doing so, we aimed to prevent any single class from dominating the training process for an extended period, thus avoiding suboptimal outcomes. Additionally, we recognized the significance of training the classifier on mini batches of 150 samples approximately independently. This approach was crucial for enhancing efficiency and avoiding local optima that could hinder class recognition accuracy. By treating each mini batch as a separate entity, we aimed to prevent biases or dependencies that may arise from observing all classes in a single batch, ultimately improving the overall performance of our classification model.

CHAPTER 4
MACHINE LEARNING CLASSIFIERS

4.1 Classifiers Used:

We tested our method with several classifier algorithms but during the evaluation of various classification algorithms, the Cubic Support Vector Machine (SVM) algorithm emerged as the most successful one with a remarkable accuracy. Support Vector Machine (SVM) is a powerful and versatile machine learning algorithm that is widely used for classification and regression tasks [28]. SVM is a supervised learning method that is particularly effective in dealing with complex datasets and finding optimal decision boundaries. The core idea behind SVM is to find a hyperplane that maximally separates the data points of different classes in a high-dimensional feature space. This hyperplane is determined by support vectors, which are the data points closest to the decision boundary. SVM aims to find the hyperplane that maximizes the margin, i.e., the distance between the hyperplane and the closest data points of each class. This margin maximization approach makes SVM robust against noise and outliers. One of the key strengths of SVM is its ability to handle both linearly separable and non-linearly separable data. In addition to the linear SVM, which uses a linear decision boundary, SVM can employ different kernel functions, such as polynomial, radial basis function (RBF), or sigmoid, to map the data into a higher-dimensional space where the classes become separable. This process is known as the "kernel trick." By using the appropriate kernel function, SVM can capture complex relationships and patterns in the data, enabling it to achieve high accuracy.

Another advantage of SVM is its ability to handle datasets with a large number of features. SVM uses a subset of the training data points, the support vectors, to define the decision boundary [29]. This property makes SVM memory-efficient and suitable for high-dimensional datasets. SVM has been successfully applied in various domains, including image classification, text classification, bioinformatics, and finance. Its performance and generalization capability have been extensively studied and documented in the machine learning community. SVM's ability to handle complex data, flexibility in handling non-linear relationships through kernel functions, and robustness against noise make it a popular choice for many classification tasks. However, it is worth noting that SVM has some considerations and limitations. The choice of the appropriate kernel function and tuning of hyperparameters, such as the regularization parameter and the kernel-specific parameters, can significantly impact SVM's performance. In some cases, SVM can be computationally expensive, particularly when dealing with large datasets. Additionally, SVM may struggle with datasets that have imbalanced class distributions or when the number of features is much larger than the number of samples. Support Vector Machine (SVM) is a versatile and powerful machine learning algorithm that excels in classification tasks. Its ability to handle linear and non-linear data, robustness against noise, and efficiency in high-dimensional spaces have contributed to its widespread usage. With appropriate parameter tuning, SVM can achieve high accuracy and provide reliable results in a variety of applications.

4.2 Cubic Support Vector Machine:

Cubic Support Vector Machine (Cubic SVM) is an extension of the standard Support Vector Machine (SVM) algorithm that incorporates cubic decision functions. It allows for more flexible and non-linear decision boundaries compared to linear or quadratic SVMs. The cubic decision functions introduce higher-order polynomial terms, enabling the SVM to capture complex relationships in the data [30]. To explain the Cubic SVM mathematically, let's consider a binary classification problem with training data consisting of N samples. Each sample is represented by a feature vector $x_i \in \mathbb{R}^d$, where i = 1, 2, ..., N, and d is the number of features. The corresponding binary class labels are $y_i \in \{-1, 1\}$.

The goal of Cubic SVM is to find a decision boundary in the form of a hyperplane that separates the two classes while maximizing the margin. The decision function for the Cubic SVM can be represented as:

$$f(x) = w_0 + w_1x + w_2x^2 + w_3x^3 \quad (4.1)$$

where x is the input feature vector and w_0, w_1, w_2, and w_3 are the coefficients to be determined.

Similar to the standard SVM, the Cubic SVM introduces the concept of slack variables ξ_i to allow for some misclassifications and errors. The optimization problem for the Cubic SVM can be formulated as:

$$minimize\ \tfrac{1}{2}\ ||w||^2 + C\xi^2 \quad (4.2)$$

subject to $y_i(f(x_i)) \geq 1 - \xi_i$,

$\xi_i \geq 0$,

where $||w||^2$ is the L2-norm of the weight vector w, C is the regularization parameter that controls the trade-off between margin maximization and error tolerance, and ξ_i represents the slack variable associated with each training sample. The objective function aims to minimize the norm of the weight vector w while penalizing misclassifications through the slack variables. The term $C\xi^2$ introduces a penalty for the amount of slack used, with C controlling the relative importance of the margin maximization versus the error tolerance. To solve the optimization problem, one can use techniques such as Quadratic Programming or convex optimization algorithms to find the optimal values of the coefficients w_0, w_1, w_2, and w_3. It's worth noting that the mathematical representation and formulation of Cubic SVM can vary depending on the specific implementation and formulation choices. The above equations provide a general idea of how the Cubic SVM introduces cubic decision functions into the SVM framework to handle non-linear classification problems.

CHAPTER 5
RESULTS AND APPLICATIONS

5.1 Results

Once the dataset was shuffled, it was divided into two distinct sets: the training dataset and the testing dataset. To ensure a comprehensive evaluation of the classifier model, 70% of the total number of rows in the feature matrix were allocated to the training feature stream, while the remaining 30% were assigned to the testing feature stream. The training dataset, consisting of 70% of the randomized data, was utilized to train various machine learning algorithms specifically designed for classification purposes. During this phase, the algorithms were exposed to a diverse range of samples, allowing them to learn the underlying patterns and relationships within the data. Following the training phase, the remaining 30% of the randomized data, constituting the testing dataset, was employed to evaluate the performance of the trained algorithms. This independent dataset served as a means to assess the generalization and predictive capabilities of the algorithms on unseen data. By evaluating the algorithms on this separate dataset, we obtained a reliable estimation of their accuracy and effectiveness in classifying new, unseen samples. This division of the dataset into training and testing subsets, along with the subsequent training and evaluation processes, ensured a comprehensive and robust assessment of the trained algorithms' performance and their ability to accurately classify hand gestures based on the provided EMG Signals. During the evaluation of various classification algorithms, the Cubic Support Vector Machine (SVM) algorithm emerged as the most successful one with a remarkable accuracy of 96.8%. This means that it correctly classified 96.8% of the instances in the dataset. The Cubic SVM is a variant of the SVM algorithm that uses a cubic kernel function to map the input data into a higher-dimensional feature space, enabling it to effectively separate different classes.

5.2 Discussion

Both the Quadratic SVM and the Wide Neural Network achieved an accuracy of 96.1%. The Quadratic SVM employs a quadratic kernel function, while the Wide Neural Network is a neural network architecture with a larger number of hidden units and layers, allowing it to capture complex patterns in the data.

The Medium Neural Network method achieved a respectable accuracy of 95.7%. This indicates that the neural network model with a moderate size and complexity performed well in the classification task, accurately predicting the class labels for a majority of the instances.

The Ensembled Bagged Tree and Narrow Neural Network classifier achieved an accuracy of 95.3%. The Ensembled Bagged Tree method combines multiple decision trees trained on different subsets of the data, utilizing the concept of bootstrap aggregating (bagging). The Narrow Neural Network classifier, on the other hand, refers to a neural network architecture with fewer hidden units and layers, providing a more compact model representation. It's important to mention that although several other classification machine learning algorithms were employed in the evaluation, the aforementioned algorithms stood out as the most successful ones in terms of accuracy.

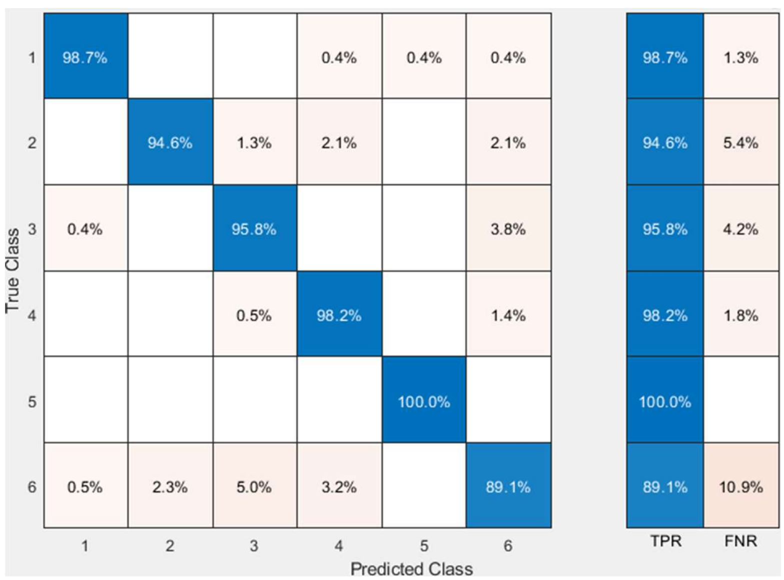

Figure 4: Confusion Matrix, True Positive Rate (TPR) and False Negative Rate (FNR)

This suggests that they were able to effectively capture the underlying patterns and relationships in the data, leading to more accurate predictions. Accurate classification is a critical aspect of machine learning models as it directly impacts the model's ability to make reliable predictions. By achieving high accuracy, these algorithms demonstrate their efficacy and suitability for the given classification task. However, it's worth noting that accuracy is not the only metric to consider when evaluating models, and other metrics such as precision, recall, and F1-score should also be taken into account depending on the specific requirements of the application.

Table 3: Comparison of proposed method result with other existing similar work

Authors	*Subjects*	*Classes*	*Subjects*
Zhang et al. [13]	11	4	94.20%
Cai et al. [14]	10	5	91.50%
Rana et al. [15]	12	3	93.30%
Liu et al. [16]	9	3	94.60%
Rana et al. [17]	10	6	94.60%
Chen et al. [18]	10	3	94.10%
Li et al. [19]	10	5	93.70%
Zou et al. [20]	10	3	92.50%
Zarei et al. [21]	8	4	90.50%
Srivastava et al. [22]	10	4	92.80%
Proposed Method	**10**	**6**	**96.80%**

5.3 Applications and Future scope

EMG signals have numerous applications in clinical diagnosis, rehabilitation, sports medicine, and ergonomics. In clinical diagnosis, EMG is a valuable tool for assessing and diagnosing a variety of neuromuscular disorders. These may include myopathies, which are disorders that affect the muscle tissue itself, neuropathies, which are disorders that affect the nerves that control the muscles, and motor neuron diseases, which are disorders that affect the nerve cells that control muscle movement. EMG can help to identify the location and severity of these conditions by measuring the electrical activity of the muscles and nerves involved. EMG can also be used to monitor the progress of rehabilitation and to evaluate the effectiveness of interventions, such as physical therapy or medication. For example, EMG can be used to assess changes in muscle strength and activation patterns following a period of physical therapy or rehabilitation. This can provide clinicians with valuable information about the effectiveness of the treatment, and can help to guide further interventions as necessary. In sports medicine, EMG is often used to assess muscle function and to identify potential areas of weakness or imbalance. By measuring the electrical activity of muscles during specific movements, clinicians can identify patterns of muscle activation that may be contributing to injury or decreased performance. This information can then be used to develop individualized training programs that target specific muscle groups or movement patterns, with the goal of improving performance and reducing the risk of injury. In ergonomics, EMG can be used to assess the physical demands of different types of work and to identify potential areas of ergonomic risk. By measuring the electrical activity of muscles during different work tasks, researchers can gain insights into the muscular demands of these tasks and identify potential areas of fatigue or strain. This information can then be used to develop strategies to reduce the risk of injury or musculoskeletal disorders in the workplace. EMG signals have a wide range of applications in clinical diagnosis, rehabilitation, sports medicine, and ergonomics. EMG can be used to diagnose and monitor neuromuscular disorders, assess muscle function and performance, and identify potential areas of ergonomic risk. The versatility and sensitivity of EMG make it a valuable tool for researchers and clinicians across a wide range of fields.

In sports medicine, EMG is a useful tool for analyzing the performance of athletes and identifying potential injury risks. EMG can be used to measure muscle activation patterns during specific exercises or movements, providing valuable information about muscle function and performance. This information can be used to develop training programs that target specific muscle groups or movement patterns, with the goal of improving performance and reducing the risk of injury. EMG can also be used to identify muscle imbalances, which can lead to overuse injuries or decreased performance. For example, an athlete with a weaker quadriceps muscle on one leg may compensate by using other muscles more during a specific movement, such as a jump or a sprint. Over time, this compensation can lead to muscle imbalances and an increased risk of injury. EMG can be used to identify these imbalances early, allowing athletes and coaches to modify training programs or techniques to reduce injury risk and improve performance. In addition, EMG can be used to assess the effectiveness of different training programs or techniques. For example, EMG can be used to measure muscle activation patterns before and after a period of strength training, providing insights into the effectiveness of the training program. This information can be used to modify the training program as necessary, with the goal of optimizing performance and reducing injury risk. Overall, EMG is a valuable tool for sports medicine professionals, providing insights into muscle function and performance that can be used to improve training programs and reduce injury risk. By measuring muscle activation patterns and identifying muscle imbalances, EMG can help athletes and coaches develop individualized training programs that optimize performance and reduce the risk of injury.

In ergonomics, EMG is a valuable tool for evaluating the impact of workplace design on muscle activity and fatigue. By measuring the EMG activity of muscles during different work tasks, researchers can identify ergonomic risk factors and recommend changes to improve worker safety and comfort. For example, EMG can be used to assess the impact of workstation design on neck and shoulder muscle activity in office workers. By measuring the EMG activity of the trapezius muscle, which is commonly associated with neck and shoulder pain, researchers can identify ergonomic risk factors such as improper desk height, poorly positioned computer monitors, or inadequate seating. This information can be used to recommend changes to workstation design, such as adjustable desks and chairs, monitor stands, or ergonomic keyboards, to reduce the risk of pain and injury. EMG can also be used to evaluate the impact of tool design on hand and wrist muscle activity in assembly line workers. By measuring the EMG activity of the forearm muscles during different work tasks, researchers can identify ergonomic risk factors such as poorly designed tools, inadequate grip strength, or awkward wrist postures. This information can be used to recommend changes to tool design, such as ergonomic handles or grips, to reduce the risk of pain and injury. Overall, EMG is a valuable tool for ergonomics professionals, providing insights into muscle activity and fatigue that can be used to evaluate workplace design and recommend changes to improve worker safety and comfort. By identifying ergonomic risk factors and recommending changes to reduce pain and injury, EMG can help create a safer and more productive work environment.

EMG signals are also used in the development of prosthetics and exoskeletons. Prosthetics are artificial limbs that replace missing or damaged body parts, while exoskeletons are wearable devices that augment or assist human movement. Both prosthetics and exoskeletons require control systems that can translate the user's intentions into movements of the device. EMG signals are ideal for this purpose because they reflect the activity of the user's muscles. By measuring the EMG activity of the remaining muscles in a limb or the muscles of the torso, researchers can identify patterns of muscle activation that correspond to different movements. These patterns can then be used to develop control algorithms that allow users to control their prosthetic or exoskeleton using their own muscle activity. For example, a person with an amputated arm may be able to use EMG signals from their remaining muscles to control a prosthetic hand. By detecting the muscle activity associated with closing and opening the hand, the control system can move the prosthetic hand in the same way. Similarly, a person with weakness in their legs may be able to use EMG signals from their thigh muscles to control an exoskeleton that assists with walking. EMG-based control systems for prosthetics and exoskeletons are still in development, but they hold great promise for improving the quality of life for individuals with limb loss or weakness. By allowing users to control their devices using their own muscle activity, these systems can provide a more natural and intuitive interface than traditional prosthetics or exoskeletons.

EMG signals provide valuable insights into the functioning of the human body, specifically the electrical activity of muscle tissue during contractions. These signals can be measured and analyzed in different ways, including time-domain analysis, frequency-domain analysis, and time-frequency analysis, depending on the specific needs of the application. The use of EMG signals has important applications in clinical diagnosis, rehabilitation, sports medicine, ergonomics, and the development of prosthetics and exoskeletons. These applications include the diagnosis of neuromuscular disorders, monitoring the progress of rehabilitation, analysing athletic performance, identifying ergonomic risk factors, and developing control algorithms for prosthetic limbs and exoskeletons. As technology continues to advance, the use of EMG signals is likely to become even more widespread and important in these fields. For example, wearable technology such as smart clothing and sensors may make it easier to collect and analyse EMG data in real-time, allowing for more personalized and precise interventions in healthcare and performance optimization. Additionally, the integration of EMG signals with other types of physiological data, such as heart rate and respiration, could provide a more comprehensive understanding of human movement and function. Overall, the study and application of EMG signals is a rapidly evolving field with significant potential to improve human health and well-being.

CHAPTER-6
CONCLUSION

6.1 Summary and Conclusion

This study aimed to develop a method for accurately classifying six different classes of eye muscle movements using electromyography (EMG) signals from the extraocular muscles (EOM). The researchers proposed a novel approach that incorporated a windowing technique and a Cubic Support Vector Machine (SVM) classifier to achieve improved accuracy compared to existing work in this field. EMG signals provide valuable information about the electrical activity of muscles, and they can be used to analyze and understand muscle movements. In this study, the researchers focused specifically on eye muscle movements, which are essential for eye coordination and vision. To classify the different eye muscle movements, the researchers employed a windowing technique. This technique involves dividing the EMG signals into smaller windows or segments, allowing for more focused analysis. By analyzing these windows individually, the method can capture and extract relevant features related to each specific eye muscle movement.

The researchers then applied a Cubic SVM classifier to classify the segmented EMG signals into their respective classes. SVM is a popular machine learning algorithm known for its ability to handle complex classification tasks by finding an optimal hyperplane that separates different classes in a high-dimensional feature space. The use of a Cubic SVM implies that a cubic kernel function was employed to map the EMG signal data into a higher-dimensional space, enabling the algorithm to effectively discriminate between the different eye muscle movements. The results of the study demonstrated that the proposed method, combining the windowing technique with the Cubic SVM classifier, outperformed existing approaches in terms of accuracy. The improved accuracy implies that the method was able to accurately classify the six different classes of eye muscle movements more reliably and consistently than previous methods. The findings of this study have important implications for various applications, such as eye-tracking technology, ophthalmology diagnostics, and human-computer interaction systems. Accurate classification of eye muscle movements can contribute to a better understanding of eye coordination disorders and help develop targeted interventions or assistive technologies.

It's worth noting that this study focused specifically on the combination of the windowing technique and the Cubic SVM classifier as a novel approach for accurate classification. However, further research and validation are necessary to assess the method's performance on larger datasets, evaluate its generalizability, and explore its applicability in real-world scenarios. While the accuracy of any classification technique can vary depending on the specific dataset and its characteristics, the implementation of the proposed method in this study yielded impressive results. The achieved accuracy indicates that the combination of the windowing technique and the Cubic SVM classifier has the potential to significantly advance the field of classifying different classes, not only in the present but also in the future. It's important to acknowledge that the performance of any classification method can be influenced by various factors, including the quality and diversity of the dataset, the complexity of the classes being classified, the choice of features, and the robustness of the classifier itself. Therefore, it is necessary to carefully evaluate the technique's performance on different datasets to assess its reliability and generalizability.

However, the fact that this method demonstrated improved accuracy over existing approaches suggests that it has the potential to make substantial contributions to the field of classification. By accurately classifying the six different classes of eye muscle movements, this technique provides a foundation for a wide range of applications and research areas. The potential benefits of this work extend to numerous fields. In medical research, the accurate classification of eye muscle movements can aid in diagnosing and monitoring eye coordination disorders, contributing to more effective treatments and interventions. This technique can also be utilized in the development of eye-tracking systems, which have applications in areas such as human-computer interaction, virtual reality, and assistive technologies. Moreover, advancements in classifying different classes can have implications in various domains beyond eye muscle movements. The proposed method's underlying principles, such as the windowing technique and the use of a powerful classifier like the Cubic SVM, can be adapted and applied to classify other types of data with multiple classes. This opens up opportunities for advancements in diverse fields, including image recognition, speech processing, natural language processing, and more.

As with any research, further investigation, refinement, and validation are necessary to fully realize the potential of this method. Future studies should focus on testing its performance on larger and more diverse datasets, comparing it with other state-of-the-art approaches, and exploring opportunities for optimization and generalization. The implementation of the proposed technique showcased impressive results in classifying different classes, underscoring its potential to make significant contributions to the field. The advancements achieved through this work have the potential to benefit various applications, foster deeper understanding in related disciplines, and inspire further research and innovation in the classification of diverse classes.

While the proposed technique for classifying different classes of eye muscle movements using EMG signals demonstrates impressive advantages, it also has some limitations that should be acknowledged. One major disadvantage is the limited study conducted with regards to available EMG or EOG (electrooculography) data. The technique's performance heavily relies on the quality and diversity of the dataset used for training and evaluation. Therefore, the availability of comprehensive and diverse EMG or EOG data can affect the generalizability and applicability of the method. Further research and studies are needed to collect and analyze a broader range of EMG or EOG data to ensure the technique's effectiveness across different populations and conditions.

Another limitation of the proposed method is that it does not explore the application of deep learning techniques. Deep learning has gained significant attention and success in various fields, including computer vision and natural language processing. Deep neural networks, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown promising results in complex pattern recognition tasks. By leveraging the hierarchical representations learned through deep architectures, deep learning models can potentially enhance the classification performance and capture more intricate relationships within the EMG or EOG signals. Incorporating deep learning approaches into the classification framework could be a valuable avenue for future research and may potentially lead to further improvements in accuracy and robustness.

Despite these limitations, the proposed technique offers several advantages that put it in a favorable light. One of the main advantages is its simplicity. The algorithm, which combines the windowing technique with the Cubic SVM classifier, provides a straightforward and interpretable approach for classifying different classes. The simplicity of the method allows for easier implementation, understanding, and deployment in real-world scenarios. Moreover, the higher accuracy achieved by the proposed technique is a significant advantage. The improved accuracy indicates that the method is effective in accurately classifying the six different classes of eye muscle movements. This high level of accuracy contributes to increased confidence in the results and enhances the reliability of the classification outcomes. Additionally, the utilization of all available data is another advantage of this technique. By incorporating the entire dataset, the method maximizes the information extracted from the EMG or EOG signals. This approach ensures that no valuable data is overlooked or discarded, potentially leading to more comprehensive and accurate classification results.

While the proposed technique for classifying different classes of eye muscle movements using EMG signals has certain limitations, such as limited data availability and the absence of deep learning exploration, its advantages, including simplicity, higher accuracy, and utilization of all data, make it a favorable approach. The simplicity of the algorithm allows for easier implementation and interpretation, while the higher accuracy contributes to more reliable classification outcomes. Despite the limitations, this work represents a significant step forward in the field of classifying different classes, and further research can build upon its strengths and address its limitations to unlock even more potential. The field of neuroscience has witnessed remarkable advancements, opening up new possibilities for utilizing the proposed method in the treatment of visually impaired or paralyzed patients. By incorporating the methodology with Human-Computer Interaction (HCI) techniques, this approach holds significant potential for improving the quality of life and functional independence of individuals with sensory or motor impairments.

For visually impaired individuals, the accurate classification of eye muscle movements using EMG signals can be invaluable. By leveraging the proposed technique, it may be possible to develop assistive technologies that enable visually impaired individuals to interact with their environment more effectively. For example, using the classified eye muscle movements, a system could be designed to provide auditory or haptic feedback to guide visually impaired individuals in tasks such as object recognition, navigation, or reading. The integration of the proposed method with HCI techniques, such as wearable devices or virtual reality interfaces, can create immersive and intuitive experiences for visually impaired individuals, enhancing their independence and overall well-being.

In the case of paralyzed patients, the ability to classify different eye muscle movements accurately opens up avenues for developing neuroprosthetic devices or brain-computer interfaces (BCIs). By capturing and interpreting the EMG signals associated with specific eye muscle movements, it becomes possible to translate these signals into commands that can control external devices or prosthetics. For example, paralyzed individuals could use their eye muscle movements to control robotic limbs, operate assistive devices, or communicate with others through speech synthesis systems. This integration of the proposed method with HCI techniques and neuroprosthetic technologies can empower paralyzed patients with greater autonomy and the ability to engage more fully in daily activities. Furthermore, ongoing advancements in neuroscience and related fields may lead to further refinements and enhancements of the proposed method. For instance, emerging technologies such as electroencephalography (EEG) or functional near-infrared spectroscopy (fNIRS) can provide additional neuroimaging modalities that complement EMG signals. Combining multiple modalities could potentially improve the accuracy and reliability of classification, leading to more precise control and interaction capabilities for visually impaired or paralyzed individuals.

It's worth mentioning that incorporating the proposed method with HCI techniques for the treatment of visually impaired or paralyzed patients requires rigorous research, development, and clinical validation. Ethical considerations, user experience, and individualized adaptation must be taken into account to ensure the safety, efficacy, and usability of the integrated systems. Collaborations between researchers, clinicians, engineers, and end-users are crucial for translating these advancements from the laboratory to real-world applications. With the advancements in the field of neuroscience, the proposed method for classifying eye muscle movements using EMG signals has the potential to revolutionize the treatment and rehabilitation of visually impaired or paralyzed patients. By integrating this methodology with HCI techniques, such as wearable devices, neuroprosthetics, or BCIs, it becomes possible to develop personalized, assistive technologies that empower individuals to regain independence, enhance communication, and interact with their environment more effectively.

LIST OF PUBLICATIONS

Paper	Author list, Title, Conference/Journal	Status
1)	Akshansh Srivastava, O.P. Verma, Avinash Ratre, **“Classification of EMG signals of Eye Movement using Windowing Technique and Cubic SVM”,** International Conference Com-IT-Con 2023	Accepted

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