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Review

An Introduction to Electromyography Signal Processing and Machine Learning for Pattern Recognition: A Brief Overview

Anuj Ojha

Department of Bioengineering, College of Engineering, University of Toledo, Toledo, OH 43607, USA

*Corresponding author's e-mail: anuj.ojha@rockets.utoledo.edu

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ABSTRACT

Electromyography (EMG) is about studying electrical signals from muscles and can provide a wealth of information on the function, contraction, and activity of your muscles. In the field of EMG pattern recognition, these signals are used to identify and categorize patterns linked to muscle activity. Various machine learning (ML) methods are used for this purpose. Successful detection of these patterns depends on using effective signal-processing techniques. It is crucial to reduce noise in EMG for accurate and meaningful information about muscle activity, improving signal quality for precise assessments. ML tools such as SVMs, neural networks, KNNs, and decision trees play a crucial role in sorting out complex EMG signals for different pattern recognition tasks. Clustering algorithms also help analyze and interpret muscle activity. EMG and ML find diverse uses in rehabilitation, prosthetics, and human-computer interfaces, though real-time applications come with challenges. They bring significant changes to prosthetic control, human-computer interfaces, and rehabilitation, playing a vital role in pattern recognition. They make prosthetic control more intuitive by understanding user intent from muscle signals, enhance human-computer interaction with responsive interfaces, and support personalized rehabilitation for those with motor impairments. The combination of EMG and ML opens doors for further research into understanding muscle behavior, improving feature extraction, and advancing classification algorithms.

Keywords: EMG; Pattern recognition; Machine learning

1 Introduction

Electromyography (EMG) is a way of recording and analyzing electrical signals made by muscles. It is the study of electrical currents produced in a muscle during contraction. Electromyography provides information on neuromuscular function as well as muscle morphology [1]. These signals, known as electromyograms, can tell us a lot about how your muscles are working, how they're contracting, and how they're performing. It's used in medicine, sports, and rehab to measure muscle health and performance.

The nervous system is always in control of how your muscles contract and relax. Therefore, the EMG is a complex signal and depends on the anatomy and physiology of your muscles. These signals are used as a valuable tool for the identification and diagnosis of different neuromuscular disorders. Neurological disorders can be diagnosed through the categorization of EMG signals into distinct categories. There are different classification techniques that are employed to classify EMG signals for the diagnosis of neurodegenerative disorders [2]. The EMG signals generated using electrodes are noisy. Research has been conducted in this field, improving algorithms, improving existing methodologies, enhancing detection techniques to minimize noise, and obtaining precise EMG signals.

There are different significances of collecting the EMG signals. Some of them are muscle health assessment, rehabilitation, prosthetic control, and study in sports science. Pattern recognition in EMG is one emerging field where the EMG signals are used in the analysis to identify and categorize specific patterns related to muscle activity. Different ML techniques are employed to develop EMG pattern recognition systems. The data obtained from EMG can be quite complex and multivariate, making it suitable for ML approaches that

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can handle this type of data. ML models can recognize EMG signals that are associated with certain conditions, helping in early detection and treatment [3, 4]. ML models can be trained to recognize muscle activity patterns associated with various movements, making it easier for users to control prosthetic limbs more naturally and intuitively [5, 6]. The use of artificial intelligence can process EMG data and provide feedback and rehabilitation programs that are tailored to the user's needs [7]. Users perform specific hand movements or muscle movements, and ML models can classify those gestures to control a computer interface, robotic device, or other technology.

The focus of this review article is on the use of ML techniques for pattern recognition applications using EMG signals. The article will delve into the integration of EMG, a technique for capturing muscle electrical activity, with ML, a technology for recognizing patterns in data. It will explain how ML techniques are employed to analyze and interpret EMG signals. The goal of this review article is to provide a comprehensive overview of the state of the art in EMG and ML for pattern recognition, highlighting the importance of this intersection and its potential to bring about positive changes in healthcare, technology, and human-machine interaction. By offering insights into the current state of the field and its future directions, the review article aims to inform and inspire further research and innovation in this exciting domain.

2 EMG Fundamentals

2.1 Basics of EMG

An EMG is a signal that can be read by electrodes from an active muscle. measures muscle electrical activity by detecting and recording the electrical signals generated by muscle fibers during muscle contractions and relaxations. EMG is a way to check how your muscles and the nerves that control them are doing. It can tell you if you have nerve or muscle dysfunction or if there's a problem sending signals from your nerves to your muscles. Motor neurons send electrical signals that cause your muscles to contract and these signals are converted into charts, sounds, or numbers that a doctor can interpret using electrodes. Muscles are triggered by a series of nerve signals sent from motor neurons in our spinal cord. These neurons take in signals from the whole nervous system and send them to the muscles, which activate them and cause them to contract. The action potential of each motor unit creates an electrical field in the surrounding environment [8]. This electrical field can be detected by placing electrodes close to the muscle fibers and at the surface of the skin.

EMG involves placing electrodes on the skin or within the skin close to the muscle of interest. The electrode placement will depend on the muscle being measured and the level of measurement needed. There are different technologies available for the generation and collection of the EMG signals using invasive as well as non-invasive methods [9]. The electric impulses are generated when a muscle contracts, and these impulses are known as action potentials. Action potentials originate when the muscle cells depolarize. The electrodes placed on the skin or within the muscle are designed to sense these electrical signals.

2.2 EMG Types

There are two primary types of EMG: surface EMG (sEMG) and intramuscular EMG (iEMG). In sEMG, electrodes are positioned on the skin's surface above the target muscle. These electrodes pick up and capture the electrical activity of the muscle fibers directly below the skin's surface. Because it doesn't involve needles or intrusive procedures, surface EMG is considered non-invasive. Adhesive gels or tapes are used to affix electrodes to the skin. Numerous fields, including sports science, ergonomics, human-computer interface, muscle rehabilitation, and assessment of muscle function, frequently employ sEMG. It is appropriate for activities such as muscle fatigue assessment and for the acquisition of signals from superficial muscles. As the name implies, iEMG records electrical activity by directly introducing tiny needle electrodes into muscle tissue. Since needles must be inserted into the muscle to perform iEMG, it is a more invasive procedure than surface EMG. Usually, a healthcare expert does this procedure. Because iEMG is near muscle fibers, it offers more accurate and focused measures of muscle activity. It is used to examine deep muscles or certain muscle groups that are difficult to access using surface electrodes. In this review article, we will mainly focus on the sEMG and its applications in pattern recognition.

2.3 EMG Signal Preprocessing

The Electromyography (EMG) signal measures electrical currents in muscles during contraction, reflecting nervous system control. As the signal travels through tissues, it picks up noise. Additionally, when detected on the skin's surface, the EMG detector collects signals from multiple motor units simultaneously, causing signal interactions. The complexity of the EMG signal is influenced by both the nervous system and the anatomical/physiological properties of muscles. It is very important for the EMG signals to be preprocessed removing all the noises before further analyzing the signal. Proper preprocessing is essential to enhance the quality of the EMG signals, improve the accuracy of subsequent analyses, and ensure meaningful interpretation. The signals from muscles (EMG) can get mixed with different types of unwanted signals like movement artifacts or electrical interference, making it hard to understand the muscle activity. Techniques like filtering and removing unwanted signals help make muscle activity clearer. This is important for tasks like recognizing patterns, assessing muscle fatigue, and studying movement. When preparing the data for ML, good preprocessing is essential to help the models accurately understand and categorize gestures or muscle activities.

Preprocessing of EMG signals using techniques like filtering and removing unwanted parts helps make sure we get the right information about muscle activity. Features like how strong, fast, or how long a muscle works are important, but noise in the signals can mess them up. Efficient preprocessing makes it easier to get the right details, which is important for tasks like pattern recognition, checking muscle fatigue, and studying movement. There are different techniques developed for pre-processing and analyzing the EMG data such as wavelet analysis, higher order statistics, empirical mode decomposition, artificial neural network, and independent component analysis [10]. Over the last few years, the pre-processing step for sEMG based on a wavelet de-noising technique has been extremely successful [11]. It is possible to efficiently eliminate white Gaussian noise using wavelet de-noising methods. Artificial intelligence neural network has been used to for noise removals from the EMG signals [12]. Noise reduction in EMG is essential for obtaining accurate, reliable, and meaningful information about muscle electrical activity. It improves the quality of the recorded signals, enabling more precise assessments.

3 ML Techniques for EMG Pattern Recognition

3.1 ML Algorithms

ML algorithms play an essential role in the processing of EMG data for pattern recognition. ML algorithms work by analyzing the complex EMG signals and classifying them into different types of patterns or actions. Some of the ML classification algorithms used in the pattern recognition are mentioned below with an example:

3.1.1 Support Vector Machine (SVM)

SVM, a supervised learning algorithm used for classification, identifies the hyperplane that is most suitable for classifying different classes in a feature space. SVM can be used to classify EMG signals according to different movement classes. This makes SVM useful for tasks such as gesture recognition. SVM has shown an improved accuracy for predicting different knee angles [13] as well as in recognizing the finger movements [14].

3.1.2 Artificial Neural Networks (ANN)

ANN is a ML model that draws inspiration from the composition and operations of the human brain. Networked nodes arranged in layers make up this structure. Neural networks are utilized in prosthesis

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control, rehabilitation, and movement prediction to recognize EMG patterns. For example, sEMG has been used to develop a ANN ML model for recognizing the hand gesture [15].

3.1.3 K-Nearest Neighbors (KNN)

KNN is an easy-to-understand algorithm that groups data points according to the majority class of their closest neighbors. KNN is used to classify EMG signals according to how closely they resemble previously identified patterns, which makes it suitable for real-time applications. A KNN model has been implemented for the recognition of human arm movement [16].

3.1.4 Random Forest (RF)

An ensemble learning technique called RF combines the predictions of several decision trees to increase generalization and accuracy. Robust EMG signal categorization can be achieved by RF, which offers good accuracy and noise resistance. Using sEMG, RF model has been built for the prediction of knee joint movement [17] and hand movement recognition [18].

3.1.5 Hidden Markov Models (HMM)

A system with unobservable states is represented by the HMM statistical model. It works especially well for time-series data modeling. HMMs are useful for situations where the sequence of muscle activations is crucial since they are used to identify temporal patterns in EMG signals. HMM model has been implemented for the classification of the gait phase [19]. It also has been used in recognition of common hand finger movements using sEMG [20].

3.1.6 Convolutional Neural Networks (CNN)

CNNs are a specific kind of neural network used to interpret organized grid data, like pictures. It automatically learns hierarchical characteristics using convolutional layers. To extract features for classification more effectively, CNNs are used to evaluate time-frequency representations of EMG signals. CNN model has shown the improvement in the hand movement recognition [21] and also has shown higher accuracy and better robustness for limb movement pattern recognition [22].

3.1.7 Long Short-Term Memory Networks (LSTM)

LSTMs are a type of recurrent neural network that can work with long-term dependencies in sequential data. LSTMs are suitable for tasks such as temporal pattern analysis of EMG signals and gesture recognition, as well as continuous movement prediction. LSTM has been shown as a reliable ML algorithm for hand movement pattern recognition [23]. It has been also implemented for sEMG feature learning and classification [24].

3.1.8 Extreme Learning Machines (ELM)

ELM is a feedforward neural network with a single hidden layer that chooses its hidden layer weights at random. It provides strong generalization and quick learning. Applications such as prosthesis control can benefit from ELM's efficient and real-time EMG signal categorization. ELM has been used to develop a model for the estimation of handgrip force [25]. It has also been used to enhance the gesture recognition using sEMG [26].

3.1.9 Linear Discriminant Analysis (LDA)

The goal of LDA is to identify the linear feature combination in the feature space that best divides various classes. LDA has been trained with sEMG signals for pattern recognition [27]. It has also been used to build a hand movement recognition system [28].

3.2 Clustering Algorithms

Not only classification algorithms, but clustering algorithms also play a significant role in analyzing and interpreting muscle activity. Some common clustering algorithms used for pattern recognition in EMG are:

3.2.1 K-Means

K-Means divides data into k groups based on similarity, with the goal of minimizing the sum of squares within a group. K-means breaks down EMG signals into groups based on how similar they are, making it easier to analyze patterns and break them down into different groups. Clustering of similar muscle activities, feature space analysis are some applications of k-means clustering in EMG signals. K-means clustering have been applied to build classification algorithms for hand movements detection [29]. K-means clustering approach has also been applied for fatigue and non-fatigue EMG segments classification [30].

3.2.2 Hierarchical clustering

Hierarchical cluster formation is the process of gradually combining or dividing existing clusters to form a hierarchical representation. This hierarchical structure creates a tree-like representation of muscle activity patterns, allowing for insights into the connections between different muscle activities. A hierarchical clustering technique has been applied to successfully group strides with similar EMG patterns of onset and offset activation [31]. Accuracy of the classification model has increased by decreasing the sEMG signal's complexity using hierarchical clustering [32].

3.2.3 Self-organizing Maps (SOM)

SOMs are a kind of artificial neural network that maintains the topological characteristics of the input data by mapping it onto a lower-dimensional grid. EMG patterns are mapped into a lower-dimensional grid via SOMs while maintaining the topological connections between patterns. SOM method has been used for feature selection and then classification of hand movements using sEMG [33]. A study has also shown that the patients can be categorized based on the activation of their jaw muscles using SOM [34].

3.2.4 Density-Based Spatial Clustering of Applications with Noise (DBSCAN)

DBSCAN classifies outliers as noise and clusters together data points that are near to one another. Dense areas of EMG patterns are identified by DBSCAN, which classifies outliers as noise. Anomaly detection, identification of unusual muscle activation pattern are some applications of DBSCAN. This method has been used to eliminate the data that deviates from the center cluster and finally apply the ML techniques for movements detection [35]. DBSCAN clustering has been compared with other clustering method observing different patterns in a movement detection study [36].

3.2.5 Fuzzy C-Means (FCM)

Data points are given membership values by FCM, which enables them to be a part of several clusters with varying levels of membership. EMG patterns can belong to several clusters with different degrees of membership since FCM assigns membership values to them. FCM clustering method has been applied on EMG signals and ML classification algorithms has been applied for hand gesture recognition [37]. The integration of FCM in building a ML based classifier system has shown an improvement in the EMG classification system [38].

3.2.6 Affinity Propagation (AP)

The most typical data points in each cluster are called exemplars, and AP finds them via a message-passing approach. Exemplars within EMG patterns are found using AP, and they stand for the most typical patterns within each cluster. AP is used with dynamic time wrapping achieving a good accuracy for gesture recognition [39].

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3.3 Feature Extraction for EMG

The process of feature extraction is an essential part of the EMG signal analysis process. It involves the transformation of the raw signal information into a collection of pertinent and informative characteristics that can be utilized for further analysis, categorization, or interpretation. Some of the common methods for feature extraction are:

3.3.1 Time-domain features

The amplitude values of the EMG signal in the time domain are directly used to compute time-domain characteristics. Some examples of time-domain features are mean absolute value, root mean square, and zero crossing rate. Time-domain feature extraction methods have been performed to improve the performance of the arm movement pattern recognition [40]. A study has been carried out to determine the most stable time-domain features for providing the robust pattern recognition model [41].

3.3.2 Frequency-domain features

The study of the EMG signal's frequency content yields frequency-domain characteristics. Some examples in the frequency domain are spectral moments that consist of mean or median frequency, power spectral density that measures the power distribution across different frequency bands. Features vector with frequency domain features have been used for implementing ML classifiers [42]. Features in the frequency domain have demonstrated the ultimate dominance and signal characterization, as determined by statistical parameters of the EMG power spectral density [43].

3.3.3 Time-Frequency features

TF characteristics give a more thorough depiction of the signal by capturing both frequency and temporal information. Short Time Fourier Transform (STFT) that represents the energy of a signal in both time and frequency domain, Wavelet transform that decomposes the signal into different frequency components and Wigner-Ville Distribution that represents the time-frequency content based on the joint time-frequency distribution are some examples for time-frequency analysis. A study has been conducted where the suitable features in time-frequency domain are determined for distinguishing fatigue and non-fatigue conditions [44]. Wavelet transform has been used to study the EMG signals in different frequency domains and also time-frequency coherence analysis has been performed between the muscle pairs for different stability conditions [45, 46].

3.3.4 Non-linear features

Non-linear features capture aspects of the signal's complexity and dynamics. It helps in measuring the signal irregularities and quantifying the recurrence of patterns in the signal. Based on sEMG signals, non-linear feature extraction has been performed based on the recurrence plot and has been used for building a classifier to estimate hand movements [47]. Non-linear parameters for surface EMG has been used for the diagnosis of Parkinson's disease [48].

3.3.5 Statistical features

The variability and dispersion of an EMG signal are described by statistical properties. It provides the measure of central tendency, asymmetry and shape of the signal distribution, measures skewness and kurtosis which are the moments above second order. Statistical analysis also helps to understand the relationship between the variables and features. Statistical analysis have helped to understand the linear relationship between different features and hand movements [49]. Statistical and frequency features were taken from the raw EMG data and used for the classification of finger movements in order to reduce the complexity of the signals and make them easier for the algorithm to interpret [50].

3.3.6 Amplitude-based features

Amplitude-based features are the features derived from the amplitude characteristics of the EMG signal. These features can be extracted using techniques like the Hilbert transform. Amplitude-based features have been used to develop a classifier for a speech recognition system [51].

3.3.7 Time-Interval features

The time-interval features are related to the timing characteristics of muscle contractions and relaxations. Duration of muscle activity, inter-contraction interval and the time taken for the signal to increase or decrease from one threshold to another are some examples of time-interval features. The time-interval features have shown to have a better classification accuracy to distinguish sEMG under fatigue and non-fatigue conditions [52].

3.3.8 Spatial features

Spatial features are the features that consider the spatial distribution of EMG signals when using multiple electrodes. Coherence and cross-correlation are examples of spatial features. Spatial feature extraction has been used and these features have shown a good result in the identification of a motor task [53]. A classifier has been implemented using the spatial features of high density EMG and have shown a good classification rate [54].

4 Applications of EMG and ML Pattern Recognition

Applications for pattern recognition using EMG and ML have been found in several sectors. The combination of EMG and ML has the potential to transform several industries by offering individualized healthcare treatments, more intuitive and adaptable interfaces, and creative methods for interacting with technology. The variety of applications and the precision and effectiveness of EMG-based pattern recognition systems are both being enhanced by ongoing research in this field. Some of the applications are briefly described below.

4.1 Prosthetic Control

Devices for prosthetic limbs are controlled by EMG signals from residual muscles. Different muscle patterns are classified by ML algorithms, giving users the ability to manipulate a prosthetic limb with natural movements. When integrated with ML, EMG can provide significant benefits for prosthetic control, improving the usefulness and performance of prosthetic devices for amputees. Prosthetic devices can be operated more naturally, enabling users to execute different movements by instinctively contracting specific muscles. Deep learning methods have been applied to control the prosthetic hands using raw EMG signals [55] and also classify the hand gesture movements [56]. By training ML algorithms to identify complex patterns in EMG signals, prosthetic movements can be made more precise and accurate. This improves the prosthetic limb's overall dexterity by enabling users to execute precise and well-coordinated movements. It has been shown that the use of appropriate features with a suitable ML classifier increases the classification accuracy [57, 58]. The integration of EMG and ML is one promising approach to increasing the usability, functionality, and functionality of prosthetic devices and, eventually, the quality of life for people who have lost limbs.

4.2 Rehabilitation and Physical Therapy

EMG-based technologies are used in the rehabilitation process to evaluate and improve muscle function. There are many advantages to using EMG with ML in physical therapy and rehabilitation. ML is used to evaluate EMG signals to customize rehabilitation treatments, monitor progress, and give immediate feedback. It has been shown that the healthcare professional will be able to improve the effectiveness of lower back pain rehabilitation by using an ML classifier to identify patients who are responding to functional restoration rehabilitation [59]. Real-time biofeedback is made possible using artificial intelligence, which encourages patient awareness and participation in activities. Adaptive rehabilitation situations and fatigue can be better understood with the application of ML-based models [60]. Appropriate EMG feature selection can improve the classification accuracy and lead to the performance increment in therapies [61, 62]. The application of EMG and ML to physical therapy and rehabilitation improves treatment programs' efficacy, precision, and personalization, which in turn leads to better patient outcomes and experiences during the healing process.

4.3 Human-Computer Interaction (HCI)

Electronic equipment and computers can be controlled without using hands by using EMG signals. ML algorithms allow users to interact with things without making physical contact by identifying muscle patterns or motions. EMG enables natural and intuitive device control via muscle signals while ML improves the precision and responsiveness of interactions. EMG enables personalized and adaptive interfaces by recognizing specific muscle patterns for personalized user experiences. In real-time processing, EMG improves speed and efficiency in HCI, enabling fast and accurate control. A study has been conducted where ML algorithms are implemented for a recognition system and has resulted in the reduction of redundant information improving the efficiency and accuracy of the system, and has been thought to strengthen the HCI's capacity for generalization over time [63, 64]. In addition, EMG integration in HCI supports applications such as gesture recognition, prosthetic control and more, broadening the scope of accessible and easy-to-use interactions. sEMG signals have been used in a hand gesture recognition system and have shown a high accuracy [65]. The use of EMG in human computer interaction has different medical applications. sEMG has been integrated with ML to study and improve the myoelectric control by pattern recognition [66]. EMG and ML together improve HCI's effectiveness, adaptability, and customization, resulting in more seamless and user-friendly interactions.

4.4 Assistive Technology

ML and EMG are used to help people with disabilities perform everyday tasks. To carry out operations like operating wheelchairs, communication devices, or smart home automation, ML algorithms analyze EMG signals. The capacity to interpret EMG data in real-time facilitates prompt and agile control, which enhances the usability and functionality of assistive devices. A study has shown that the integration of EMG and ML is very important for assistive technological applications [67]. The use of EMG signal with a combination of a ML algorithm helps to achieve the best classification accuracy and can enhance the performance of the assistive devices [68]. The use of assistive technology is expanding to increase the independence of individuals with disabilities and facilitate their interactions with their surroundings. sEMG and ML based assistive device have shown better performance than the conventional interfaces [69]. The combination of EMG and ML significantly enhances the usability, functionality, and adaptability of assistive technology, ultimately enabling users with physical limitations to live more independently and with a higher quality of life.

4.5 Sports Science and Biomechanics

Muscle activation during sports and physical exercise is analyzed using EMG. EMG data is processed by ML algorithms to identify trends pertaining to muscle function, coordination, and exhaustion. It offers useful insights for maximizing athletic performance and avoiding injuries. EMG records precise information on muscle activity, which is then processed by ML to examine movement patterns, coordination, and biomechanics. The integration makes it possible to identify the best performance tactics and create individualized training plans for each athlete [70, 71]. It can also be used in the study of muscle fatigue dynamics [44] and can potentially prevent back pain [72]. Pattern recognition analysis can help find muscular imbalances or aberrant patterns to help sports scientists create focused injury prevention techniques.

4.6 Gait Analysis

EMG signals are used to investigate and evaluate the walking patterns of humans. ML algorithms help identify and categorize aberrations or anomalies in gait based on EMG inputs. Muscle activity is recorded by EMG, and ML analyses this data to identify patterns and abnormalities. This combination makes it possible to precisely analyze gait mechanics, which helps to identify ideal movement patterns and possible problems. The use of ML algorithms to identify minute variations in muscle activation can help identify anomalies in gait early on [73] and enable individualized treatment plans. Furthermore, the technology allows for objective and quantitative evaluations, which improves the precision of gait analysis. sEMG has been integrated with ML to predict the gait events [74] and phases [75]. It has been shown that EMG study integrated with deep learning methods can develop muscle synergy based gait analysis technique [76]. The integration of ML and EMG improves gait analysis by offering individualized gait mechanics improvement plans, early abnormality detection, and thorough insights.

4.7 Gesture Recognition

ML algorithms categorize EMG signals that are associated with gestures. EMG records the muscle impulses connected to motions, and ML uses this information to recognize and understand gestures with accuracy. With the use of this technology, gesture control is made simple and natural, allowing for accurate real-time identification of a wide range of actions. The use of deep learning in EMG based hand gesture recognition has shown improvement in the classification accuracy [77, 78]. Use of the spectral feature domains for building ML hand gesture recognition system might assist physically challenged persons with non-invasive machine communication and disabled people with nonverbal communication [79]. Because ML algorithms may adjust to individual differences, the system is robust and individualized. The use of effective feature extraction techniques and then application of ML can increase the accuracy of the system [80, 81]. EMG and ML together improve gesture detection by offering precise, flexible, and user-friendly control interfaces for a range of applications.

4.8 Biomedical Research

In biomedical research, EMG and ML are used for understanding neuromuscular diseases and muscle function. ML facilitates the study of intricate EMG patterns, enabling the discovery of patterns and biomarkers linked to certain diseases. It enables more in-depth examination of muscle function, which helps with understanding neuromuscular diseases, the development of rehabilitation, and biomechanics. ML improves the effectiveness of data interpretation by making it easier to spot irregularities or subtle trends in big datasets. Understanding stroke-impaired gait modifications and making decisions about post-stroke therapy can be made easier [82]. ML approach can help distinguish healthy individuals and patients with amyotrophic lateral sclerosis [83]. The ML can help in the identification of critical biomarkers that differentiates EMG patterns between patients with certain disease and the healthy individuals [84]. It also helps in the identification of a biomarker that causes pain [85]. EMG and ML work together in biomedical research to provide accurate, data-driven studies that advance our knowledge of neurological disorders, muscular function, and individualized treatment plans.

5 Challenges and Considerations

Despite the many benefits that come from combining ML with EMG data collecting for pattern identification, researchers and practitioners in this field must also contend with a number of challenges and limitations. It is difficult to create universal models since EMG signals can differ greatly between people and even within the same person. Personalized calibration is necessary since ML models that are trained on one person might not generalize well to another. Work has been conducted to develop ML models robust to inter-subject variability and preventing the need for recalibration [86]. The accuracy of signal interpretation is affected by crosstalk from adjacent muscles and outside noise sources, which can affect EMG signals. Errors in pattern recognition caused by misinterpreting muscle activity might impair the functionality of applications such as prosthesis control. Crosstalk-induced signal contamination is still a significant obstacle in the use of surface myography techniques [87]. It is very important to reduce the crosstalk and different approaches have been carried out for its reduction and elimination [87]. EMG signal interference caused by movement artifacts during dynamic activities can make interpretation more difficult. The accuracy of pattern recognition may be impacted by ML models' inability to distinguish between artifacts and purposeful muscle activations. Motion artifacts has been studied and the signals have been classified as clean or contaminated [88, 89].

Accurate signal acquisition depends on the location of the electrodes. Signal distortion may be caused by low contact impedance or incorrect positioning. The performance of ML models can be impacted by inaccurate electrode placement, which can produce unreliable data. Appropriate electrode placement protocol has been developed which can help in obtaining a good classification accuracy and promote future clinical applications [90]. To avoid the variability coming from electrode placement, normalization of EMG is necessary [91]. EMG features have been studied for the determination of proper electrode placement [92].

The stability of feature extraction and categorization is impacted by changes in EMG signals brought on by muscle fatigue and adaptation over time. It's possible that ML models developed using adapted or exhausted muscle signals won't adapt effectively to other muscular states. EMG signal interference caused by movement artifacts during dynamic activities can make interpretation more difficult. The accuracy of pattern recognition may be impacted by ML models' inability to distinguish between artifacts and purposeful muscle activations. ML has been applied to distinguish different EMG artifacts and contaminants [93].

ML models may be biased in favor of the majority class by imbalanced datasets, in which some classes are underrepresented. As a result, minority class accuracy will decrease, which will weaken the robustness of applications like gesture recognition. So, accuracy cannot be used as a reliable measure for an imbalanced dataset [94]. ML models may exhibit poor generalization to new, unknown data due to overfitting to the training set. When applied to real-world circumstances, this will result in decreased performance, particularly if the training data does not accurately reflect the variability in EMG patterns. Feature selection method along with suitable ML algorithm selection can be applied to reduce the overfitting problem [2].

It might be difficult to create models that generalize well due to individual variability as well as within-individual variability. ML models might not function reliably for various users or sessions. Low-latency processing is necessary for real-time applications like prosthesis control, which could be difficult for computationally demanding ML systems. The usability and efficacy of the real-time systems may be impacted by delayed responses. ML algorithms have been designed to optimize latency preserving the accuracy [95].

There are ethical questions about consent, privacy, and possible exploitation of personal data when using EMG data for pattern recognition. Gaining the trust of users and complying with regulations requires addressing privacy concerns and adhering to ethical norms. Since pattern recognition involves relevant data acquired from individuals along with their behavioral and personal information, ethical and privacy concerns should be taken into consideration. Real-time EMG signals have been collected without compromising the user's privacy [96].

6 Conclusion

Several important conclusions are drawn from the analysis of ML and EMG pattern recognition. For successful EMG pattern detection, signal processing methods including RMS, MAV, and frequency-domain characteristics are essential. SVMs, neural networks, KNNs, and decision trees are a few of the diverse classification methods that have been effectively used on EMG data for a range of pattern recognition applications. Applications of EMG and ML in a variety of domains, such as rehabilitation, prosthetics, and human-computer interface, demonstrate how versatile these technologies are. However, because real-time EMG pattern identification must be implemented with low latency, high accuracy, and adaptability to dynamic muscle actions, this creates obstacles. The revolutionary effects of EMG and ML on prosthetic control, human-computer interface, rehabilitation, and research prospects highlight the significance of these technologies in pattern recognition. By interpreting muscle signals to determine the user's intent, EMG and ML allow prosthetic device control to be more intuitive and natural. They improve the creation of responsive interfaces in human-computer interaction, which enhances the user experience. EMG-based pattern recognition helps people with motor impairments regain functional movement by supporting individualized rehabilitation programs in the fields of healthcare and rehabilitation. The combination of electromyography and ML provides opportunities for additional investigation into the behavior of muscles, enhancement of feature extraction techniques, and progression of classification algorithms. To improve the overall comprehension and advancement of EMG-based pattern recognition systems, it is recommended for this subject that researchers in biomechanics, signal processing, and ML collaborate transdisciplinary. Standardized EMG datasets should be freely shared to facilitate comparison, benchmarking, and replication of study results. User-centric design requires giving priority to user input and participation in the development and assessment of EMG-based applications, especially in the fields of healthcare and assistive technology. Establishing moral standards for the appropriate application of ML and EMG technology should be a priority for policymakers, particularly in the fields of healthcare and rehabilitation. Finally, funding educational activities and training programs will improve practitioners' and researchers' abilities in this developing field of pattern recognition, ML, and EMG interaction.

7 Declarations

7.1 Competing interest

The authors declare that they have no competing interests.

7.2 Publisher's Note

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