*Pak. J. Biotechnol. Vol. 20(2), 225-237, **2023*** http://doi.org/10.34016/pjbt.2023.20.02.804

Review Article

OPEN ACCESS

Available on http://www.pjbt.org
Pakistan Journal of Biotechnology (PJBT)
(P-ISSN: 1812-1837 and E-ISSN: 2312-7791)

MACHINE LEARNING TECHNIQUES APPLIED IN SURFACE EMG DETECTION- A SYSTEMATIC REVIEW

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Article Received 20-03-2023, Article Revised 16-04-2023, Article Accepted 02-05-2023

ABSTRACT

Surface electromyography (EMG) has emerged as a promising clisnical decision support system, enabling the extraction of muscles' electrical activity through non-invasive devices placed on the body. This study focuses on the application of machine learning (ML) techniques to preprocess and analyze EMG signals for the detection of muscle abnormalities. Notably, state-of-the-art ML algorithms, including Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Random Forests (RF), and Naive Bayes (NB), have been harnessed by researchers in the biomedical sciences to achieve accurate surface EMG signal detection. Within this paper, we present a meticulously conducted systematic review, employing the PRISMA method to select relevant research papers. Various databases were thoroughly searched, and multiple pertinent studies were identified for detailed examination, weighing their respective merits and drawbacks. Our survey comprehensively elucidates the latest ML techniques used in surface EMG detection, offering valuable insights for researchers in this domain. Additionally, we outline potential future directions that can guide further advancements in this critical area of research.

Keywords: Surface EMG detection, Muscles, Machine Learning, Healthcare, Electromyograph, Artificial Neural Network

INTRODUCTION

Electromyography (EMG) is a technology for analyzing and assessing electric activities/conditions developed by muscles. EMG of muscles is performed by using an electromyograph to provide data called an electromyogram. The device detects electric signals of the muscle's cells during their electrical and neurologically activated motion (Reaz, Hussain, & Mohd-Yasin, 2006).

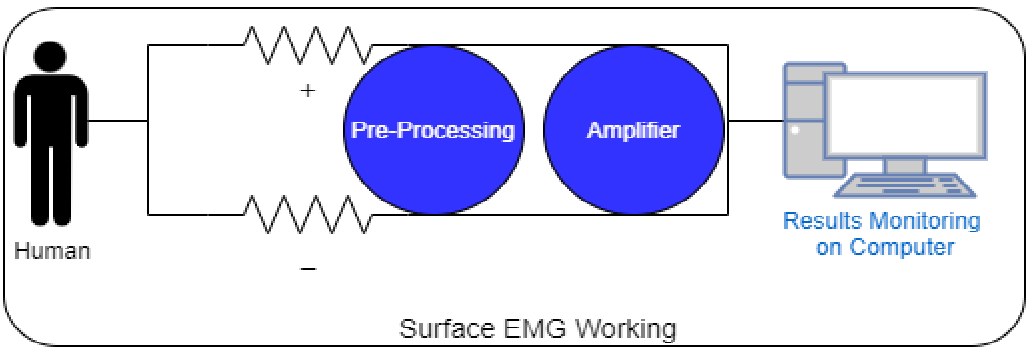

Figure.1 EMG Working diagram

In figure 1, the working diagram of EMG is provided. Electrodes/Device is connected to the human surface for muscle electric protentional detection. The electric signals in the form of positive and negative signals are pre-processed by a powerful computing device, after that, an amplifier converts the electrical signals, and the results show on the computer monitor.

There are two types of EMG, namely: Surface EMG and Intramuscular EMG (Szyszka-Sommerfeld, Sycińska-Dziarnowska, Spagnuolo, & Woźniak, 2023). The first kind of EMG (surface EMG) places a metal on the skin of the living thing's body and extracts muscles' electrical signals. In simple words surface EMG is working on the surface of the skin. The second kind of EMG is Intramuscular EMG which works inside of the skin and sends electrical signals for further analysis. For surface EMG two electrodes are required to differentiate between voltages.

Surface EMG (sEMG) is a non-invasive technique used to measure the electrical activity of muscles. It has been widely used in the field of physiotherapy for monitoring muscle activation levels during exercises, as well as in sports to improve athletes' performance and reduce the incidence of soft tissue injuries. In recent years, machine learning techniques have been applied to sEMG data to improve the accuracy of muscle activation detection and classification. These techniques use algorithms to automatically detect and classify sEMG signals, making the analysis process faster and more accurate. This is important for identifying the timing of muscle activity during movements and exercises, which can help physiotherapists and coaches to optimize training programs and prevent injuries. By analyzing sEMG signals from different muscles, machine learning algorithms can classify movements and identify specific muscle activation patterns associated with different tasks. The application of machine learning techniques to sEMG data has the potential to revolutionize the field of physiotherapy and sports medicine. By improving the accuracy and speed of muscle activation detection and classification, these techniques can help clinicians and coaches to optimize training programs and prevent injuries, leading to better outcomes for patients and athletes. In this paper, we will focus on the first kind of EMG (Surface EMG) detection using Machine Learning techniques.

S-EMG monitor during intended muscle movement can be as a signal, while the connection of all active motor units (MUs) is called an interference pattern. Interference means that the signals are mixed with different wavelengths and dimensions. The Surface EMG signal characteristics largely depend on pattern and interdependency (Stegeman, Blok, Hermens, & Roeleveld, 2000). Motor Unit (MU) is basically the complete model for S-EMG regarding the interference pattern as a linear summation.

Different kinds of approaches are used but the two are the most popular approaches to studying the connection between the S-EMG and the characteristics of the neuromuscular system (Farina, Merletti, & Enoka, 2004). The first is the conventional method, while the second is the backward method. The initial method was using models to forecast how various physiological processes would influence S-EMG characteristics. In the inverse method, electromyography (EMG) is used to discover the physiology at play. The accuracy of Surface-EMG measurements relies heavily on the converter and amplifier design, as well as the electrodes' interface with the skin, and afterward storing of the signals in digital form from their analog form (A/D Conversion). Measured EMG signals and Noise are two measurements of the electric signals for analysis. The main goal of Surface EMG detection is to increase the signal amplitude and to decrease noise for correct results for the muscles (Day, 2002; Ferrario, Tartaglia, Galletta, Grassi, & Sforza, 2006). Connecting the electrode devices to the skin surface correctly can reduce noise.

Motor Units (MUs) play an important role in surface-EMG, as when the number of Mus increases then the difference between noise and amplitude can be seen by necked eyes (De Luca, Adam, Wotiz, Gilmore, & Nawab, 2006). In the previous decades, the effect of the electrodes on a number of estimation conduction velocity (CV), spectral variables, and amplitude of the Surface-EMG has been addressed in various studies. The considered muscles range from the muscles of the shoulder, arm, and leg to the muscles of masticatory. The most significant effort to standardize was made in 1997-1999 within the European project on "Surface EMG for Non-Innovators". Muscle Diagnosis "(Cinema) [www.seniam.org], where a detailed analysis of the literature was presented (Mesin, Merletti, & Rainoldi, 2009).

"Intelligent agents" are defined as "tools that recognize their environment and take acts that maximize the probability of successfully achieving their goals" (Crevier, 1993). The field of Artificial Intelligence (AI) has been around since the latter half of 1956. Enhancing whiz systems was the first step in applying AI in the medical field; from there, rules were gleaned via discussions with doctors and then implemented into software (Zhang, 2020). In 1976, an initial expert system called "MYCIN" was developed to recommend antibiotics for bacterial illnesses; it followed close to 450 rules/SOPs. The sheer number of rules made the expert system impractical for application in actual hospitals. Machine Learning was created (Zhang, 2020) to overcome the constraints of expert systems. When it comes to clinical decision support systems, ML's ability to replace manual rules with system-generated ones is invaluable. This is because ML algorithms may learn from their surroundings and apply what they've learned in the future. Deep learning-based artificial neural networks (Hinton, 2018) are the most well-known and efficient ML approach currently available. Because ML relies so heavily on having access to large amounts of high-quality data, it is frequently referred to as Data-Intensive Systems. The proliferation of low-cost, Internet-enabled electronics has led to a surge of healthcare data. Expert systems dominate the clinical decision-support space, although ML-based CDSS are gaining traction thanks to their efficient learning and prediction algorithms (Rawson, Ahmad, Toumazou, Georgiou, & Holmes, 2019). X-rays, MRI scanners, and the identification of malignant nodules in the lungs and other tissues are only some of the many applications of ML in the systems used by medical professionals. In this work, we will examine the effectiveness of Machine Learning strategies for detecting Surface-EMG.

Surface EMG detection using Machine learning is the recent advancement in EMG patterns evaluation for accurate results (Phinyomark & Scheme, 2018). In Machine Learning we can train datasets and acquire accurate results from raw data, and it has three steps namely: A Model, A Dataset, and the Hardware (Ahamed, Benson, Clermont, Osis, & Ferber, 2017; Ahamed *et al.*, 2018). In recent times, Machine Learning Algorithms are applying to analyze the skill of myoelectric prostheses or any other rehabilitation device. As a result, the characterization of two prime muscles is difficult to diagnose neuromuscular diseases (Islam *et al.*, 2014). Machine learning techniques will be best to accurately analyze the above diseases of neuromuscular (Gu, Yang, Huang, Yang, & Liu, 2018). There are different Machine Learning algorithms that are used to investigate muscles disorder using Surface-EMG signals with a single ML technique. A Support Vector Machine (SVM) classifier was commonly used for EMG-based muscles pattern analysis recognition (Saponas, Tan, Morris, & Balakrishnan, 2008; Yoo, Park, & Lee, 2018). In (Benalcázar, Jaramillo, Zea, Páez, & Andaluz, 2017) the author proposed real-time muscles recognition system using five types of hand gestures (Fist, Open, Wave-In, Pinch, and Wave-Out) using Surface-EMG while sensors were plugged-in the forearm and used the ML (K nearest Neighbor Classifier) technique. Some other researchers used ML algorithms as a single classifier such as Artificial Neural Network (ANN)(Su, Chen, Cao, & Zhang, 2016; Uvanesh *et al.*, 2016), Random Forest, and Bayesian Classifier (Chen *et al.*, 2007). Upper limb muscles are also analyzed by different researchers by using machine learning algorithms (Kim, Choi, Moon, & Mun, 2011; Pancholi & Joshi, 2018). In this paper, we provided a detailed overview of the available work on Surface-EMG detection using machine learning algorithms. As in the available literature, no one provided a detailed survey paper on Surface-EMG detection using Machine Learning techniques with the latest issues and future directions.

The outcomes of the proposed study are as follows:

- We discussed the various Machine Learning strategies that may be used for Surface-EMG detection.
- Provided the latest issues in the field of Surface-EMG detection and future directions.
- Different Machine Learning Techniques such as KNN, ANN, RF, and DCN, BC ET are discussed in detail applied in the field of Surface EMG detection used for muscles pattern recognition.
- Detail overview/literature is provided on Surface EMG using Machine Learning Techniques with pros and cons.
- At the end of the paper, we summarized the results of the available work and discussed them in detail with comparison.

Further, the paper is planned as follows: In **Section 2** we provided Method, in which we detail explained Article Search Procedure, Article Inclusion, and Exclusion Criteria, Data Extraction, Article Search Results (PRISMA flowchart). In **Section 3** we provided detailed literature on the selected papers. **Section 4** consists of the discussion and future directions. **Section 5** consists of the conclusion of the systematic review paper.

METHOD

In this section, we provided a detailed explanation of Article Search Procedure, Article Inclusion, and Exclusion Criteria, Data Extraction, and Article Search Results (PRISMA flowchart). In the following sub sections, we provided the method of the systematic study on Surface-EMG detection using Machine Learning Techniques:

Article Search Procedure: In this sub-section, we provided an article search procedure. We used a systematic searching procedure to find out related papers in the field of Surface-EMG detection using Machine Learning Techniques. In the searching process, we targeted different databases such as, (Scopes, Web of Science, PubMed, Science Direct, and IEEE Xplore) using three keywords "Surface EMG", "Machine Learning", and "electromyography (EMG)". We have selected conferences and journal papers, and we also selected some book chapters.

Article Eligibility Requirements: In the searching procedure, we found different papers, but we used inclusion criteria based on the two words namely: Surface EMG, and Machine Learning. We studied the papers thoroughly such as their title, abstract, proposed model, and conclusion. When we found the papers mostly related to our title then we added them to our literature and introduction. Such articles were excluded that were related to EMG or Intramuscular EMG the second kind of EMG (Szyszka-Sommerfeld *et al.*, 2023). Articles were selected that were related to the first kind of EMG (Surface EMG).

Data Extraction: The selected papers were then read carefully and summarized the important information about their used machine learning techniques and proposed method with results. The main criteria for studying papers were the following:

- Electrodes/Sensors placed on the surface of the skin
- Pre-Processing process used by the authors
- Amplifiers used by the authors
- Machine Learning techniques
- Surface EMG patterns

Prisma Flowchart: In this subsection, we provided Prisma based flowchart of the selected papers from different databases, which were discussed in subsection 2.1. The following figure 2 and 3 shows the Prisma Flowchart of the selected papers in this resear

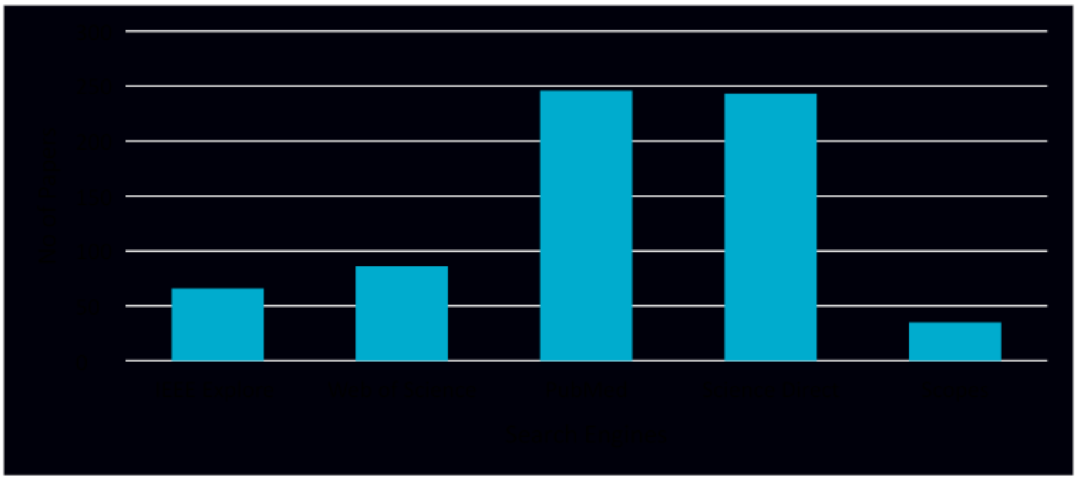

Figure. 2 No of papers according to the search engines

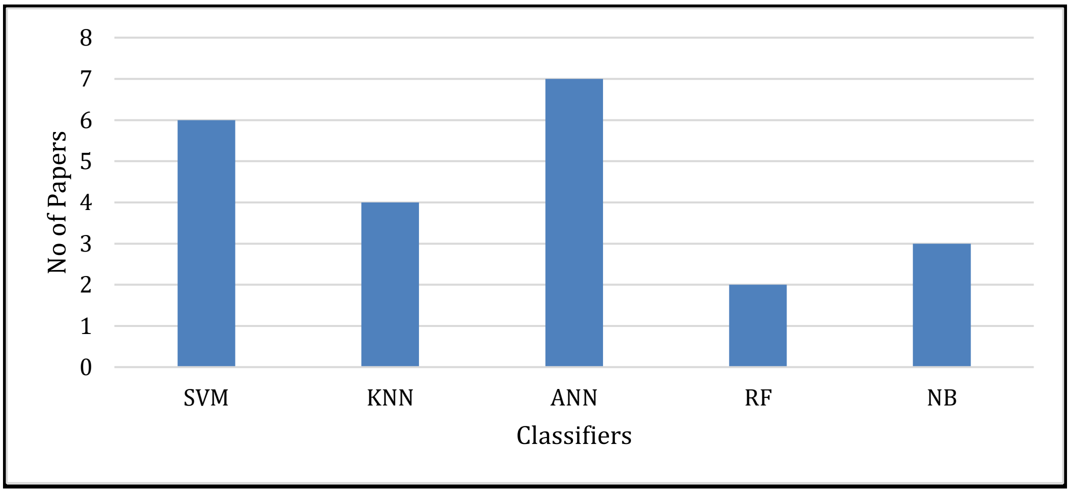

Figure. 3 No of papers related to classifiers.

In the flowchart, we provided the different databases that are searched for Surface EMG papers selection using Machine Learning techniques. Furthermore, a total of 676 papers were found in the databases using the keywords "Surface EMG", "Machine Learning", and "electromyography (EMG)". After applying a filter of conferences papers, journal papers, and book chapters, the articles were reduced to 531. Similarly, exclusion and inclusion criteria are applied such as to remove duplicate papers, not related to the topic (such as Machine Learning), and not related to the first kind of EMG (Surface EMG) then 47 papers remained. The further filter is used for a detailed study of the remaining papers and removed 16 papers, then we have the remaining 31 papers, which we discussed in detail in section 3 of the literature of Machine Learning Techniques used for Surface EMG detection. In figure 4 we also provided keywords used for searching and years as well.

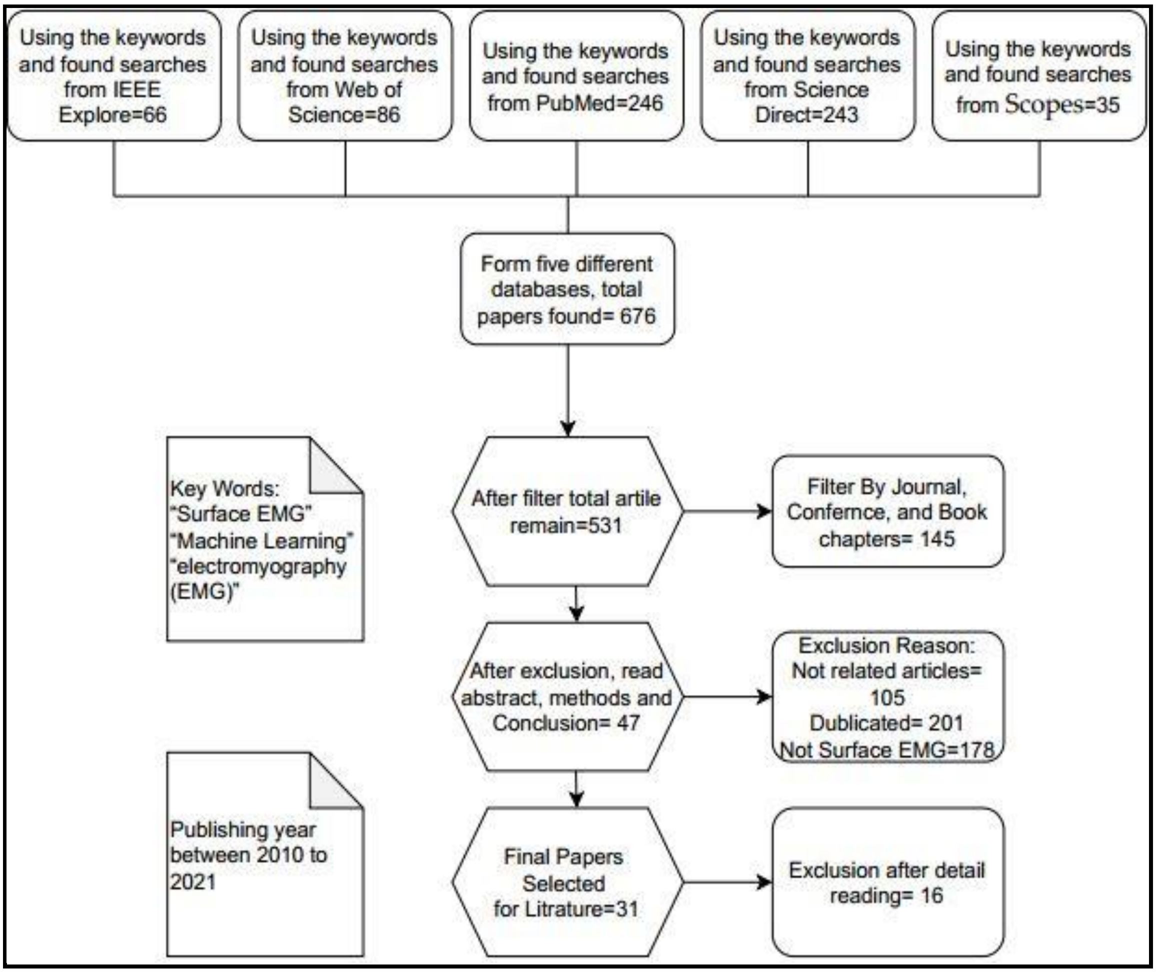

Figure. 4 Prisma Flowchart of the systematic searching procedure of the paper's selection

Literature based on Surface-EMG Detection Using Machine Learning: In this section, we provided a detailed overview of the literature on ML Techniques used for Surface EMG detection in the medical field. The following ML techniques are used to detect Surface EMG:

Support Vector Machine (SVM): SVM is an old machine learning technique used for classification and provided better results as compared with other available machine learning techniques. Many authors used the SVM technique for surface EMG signals detection and found a very accurate and efficient technique. In our systematic review on surface EMG, we found several SVM-based techniques used which we provided in detail. In (Kakoty & Hazarika, 2011) the author used the kernel-based Support Vector Machine technique and normalized the surface EMG signals into six different clenches. From the results, the author concluded that they achieved 97.5% accuracy through fold cross-validation. Similarly, in (Pomboza-Junez & Terriza, 2016) the author used SVM for surface EMG signals for upper limb detection. They used the machine learning technique on fifteen different hand gestures of the upper limb. From the result, they concluded with satisfactory results and provided an accurate classification of the muscles signals. Furthermore, in (Wahid, Tafreshi, Al-Sowaidi, & Langari, 2018a) detailed overview and comparison are provided of SVM with KNN, NB, RF, and DA to recognize different hand gestures. The results are compared and provided that SVM performed well in terms of accuracy of surface EMG detection of muscles. Similarly, in another comparison paper (Paul, Goyal, & Jaswal, 2017), from the comparison results, they concluded that SVM performed better compared with the KNN machine learning technique. In (Subasi & Qaisar, 2022) hand movement is recognized by surface EMG using the SVM technique with TQWT. From the results, it is concluded that the modified version of SVM with TQWT performs well and increased accuracy as compared with simple SVM. In (Krishnan *et al.*, 2019) similarly, they used linear discriminant analysis (LDA) with a support vector machine to increase the accuracy rate.

Figure. 5 SVM general architecture

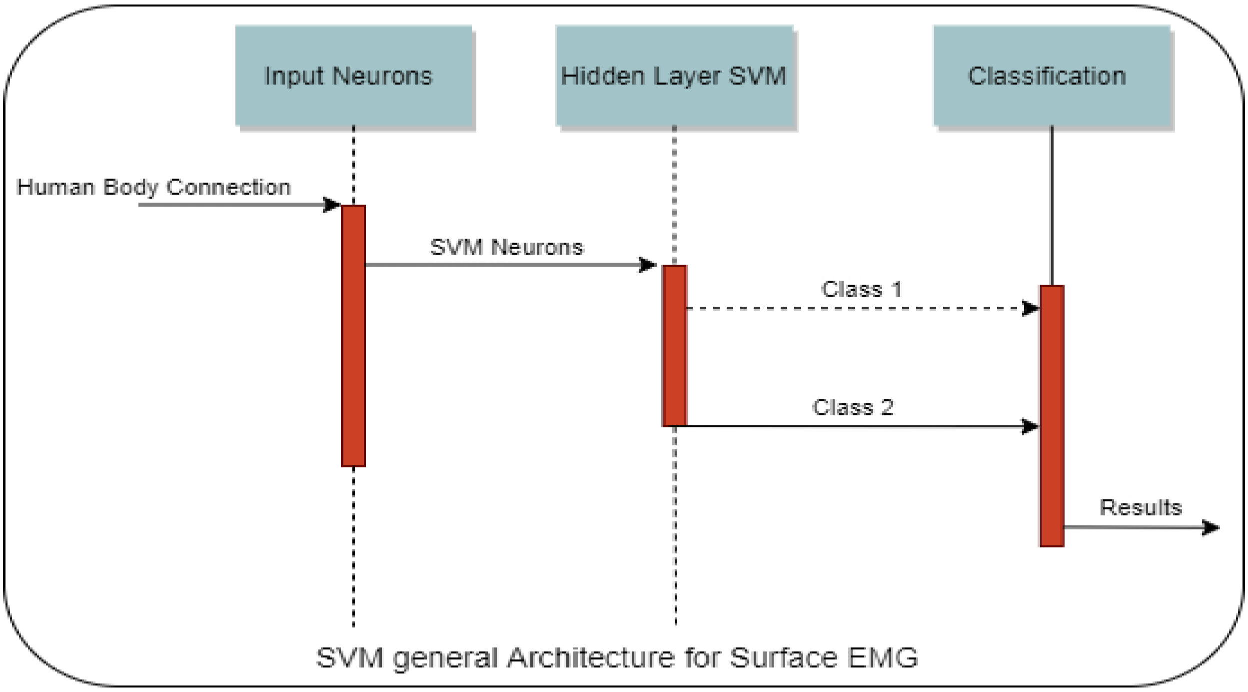

Figure 5 shows the general architecture of the SVM machine learning technique used for surface EMG detection.

Random Forest (RF): Random Forest (*RF*) is a supervised machine learning technique that is constructed from the decision tree technique and used for dataset classification. This machine learning technique can be used for different datasets such as banking, E-Commerce, and big data analysis. It has been used for clinical and biomedical problems and performed very well in terms of the accuracy of the classifications. *RF* can be used both for classification and regression problems simultaneously. We have found many papers that have used *RF* for surface-*EMG* detection. In (Liarokapis, Artemiadis, Kyriakopoulos, & Manolakos, 2013) the author used RF for surface *EMG* detection. From the results of the proposed model, they concluded better accuracy as compared with the available work. Similarly, in (Liarokapis *et al.*, 2013) and in (Wahid *et al.*, 2018a) the authors used RF combined with other machine learning techniques to enhance the performance of the *RF* for surface *EMG* detection. The RF technique used with other models provided 96.38% overall accuracy which is better than other available surface EMG detection techniques.

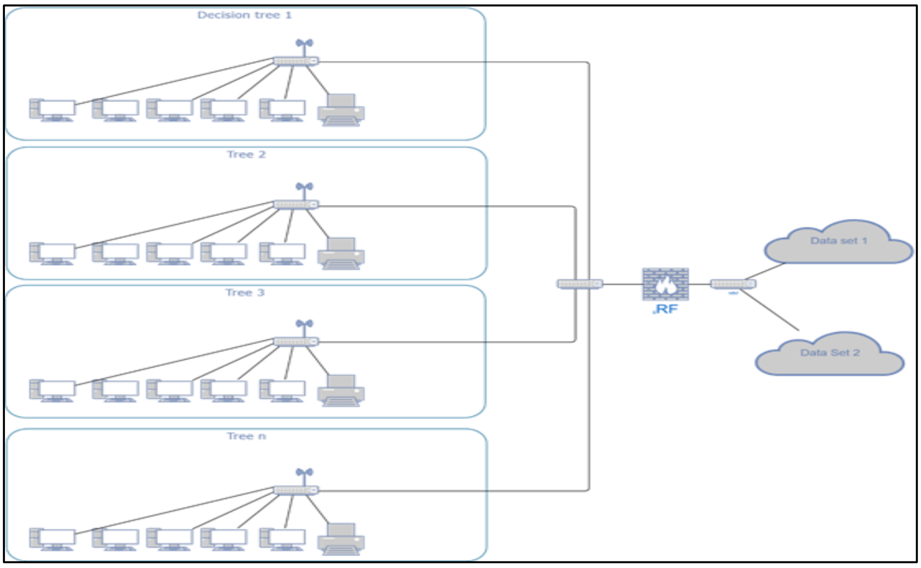

Figure. 6 Random Forest general architecture

Figure 6 shows the general architecture of RF for surface EMG detection. The available data is classified into different decision trees and the tree with more children's return to the system for results.

Artificial Neural Network (ANN): An artificial Neural Network *(ANN)* is a technology-based that mimics the human brain and nervous system as shown in figure 7. *ANN* models simulate the electrical activities of the brain along with nervous systems. Nowadays it is basically used for clinical decision support systems, especially for surface *EMG* detection and giving better results. In (Liarokapis *et al.*, 2013) the author used *ANN* as a hidden layer for surface *EMG* detection classification and compared it with the other machine learning techniques such as *RF* and *SVM*. In the environment where fewer data were available, the ANN outperformed while where huge data were available then *SVM* and *RF* performed well.

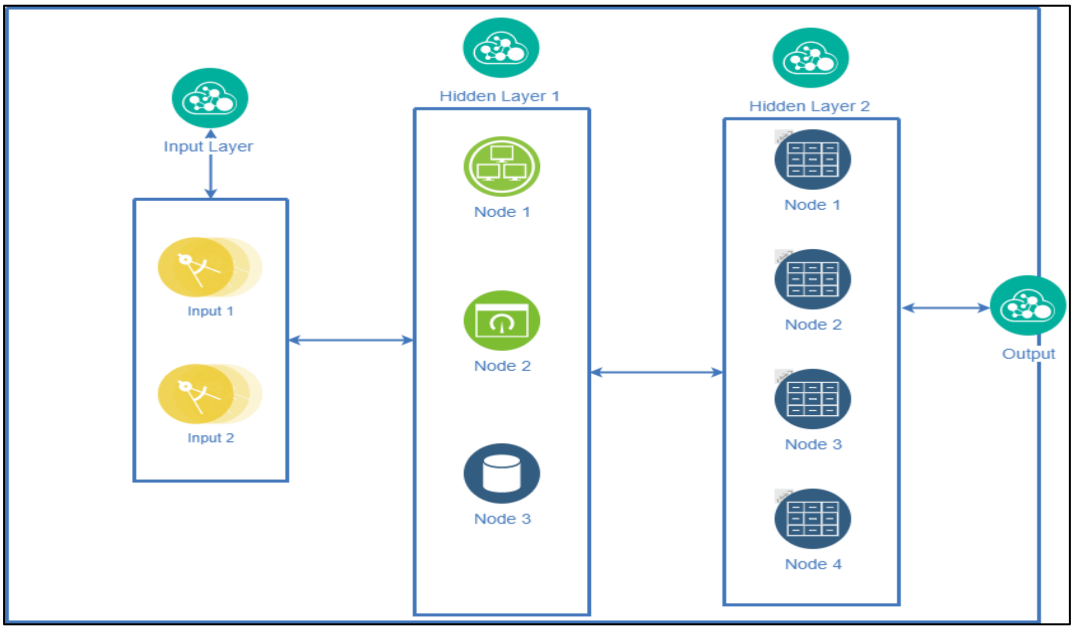

Figure. 7 *ANN* general architecture

In (Tibold & Fuglevand, 2015) the author used *ANN* to predicate Surface *EMG* signals on muscles using loaded and unloaded situations. They used four layers of ANN for classifications. From the result, they concluded that ANN is the best machine learning technique where when we received complex patterns of muscles. Similarly, another author (Ahsan, Ibrahimy, & Khalifa, 2011) used *ANN* for backpropagation and their success rate was 88.4% to recognize the complex patterns for analyzing *EMG* signals. Moreover, in (Jose, Raj, Adithya, & Sivanadan, 2017) the author compared and presented the accuracy rate for complex patterns in muscles detection for ANN was 91.6 % while for Random Forest it was 97.7%. In (Saeed *et al.*, 2021) the author proposed an ANN-based model, which combined *ANN* and *LDA* for the classification of EMG signals. Their accuracy was 99.27% & 93.64% respectively for surface EMG. The results showed that combined *EMG* and S *EMG* signals performed with better accuracy up to 98.24% and 89.25%. Similarly, in (Li *et al.*, 2023) the author used *GRNN* neural network for surface EMG signals detection. They used the proposed model for redundant information reduction of the signals. The accuracy rate was noted as 95.1% for *EMG* signals. In (Qi, Jiang, Li, Sun, & Tao, 2020) armband and sliding window, the concept was used for surface EMG signals detection, to extract the features. They used a real-world dataset and the accuracy rate provided was 98.7%.

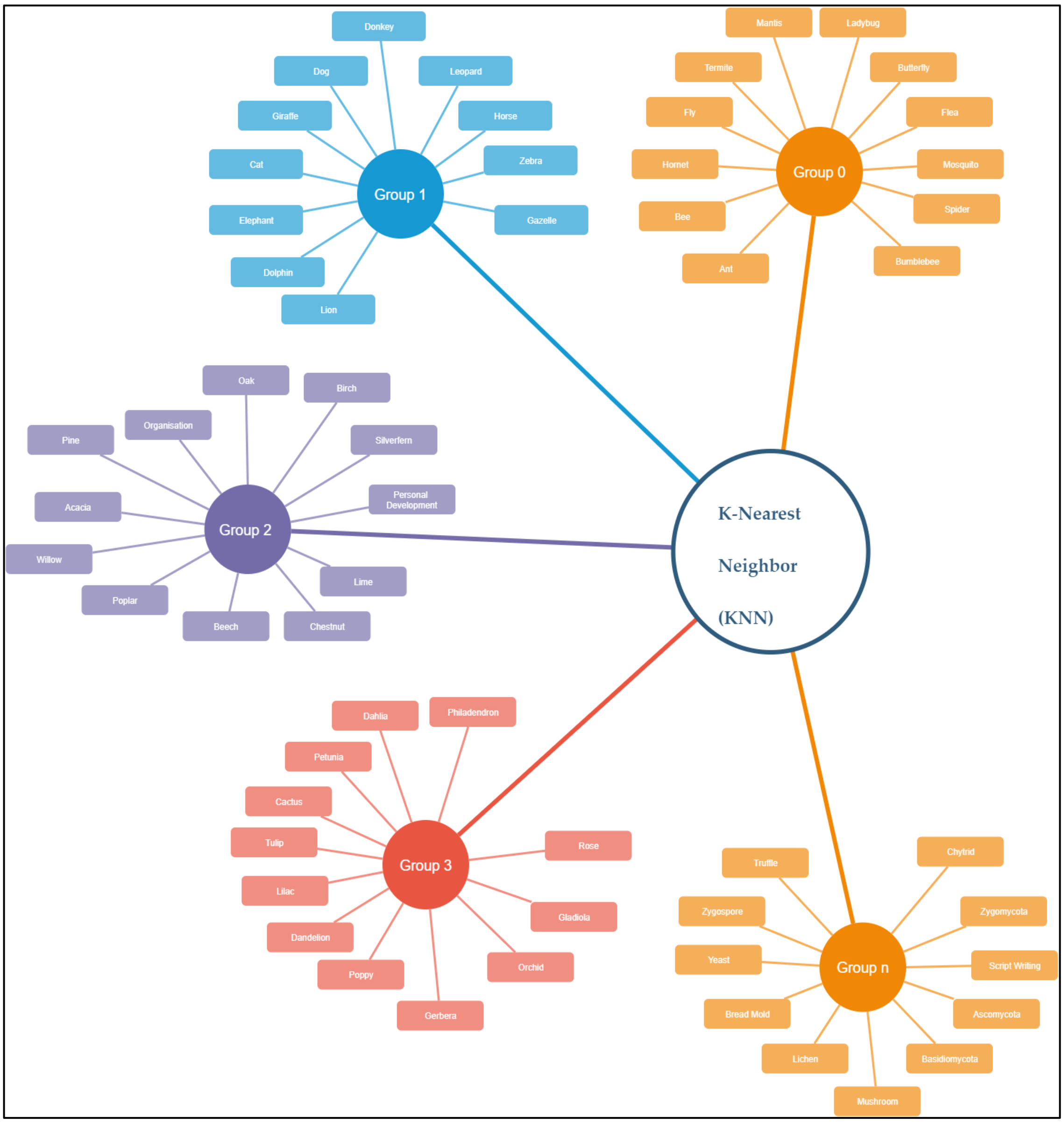

Figure. 8 KNN general architecture

K-Nearest Neighbor (KNN): K Nearest Neighbor (KNN) is a supervised learning ML technique used for regression and classification problems. Recently this technique is mostly used for clinical decision support systems in the field of biomedical sciences, especially used for surface EMG detection of muscles, as shown in figure 8.

In this survey paper, several papers are selected in which KNN was the primary ML technique used for surface EMG detection. Such as, in (Kim *et al.*, 2011) the author proposed a comparison-based study in which they used Quadratic discriminant analysis, linear discriminant analysis, and KNN. They used the above techniques for wrist motions detection using surface EMG. In the proposed study the author concluded that KNN performs well in comparison with the other two classifiers. Similarly in another study (Paul *et al.*, 2017), the author provided that SVM ML techniques beat KNN in terms of accuracy of surface EMG detection. Moreover, in (He, Yang, Wang, Cheng, & Hu, 2017) the author proposed a new method for analyzing hand gesture based KNN technology. They classify surface EMG signals and provide more accuracy as compared with simple KNN-based technology. From the study, it is concluded that in upper limb muscles KNN performed very well in terms of accuracy. In (Tuncer, Dogan, & Subasi, 2020) the authors used a novel ternary pattern and discrete wavelet (TP-DWT) method for surface EMG signals detection. They used three levels such as low, high, and moderate. The accuracy rate they achieved were 97.78 %, 93.33 %, and 92.96 %

respectively. Similarly, in (Khan, Alam, Khan, & Farooq, 2021) the author used the KNN technique for features extraction and found that regression coefficient and Willison Amplitude features performed well.

Naïve Bayes (NB): Naïve Bayes classification is a classification-based algorithm used for features classification. It is based on the Bayes theorem and used in the field of medicine for clinical decision support systems and other parts of medical fields. In (Wahid, Tafreshi, Al-Sowaidi, & Langari, 2018b) the author compared SVM, KNN, RF, DA, and NB, from the comparison result the author proved that NB performed well where the dataset was defined proper, while in all other situations SVM and RF performed well.
In the following table 1 we have provided the detail summary of the discussed Machine Learning Model

Table 1. Summary of the discussed algorithms

S. No	Paper Reference	Feature extraction Model	Classifier	Accuracy in percentage
1	(Liarokapis *et al.*, 2013)	Empirical Mode Decomposition	LDA	94.8
2	(Tibold & Fuglevand, 2015)	Time Domain Features	ANN	98.6
3	(Ahsan *et al.*, 2011)	Time–Frequency Features	LDA	95.16
4	(Jose *et al.*, 2017)	Wavelet Packet Decomposition	SVM	98.81
5	(Saeed *et al.*, 2021)	Time Domain Features + AR	Logistic model tree (LMT)	91.2
6	(Li *et al.*, 2023)	Sample entropy (SampEn), the fourth order cepstrum coefficients, root mean square and waveform length	Linear discriminant analysis (LDA)	98.87
7	(Qi *et al.*, 2020)	Root mean square	SVM	70
8	(He *et al.*, 2017)	Ensemble EMD (EEMD)	ANN	98.20
9	(He *et al.*, 2017)	Time Domain Features + AR	LIBSVM	95.2
10	(Tuncer *et al.*, 2020)	Wavelet Transform	ANN	98.6
11	(Khan *et al.*, 2021)	Tunable Q wavelet transform (TQWT)	Boosting of Support Vector Machine (SVM)	100.00

The following challenges are identified through the study of the papers:

- Machine Learning based algorithms are required to identify the damage area and to detect early Alzheimer diseases.
- Machine Learning based techniques and studies are required to forecast and train the already data.
- Hybrid classification models are required to increase the detection accuracy.

The following table 2 is used for the abbreviations of the terms used in this paper:

Table. 2 List of abbreviation

Term	Abbreviation	Term	Abbreviation
SVM	Support Vector Machine	KNN	Convolutional neural network
EMG	Electromyography	Mus	Motor Units
S-EMG	Surface Electromyography	MRI	Magnetic resonance imaging
CDSS	Clinical Decision Support System	ML	Machine Learning
RF	Random Forest	ANN	Artificial Neural Network
KNN	K-Nearest Neighbor	NB	Naïve Bayes

Applications of Surface EMG: The following are the different types of applications of Surface MEG:
Physiology and Basic Clinical Studies: The use of surface EMG (sEMG) has become widespread in both basic and clinical neurophysiology. For example, in the realm of neurorehabilitation, an understanding of the pathophysiology of muscles through sEMG analysis is necessary to develop therapeutic treatments and find solutions to clinical issues. For instance, researchers have employed sEMG to investigate muscle activation patterns in patients recovering from stroke, enabling them to tailor rehabilitation protocols

for optimized recovery. Additionally, sEMG has been instrumental in studying muscle fatigue during various physical activities, shedding light on the mechanisms underlying performance limitations and aiding athletes in improving their training regimens. By providing real-time insights into muscle activity, sEMG facilitates the assessment and monitoring of neuromuscular disorders, leading to early intervention and better patient outcomes. These examples illustrate the invaluable role of sEMG in advancing both physiological knowledge and clinical practices in the field of neurology.

Muscle Coordination: It was early on shown that sEMG is appropriate for detecting co-activation of agonist and antagonist muscles, allowing for differentiation between normal and pathological activation patterns. With the development of sEMG methods, the clinical significance of muscle coordination increased, and it is now an essential aspect of any biomechanical investigation of movement. For example, clinical gait analysis is the most prevalent use of sEMG for evaluating muscle coordination. In this context, it may be utilized for either functional diagnosis or therapy outcome monitoring. The interpretation of sEMG signals in terms of motor control, however, calls for some caution. Because of this, several signal processing techniques have been developed to aid in the analysis of sEMG data. Primitive synergy extraction with sEMG is now popular. When classifying the pattern of normal or pathological muscle coordination, modern methods take into consideration the biomechanical aspects on which the sEMG signal relies.

Extraction of Primitive Synergies: Muscle activation patterns, as seen by the sEMG envelopes of a few muscles, may be broken down into a small set of "primitive" functions. The modular arrangement of multi-muscle actions seems to arise from the combination of these simple patterns with varying individual weights, and this holds true across a wide range of motor tasks. For instance, in a study involving healthy subjects performing various gripping tasks, researchers identified a consistent set of basic activation patterns in the forearm muscles, which were then observed to be flexibly combined depending on the specific task requirements. It has been speculated that the nervous system streamlines muscle regulation through modularity, activating groupings of muscles via these fundamental synergies (primitives). For example, during gait analysis, it has been observed that the same basic muscle patterns recur with varying activation intensities and timings, providing a modular framework for generating different locomotion patterns, such as walking, running, or climbing stairs.The implications of this finding for the study of motor control and neurorehabilitation are profound, since they suggest that the central nervous system (CNS) creates forces and motions by maximizing the control strategy of either one of the muscles or (more likely) muscle combinations.

sEMG-based Muscle Force Estimation: The net torque at a joint is the result of contributions from several different sources, including dynamic muscles, passive ligaments and tendons, and outside forces. Even though the forces created by individual muscles (and the amplitude of the muscle's sEMG) fluctuate, the total torque reported may remain constant. Since Perry's seminal study on this issue 30 years ago, several scientists have attempted and failed to estimate force sharing among synergic muscles using sEMG. For example, in a recent study investigating force distribution during handgrip tasks, researchers analyzed sEMG signals from the muscles of the forearm and hand. Despite sophisticated signal processing techniques, accurately determining the precise force contribution of each individual muscle proved challenging due to complex interactions and the inherent limitations of sEMG-based methods.

Future Directions: Through a comprehensive review of the existing literature, numerous researchers have employed Machine Learning (ML) methodologies, including Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Random Forests (RF), Naive Bayes (NB), and others, to address surface Electromyography (EMG) detection challenges within the realm of biomedical sciences. Looking ahead, the refinement of current surface EMG detection models utilizing ML can be further augmented by integrating fuzzy logic, a prominent research paradigm with significant relevance in contemporary scientific investigations. The amalgamation of fuzzy logic with ML techniques holds the potential to yield improved accuracy in the detection of muscular activities.

Moreover, the exploration of cloud and fog computing as means for dataset storage and computation offers promising avenues to enrich the available datasets dedicated to surface EMG detection. By harnessing the capabilities of cloud and fog computing, researchers can access diverse and substantial datasets, consequently contributing to the advancement of surface EMG detection methods and fostering progress in the field of biomedical research.

CONCLUSION

In conclusion, the utilization of surface electromyography (sEMG) in the study of muscle activation patterns has provided valuable insights into the modular organization of multi-muscle actions across diverse motor tasks. Through the identification of fundamental synergies, characterized by simple patterns with varying individual weights, the nervous system appears to streamline muscle regulation to achieve a versatile and efficient control strategy. This finding holds substantial implications for the fields of motor control and neurorehabilitation, suggesting that the central nervous system optimizes force and motion generation by leveraging these foundational synergistic patterns.

Despite the significant potential of sEMG-based investigations, estimating force sharing among synergic muscles remains a challenging endeavor. The fluctuations in individual muscle forces, as captured by sEMG amplitudes, complicate the accurate determination of their precise contributions to net joint torque. Over the past three decades, numerous efforts have been made to elucidate force distribution, yet the complexity of neuromuscular coordination during dynamic tasks has hindered precise estimations using sEMG alone.

To address this challenge, future research endeavors may benefit from complementary approaches that integrate sEMG data with advanced biomechanical analyses or leverage cutting-edge machine learning techniques. By combining multiple data modalities, a more comprehensive understanding of force sharing among synergistic muscles can be achieved, unlocking new avenues for the optimization of rehabilitation protocols, enhanced athletic performance, and the advancement of bio-inspired robotics.

REFERENCES

Ahamed, N. U., Benson, L., Clermont, C., Osis, S. T., & Ferber, R. Fuzzy inference system-based recognition of slow, medium and fast running conditions using a triaxial accelerometer. *Procedia computer science*, ***114***, 401-407.(2017).

Ahamed, N. U., Kobsar, D., Benson, L., Clermont, C., Kohrs, R., Osis, S. T., & Ferber, R. Using wearable sensors to classify subject-specific running biomechanical gait patterns based on changes in environmental weather conditions. *PLoS One*, ***13***(9), e0203839.(2018).

Ahsan, M. R., Ibrahimy, M. I., & Khalifa, O. O.*Electromygraphy (EMG) signal based hand gesture recognition using artificial neural network (ANN).* Paper presented at the 2011 4th international conference on mechatronics (ICOM). (2011)

Benalcázar, M. E., Jaramillo, A. G., Zea, A., Páez, A., & Andaluz, V. H.*Hand gesture recognition using machine learning and the Myo armband.* Paper presented at the 2017 25th European Signal Processing Conference (EUSIPCO). (2017)

Chen, X., Zhang, X., Zhao, Z.-Y., Yang, J.-H., Lantz, V., & Wang, K.-Q.*Multiple hand gesture recognition based on surface EMG signal.* Paper presented at the 2007 1st International conference on Bioinformatics and Biomedical Engineering. (2007)

Crevier, D. *AI: the tumultuous history of the search for artificial intelligence*: Basic Books, Inc. (1993).

Day, S. Important factors in surface EMG measurement. *Bortec Biomedical Ltd publishers*, 1-17.(2002).

De Luca, C. J., Adam, A., Wotiz, R., Gilmore, L. D., & Nawab, S. H. Decomposition of surface EMG signals. *Journal of neurophysiology*, ***96***(3), 1646-1657.(2006).

Farina, D., Merletti, R., & Enoka, R. M. The extraction of neural strategies from the surface EMG. *Journal of applied physiology*, ***96***(4), 1486-1495.(2004).

Ferrario, V., Tartaglia, G., Galletta, A., Grassi, G., & Sforza, C. The influence of occlusion on jaw and neck muscle activity: a surface EMG study in healthy young adults. *Journal of oral rehabilitation*, ***33***(5), 341-348.(2006).

Gu, Y., Yang, D., Huang, Q., Yang, W., & Liu, H. Robust EMG pattern recognition in the presence of confounding factors: features, classifiers and adaptive learning. *Expert Systems with Applications*, ***96***, 208-217.(2018).

He, S., Yang, C., Wang, M., Cheng, L., & Hu, Z.*Hand gesture recognition using MYO armband.* Paper presented at the 2017 Chinese Automation Congress (CAC). (2017)

Hinton, G. Deep learning—a technology with the potential to transform health care. *Jama*, ***320***(11), 1101-1102.(2018).

Islam, M. A., Sundaraj, K., Ahmad, R. B., Sundaraj, S., Ahamed, N. U., & Ali, M. A. Longitudinal, lateral and transverse axes of forearm muscles influence the crosstalk in the mechanomyographic signals during isometric wrist postures. *PLoS One*, ***9***(8), e104280.(2014).

Jose, N., Raj, R., Adithya, P., & Sivanadan, K.*Classification of forearm movements from sEMG time domain features using machine learning algorithms.* Paper presented at the TENCON 2017-2017 IEEE Region 10 Conference. (2017)

Kakoty, N. M., & Hazarika, S. M.*Recognition of grasp types through principal components of dwt based emg features.* Paper presented at the 2011 IEEE International Conference on Rehabilitation Robotics. (2011)

Khan, S. M., Alam, M. U., Khan, A. A., & Farooq, O.*A Preliminary Study on ReliefF based Feature Ranking for Classification of Myoelectric Signals.* Paper presented at the 2021 Seventh International conference on Bio Signals, Images, and Instrumentation (ICBSII). (2021)

Kim, K. S., Choi, H. H., Moon, C. S., & Mun, C. W. Comparison of k-nearest neighbor, quadratic discriminant and linear discriminant analysis in classification of electromyogram signals based on the wrist-motion directions. *Current applied physics*, ***11***(3), 740-745.(2011).

Krishnan, S., Akash, R., Kumar, D., Jain, R., Rathai, K. M. M., & Patil, S.*Finger movement pattern recognition from surface EMG signals using machine learning algorithms.* Paper presented at the ICTMI 2017: Proceedings of the International Conference on Translational Medicine and Imaging. (2019)

Li, G., Bai, D., Jiang, G., Jiang, D., Yun, J., Yang, Z., & Sun, Y. Continuous dynamic gesture recognition using surface EMG signals based on blockchain-enabled internet of medical things. *Information Sciences*, 119409.(2023).

Liarokapis, M. V., Artemiadis, P. K., Kyriakopoulos, K. J., & Manolakos, E. S. A learning scheme for reach to grasp movements: On EMG-based interfaces using task specific motion decoding models. *IEEE journal of biomedical and health informatics,* ***17***(5), 915-921.(2013).

Mesin, L., Merletti, R., & Rainoldi, A. Surface EMG: the issue of electrode location. *Journal of Electromyography and Kinesiology,* ***19***(5), 719-726.(2009).

Pancholi, S., & Joshi, A. M. Portable EMG data acquisition module for upper limb prosthesis application. *IEEE Sensors Journal,* ***18***(8), 3436-3443.(2018).

Paul, Y., Goyal, V., & Jaswal, R. A.*Comparative analysis between SVM & KNN classifier for EMG signal classification on elementary time domain features.* Paper presented at the 2017 4th international conference on signal processing, computing and control (ISPCC). (2017)

Phinyomark, A., & Scheme, E. EMG pattern recognition in the era of big data and deep learning. *Big Data and Cognitive Computing,* ***2***(3), 21.(2018).

Pomboza-Junez, G., & Terriza, J. H.*Hand gesture recognition based on sEMG signals using Support Vector Machines.* Paper presented at the 2016 IEEE 6th International Conference on Consumer Electronics-Berlin (ICCE-Berlin). (2016)

Qi, J., Jiang, G., Li, G., Sun, Y., & Tao, B. Surface EMG hand gesture recognition system based on PCA and GRNN. *Neural Computing and Applications,* ***32***, 6343-6351.(2020).

Rawson, T. M., Ahmad, R., Toumazou, C., Georgiou, P., & Holmes, A. H. Artificial intelligence can improve decision-making in infection management. *Nature human behaviour,* ***3***(6), 543-545.(2019).

Reaz, M. B. I., Hussain, M. S., & Mohd-Yasin, F. Techniques of EMG signal analysis: detection, processing, classification and applications. *Biological procedures online,* ***8***, 11-35.(2006).

Saeed, B., Zia-ur-Rehman, M., Gilani, S. O., Amin, F., Waris, A., Jamil, M., & Shafique, M. Leveraging ANN and LDA classifiers for characterizing different hand movements using emg signals. *Arabian Journal for Science and Engineering,* ***46***, 1761-1769.(2021).

Saponas, T. S., Tan, D. S., Morris, D., & Balakrishnan, R.*Demonstrating the feasibility of using forearm electromyography for muscle-computer interfaces.* Paper presented at the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. (2008)

Stegeman, D. F., Blok, J. H., Hermens, H. J., & Roeleveld, K. Surface EMG models: properties and applications. *Journal of Electromyography and Kinesiology,* ***10***(5), 313-326.(2000).

Su, R., Chen, X., Cao, S., & Zhang, X. Random forest-based recognition of isolated sign language subwords using data from accelerometers and surface electromyographic sensors. *Sensors,* ***16***(1), 100.(2016).

Subasi, A., & Qaisar, S. M. Surface EMG signal classification using TQWT, Bagging and Boosting for hand movement recognition. *Journal of Ambient Intelligence and Humanized Computing,* ***13***(7), 3539-3554.(2022).

Szyszka-Sommerfeld, L., Sycińska-Dziarnowska, M., Spagnuolo, G., & Woźniak, K. Surface electromyography in the assessment of masticatory muscle activity in patients with pain-related temporomandibular disorders: a systematic review. *Frontiers in Neurology,* ***14***, 1184036.(2023).

Tibold, R., & Fuglevand, A. J. Prediction of muscle activity during loaded movements of the upper limb. *Journal of neuroengineering and rehabilitation,* ***12***(1), 1-12.(2015).

Tuncer, T., Dogan, S., & Subasi, A. Surface EMG signal classification using ternary pattern and discrete wavelet transform based feature extraction for hand movement recognition. *Biomedical signal processing and control,* ***58***, 101872.(2020).

Uvanesh, K., Nayak, S. K., Champaty, B., Thakur, G., Mohapatra, B., Tibarewala, D., & Pal, K. Classification of surface electromyogram signals acquired from the forearm of a healthy volunteer *Classification and clustering in biomedical signal processing* (pp. 315-333): IGI Global.(2016)

Wahid, M. F., Tafreshi, R., Al-Sowaidi, M., & Langari, R.*An efficient approach to recognize hand gestures using machine-learning algorithms.* Paper presented at the 2018 IEEE 4th Middle East Conference on Biomedical Engineering (MECBME). (2018a)

Wahid, M. F., Tafreshi, R., Al-Sowaidi, M., & Langari, R. Subject-independent hand gesture recognition using normalization and machine learning algorithms. *Journal of computational science,* ***27***, 69-76.(2018b).

Yoo, H., Park, H., & Lee, B. Optimized method for surface electromyography classification regarding channel reduction in hand prosthesis: a pilot study. *Annals of Physical and Rehabilitation Medicine,* ***61***, e468.(2018).

Zhang, X.-D. A matrix algebra approach to artificial intelligence.(2020).