A REVIEW OF CLASSIFICATION TECHNIQUES FOR ELECTROMYOGRAPHY SIGNALS

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ABSTRACT: Electromyography (EMG) signals can be used in various sector such as medical, rehabilitation, robotics, and industrial fields. EMG measures muscle response or electrical activity in response to a nerve's stimulation of the muscle. To detect neuromuscular abnormalities, these test is very useful. EMG can measures the electrical activity of muscle during rest, slight and forceful contraction. Normally, during rest our muscle tissue does not produce electrical signals. Machine Learning (ML) is an area of Artificial Intelligent (AI) with a concept that a computer program can learn and familiarize to new data without human intervention. ML is one of major branches of AI. Aim for this paper is to recover the latest scientific research on ML methods for EMG signal analysis. This paper focused on types of ML classifiers that are suitable for analysis the EMG signal in terms of accuracy. During the content review, we understood that ML performed for big and varied datasets. All of the ML classifiers have their own algorithm, special specification, pros and cons based on the available input. In this review revealed that Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Linear Discriminant Analysis (LDA) are most popular algorithms in ML that used in diagnosis of EMG signal especially for upper limbs of our body because mostly the accuracy for the respective classifier shows that more than 80 to 90% accurate results. This article depicts the application of various ML algorithms used in EMG signal analysis till recently, but in the future, it will

be used in more medical fields to improve the quality of diagnosis.

KEYWORDS: *Electromyography; Machine Learning; Classification*

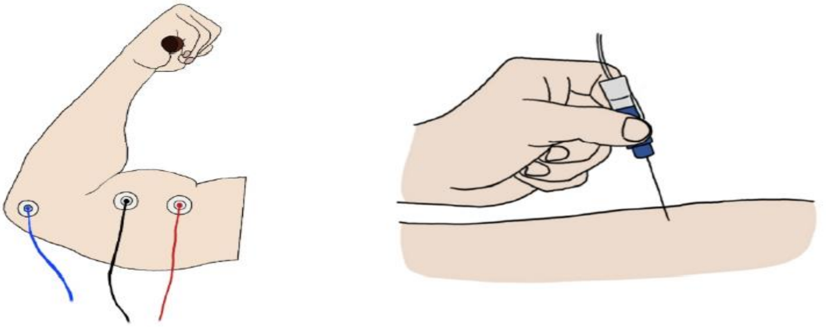
1.0 INTRODUCTION

Surface electromyography, often known as sEMG, is a technique that is used to assess the electrical activity of a muscle in a non-invasive manner by placing surface electrodes on the skin at sufficient positions [1]. When flexing or extending an articulation, it can assist in retrieving muscle information during contractions. In addition, there are implants that can be inserted beneath the skin to assist with signal acquisition; however, these are not commonly used [2]. To perform pattern recognition for EMG applications, features can be extracted from sEMG signals and analyzed. The signal analysis can be performed in time domain or by using other domains, including the frequency domain (also known as the spectrum domain), time scale, and time–frequency, among others.

Machine Learning (ML) is an Artificial Intelligence (AI) applications that using mathematical algorithms to learn and interpret patterns without direct instruction. There are many ML algorithms that have been proposed as classification technique for pattern recognition. In sEMG signal analysis, the popular techniques include Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), K-nearest-neighbour's (KNN) and Naïve Bayes (NB). Each of the classifier have their own potential to recognize complex patterns in sEMG signals.

2.0 ELECTROMYOGRAPHY (EMG)

Electromyography (EMG) is an electrical signal analysis to evaluate muscle activities by detecting electrical potential signals generated by muscle cells [3]. Since EMG signals provide more information on the activity of the muscle, this technique has also emerged as the gold standard for identifying muscular tiredness [4]. Surface electromyography (sEMG) is a scientific tool used to quantify muscle activity of workers during prolonged standing tasks. [5]. It can be measured by two methods: (a) applying electrodes to the skin surface (non-invasive) or (b) intramuscular (invasive) within the muscle [6]. Both methods are shown in Figure 1.



(a) **(b)**

Figure 1 : (a) Image of surface Electromyography(sEMG) or non-invasive electrode and (b) Needle Electromyography or invasive electode [7]

sEMG is more extensively employed because of its significant stability advantage. However, because needle EMG involves physically inserting a needle into the muscle, it provides more reliable data than sEMG. As a result of studying the relationship between the trigger point and the central nervous system to discover issues connected with muscle pain syndrome and conducting EMG-based research, the necessary EMG could not be detected using surface recording techniques. [7]. Electromyography have some phenomena [8] or it can call spontaneous activity that consists of Fibrillation, Fasciculation, Myotonia, Neuromyotonia and Myokymia. The detailed explaination for EMG phenomena have been study by previous researcher in [9].

Figure 2 shows the abnormal spontaneous activity based on EMG signal. Signal in (figure 2A) shows th fibrillation (*) and positive sharp wave (**) in an acutely denervated hand muscle . Next, signal in (figure 2B) shows the single, doublet, triplet, and multiplet motor unit neuromyotonic discharges is up to 200Hz. While, signal in (figure 2C) shows fasciculations in the tonque in a patient with amyotopic lateral sclerosis.The single discharges are irregular and occur on a background of ongoing EMG activity cause by poor relaxation. Lastly, signal in (figure 2D) shows Myotonic discharges in a patient with dystrophia myotonica. There is a characteristic waxing and waning in frequency [9].

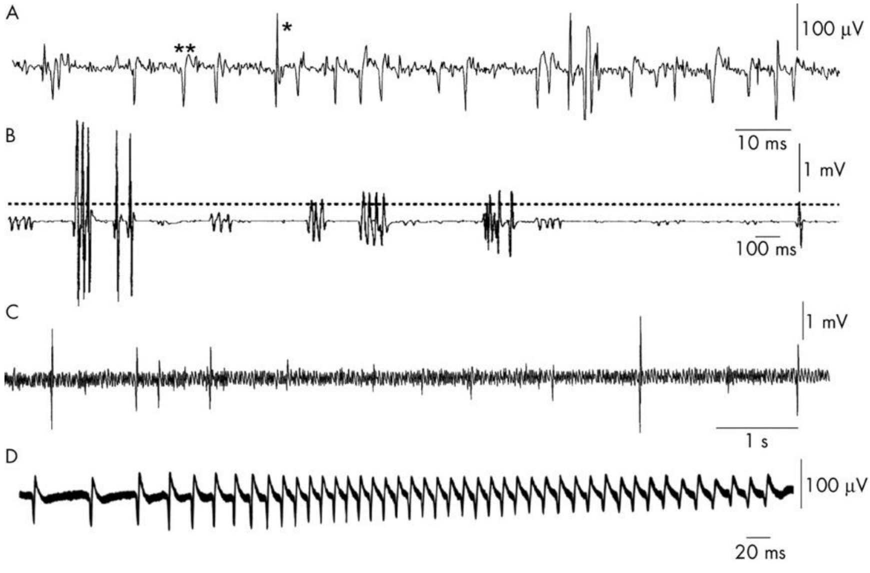


Figure 2 : Abnormal spontaneous activity : (A) Fibrillations , (B) Neuromyotonic, (C) Fasciculations and (D) Myotonic [9]

3.0 MACHINE LEARNING

The name of the psychologist Frank Rosenblatt from Cornell University is typically associated with the origin of Machine Learning (ML) in its modern sense. Rosenblatt was the leader of a group that developed a machine for recognising the letters of the alphabet Rosenblatt. These ideas were based on Rosenblatt's speculations regarding the operation of the human nervous system. (1957, 1959, 1960). The system, which its developer named the "perceptron," utilised both analogue and discrete impulses and had a threshold element that transformed analogue signals to discrete ones [10].

ML is a subset of Artificial Intelligence (AI) that holds that a computer algorithm can learn and adapt to new data without the need for human intervention. ML is an important subfield in Artificial Intelligence (AI). In contrast to the goal of AI, which is to create an intelligent system or assistant using various ML approaches to solve problems, the goal of ML is to create computer systems that can learn and respond based on their prior observation. [11]. Figure 3 shows the relation between AI and ML.

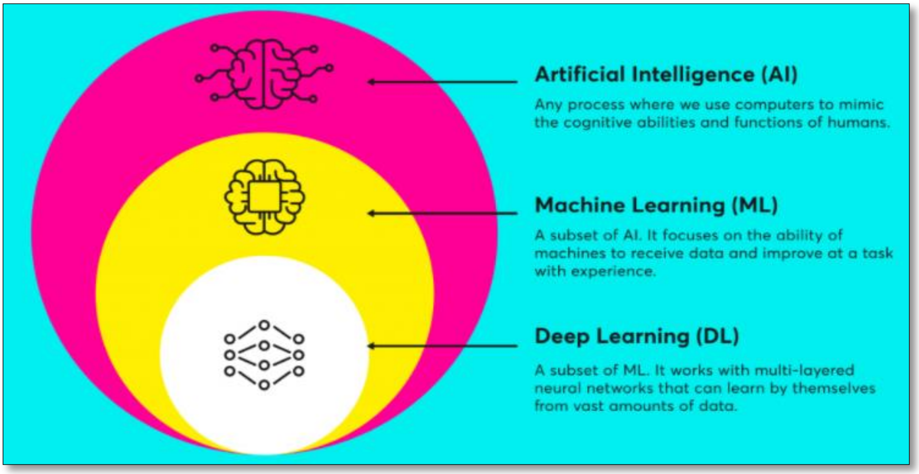


Figure 3 : Relation between Artificial Intellegent (AI) , Machine Learning (ML) and Deep Learning (DL)[12].

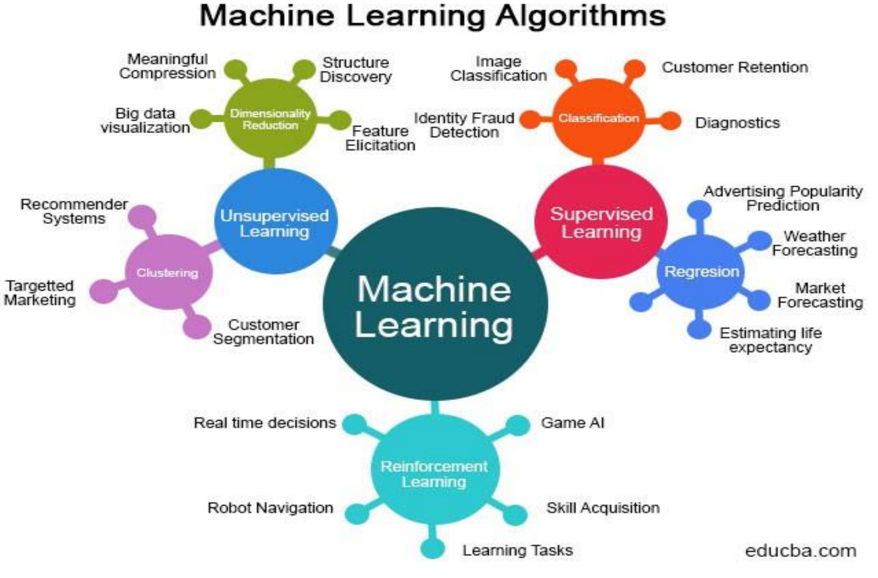


Figure 4 : Types of ML algorithm for data processing [16].

ML methods, are generating a lot of interest in commercials, professionals and academic applications [13] [10] . ML has also been very successful in getting important information out of data for a wide range of applications. Most of the researchers today agree that there is no intelligent without learning [14]. It reduces costs and the amount of labour needed while simultaneously improving data-oriented analysis and increasing hit ratio. On the other hand, there is still a requirement to investigate the outcomes using a variety of classifiers on a dataset taken from the real world..[15]. Since their inception, ML algorithms have been used to analyse medical datasets. Today, ML offers a variety of vital tools for intelligent data analysis. Figure 4 depicts the data processing ML algorithms.

ML Algorithms vary in their approach, the data they utilise as input and output, and the tasks or problems they are designed to address. Figure 4 shows that ML algorithm can be categorized into supervised learning, unsupervised learning and reinforcement learning. Among those techniques, supervised learning is the most frequently used, which becomes the major focus in this paper. The summary of explanation about ML algorithm have been revealed by [17] as shows in Table 1 below:

Table 1 : Category of ML algoritms

Categorized ML Algorithm	**Summary of Explaination**
Supervised Learning	The various algorithms generate a function that maps inputs to desired outputs. One standard formulation of the supervised learning task is the classification problem: the learner is required to learn (to approximate the behavior of) a function which maps a vector into one of several classes by looking at several input-output examples of the function
Unsupervised Learning	Models a set of inputs: labeled examples are not available
Reinforcement Learning	The algorithm learns a policy of how to act given an observation of the world. Every action has some impact in the environment, and the environment provides feedback that guides the learning algorithm

4.0 TYPES OF MACHINE LEARNING CLASSIFIER

In this subtopic, the details of supervised ML classifier are pointed. Supervised learning which we use an algorithm to learn the mapping function (f(X)) from the input variables (X) so that we can predict the outcome (Y) for the dataset. Supervised learning can be categorize into classification and regression. However, the classification is the most widely used techniques. The processs flow of applying supervised ML is described in Figure 5.

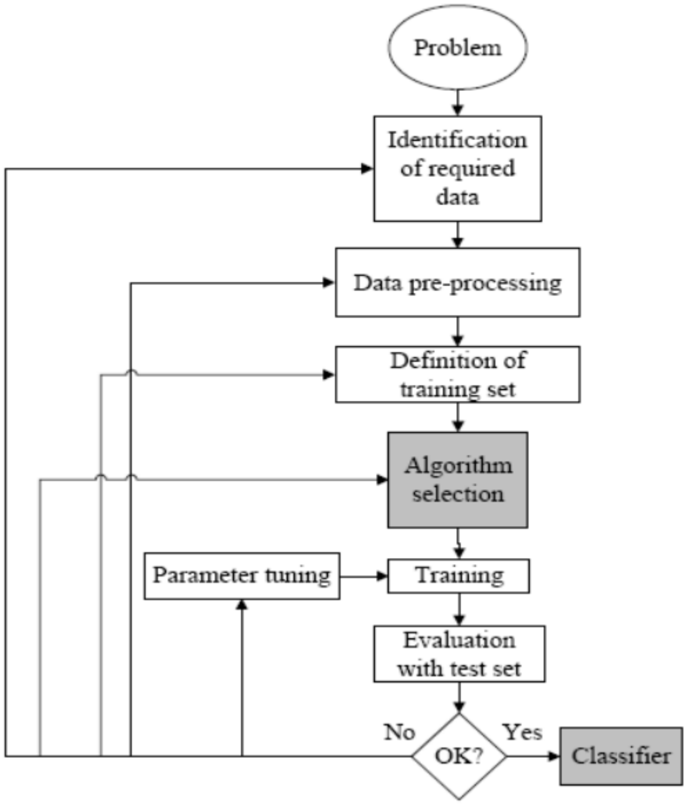


Figure 5 : Supervise ML Process Flow [18]

Types of ML algorithm (classifier) can be used in classification tasks such as k-nearest (KNN), discriminate analysis (DA), naïve Bayes (NB), random forest (RF), decision tree (DT) , logistic regression (LR) , support vector machine (SVM) and Neural Network (NN). There are numerous classification algorithms now available, however it is impossible to determine which one is preferable. It depends on the application and the type of data set provided.

i. K-nearest-neighbour's (KNN)

KNN is supervised learning method and has a useful and accurate classification [19], [20]. The data represented in KNN method in form of vector space[21]. The Euclidean distance is used to measure the distance between points using the given Eq. (1) [21], [22]:

$$D_i = \sum_{k}^{h} \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2} \quad (1)$$

Where k represents a variable and selects as an essential factor while h represents the least distance from the selected point if k is equal to h, which means unselected point.

ii. Linear Discriminant Analysis (LDA)

LDA (linear discriminate analysis) is a well-known ML approach that gives accurate findings, according to [23][24]. This shows that LDA may offer high consistent outcomes for a long-term EMG impact. LDA is also seen as a less troublesome ML method, particularly overtraining. LDA is a statistical algorithm which is not only covering the boundary points but also the different data points lie on the hyperplane. In addition , LDA calculates the parameter of discriminate function from the training data eveluation the boundary sapce in hyperplane among multiple clasess.

In LDA, it is assumed that the feature vector variables to be multivariate normally distributed. Let C_g (g [1,G]) denotes the movement classes: $\bar{f}$ is the feature vector in one analysis window. The idea of discriminant analysis is to classify the observed features to movement class in which the posterior probability $P(C_g \mid \bar{f})$ can be maximized. The posterior probability is the probability of class C_g given the observed feature vector $\bar{f}$ and can be expressed as:

$$P(C_g \mid \bar{f}) = \frac{P(\bar{f} \mid C_g)\, P(C_g)}{P(\bar{f})} \quad (2)$$

Where $P(C_g)$ is the priori possibility, $P(C_g \mid \bar{f})$ is the likelihood, and $P(\bar{f})$ is the possibility of observed feature vector $\bar{f}$.

iii. Naïve Bayes (NB)

According to [25][26], Naive Bayes (NB) is a ML approach that has been used to categorize and diagnose the location and kinds of harmonic sources. NB is a well-known and trustworthy ML technique that has been widely used in pattern recognition research. In general, NB estimates the probability of data using the Bayes theorem, provided that all characteristics are independent. NB considers the most likely class while assessing the probability of a feature vector. Naive Bayes may also compete with more difficult classifiers and attain success levels, according to (Yaman 2019)(Nazmi et al., no date). The detection capacity of Nave Bayes is degraded because of the relationships between characteristics. NB make use of bayes theorem to estimate the probability of model would be the self detemining feature model. In basic term, a NB classifier asssumes that the presence of a particular feature of a class is unrelated to the presence of any other feature [27].Mathematically, the model posterior probability based on Bayes rule can be represented as:

$$P (Y = k \mid X_1 \ldots, X_p) = \frac{\pi\ (Y=k) \prod_{j=i}^{p} P\ (X_j\ |Y=k)}{\sum_{k=1}^{K} \pi\ (Y=k)\ \prod_{j=i}^{p} P\ (X_j\ |Y=k)} \qquad (3)$$

Where K is the number of classes, Y is random variable corresponding to class index k of an observation , X is the random predictor of observation, and $\pi\ (Y = k)$ is the prior probability that a class index is k.

Naturally, NB identifies the most probable class by evaluating the probability of new features.The advantage of the NB classifier is that it only requires a small amount of training data to estimate the means and variances of the variable necessary for classification.Because of independent variablex are unspecified, only the variances for each label need to be determined and not the entire covariance matrix [28]. However, NB is very sensitive to the appearance of noise and redundancy. There are severaly types of distribution that can be used in NB such as normal distribution or Gaussian distribution fo kernel smoothing density prediction.

iv. Support Vector Machine (SVM)

ML approaches such as support vector machines (SVM) are utilized to detect and diagnose the location and kind of harmonic sources, according to (Jopri et al., 2020). SVM is a complex ML technique that has been used in a wide range of applications. By increasing the feature vector size, SVM applies the notion of hyperplane separation to data. According to [23], the support vector machine (SVM) has been identified as one of the most successful and efficient ML methods in the field of EMG pattern recognition. SVM has lately emerged as a high-potential classifier that outperforms others in terms of accuracy. SVM partitions the data set on the hyperplane using the concept of separation, enabling all data to be divided linearly. Furthermore, SVM is the best classification function for discriminating between classes in a spectrogram feature set since it maps data on a high-dimensional space. On the other hand, SVM has a kernel function selection limitation and a high processing cost.

Furthermore, according to [29][2], both linear and nonlinear data are identified using SVM. SVM translates the primary training set into an upper-level size via a nonlinear mapping. In this increased size, SVM searches for the linear optimal separation hyperplane, a decision border between two classes of tuples. A hyperplane with an appropriate nonlinear mapping to an upper dimension can be employed to split data into two groups. This hyperplane creates support vectors, important training vectors, and margins. In comparison to other procedures, they are particularly resistant to overfitting.

Figure 6 shows the graphical of SVM classifier. It is shown that the two separable classes of observations with the maximum margin separating line (solid) and second separating line (dashed). Blue and red denote the two classes (y values) and denote support vectors[30].

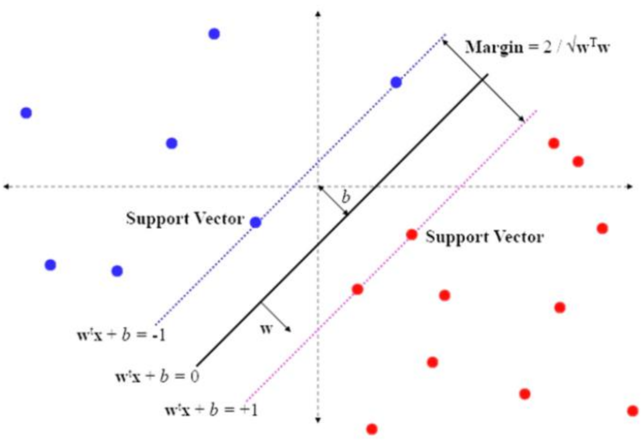


Figure 6 : The graphical SVM classifier [30]

A binary classifier is a function f:X → Y that assigns each point as x ∈ X with some y ∈ Y. Both linear SVM and quadratic SVM use kernel version classifiers as its foundation.

$$f(x) = \sum_i \propto_i y_i \ (x_i^T \ x) + b \tag{4}$$

where w > x + b = 0 and c (w > x + b) = 0 define the same plane [30][31].

The normalization of w for both cases as positive and negative support vectors can be choose. Choose normalization such that:

$$(w_i^T \ x_+) + b = \ 1 \tag{5}$$

$$(w_i^T \ x_-) + b = \ 1 \tag{6}$$

The margin is expressed as:

$$\frac{w}{||w||} \cdot (x_+ - \ \ x_-) = \frac{w^T \ \ (x_+ - \ \ x_-)}{\left||w|\right|} = \frac{2}{||w||} \tag{7}$$

The mathematical formulated of learning SVM algorithm as below:

$Max_w \frac{2}{||w||}$ $subject\ to\ w^T \ x_+ + b$ $\quad \geq 1$ if $y_i \ = +1$

≤ 1 if $y_i \ = -1$

For i = 1…N

Min$\left||w|\right|^2$ $subject\ to\ y_i \ (w^T \ \ x_+ + b) \ \geq 1$ for $i = 1 \ldots N$

5.0 APPLICATION OF MACHINE LEARNING METHOD FOR EMG SIGNAL ANALYSIS

Electromyography (EMG) is the study of muscle function by electrical signal analysis during muscular contractions. [32]. The electrodes, which are the electrical sensors, are positioned on the skin directly above the muscles of interest, and the EMG signals provide information regarding the activation of the muscle, the force produced by the muscle, and the state of the muscle. [33] . All of these components are superimposed, meaning that the EMG signal measurement combines the contributions from many sources. Consequently, it is challenging to obtain information about a specific element by examining the EMG signal. Table 2 shows the details research work which describe the ML methods used to analyse the EMG signal. Individual columns healthcare application area, ML algorithm, the data used for the study, and the study results.

Table 2 : Summary of works carried out using ML algorithms with EMG signals

Author	Application	ML Algorithm	Data	Results
[34]	Kinematic and Dynamic Biomechanical Variables	RNN RCNN	17 healthy right-handed (9 Females and 8 Males; performing lifted and lowered a weighted object between two target locations	Complete estimation for biomechanical signal reach accuracy (96.9%)
[30]	Hand Movement classification	QDA, SVM, random forest, ensemble (subspace KNN)	10 healthy subjects (5 males and 5 females) performing 4 gesture movements include stationary, double tap, single finger movement and finger spread	Accuracy of 83.9%
[35]	Smart Terrain Identification for Lower Limb Rehabilitation	SVM	10 healthy subjects (6 males and 4 female) instructed to work at confortable speed (walking habit)	Accuracy of 96.8%
[36]	Finger Movements for Prosthesis Control	ANN	5 healthy subjects (4 males and 1 female) performing 11 finger movements	Recognation accuracy reach (91.10%)
[37]	Ambulation mode for lower limb	SVM	18 participants performing 4 different ambulatory activities	Recognize ambulation task categories with best accuracy (94.29%).
[38]	Hand movement classification	LDA	5 healthy subjects (2 males and 3 females) performing six different hand movement	Accuracy of 97.56%
[39]	Shoulder motion classification	RF	6 upper limb amputee subjects performing rest,	Accuracy of 98%

	for upper limb amputees		elevation,retraction and protraction motion	
[31]	Robust Control of hand prostheses	LDA and SVM (WT/SVM-OVO)	Transradial amputees performing fist, fingers spread, four-finger close, forearm supination, forearm pronation, open, and no motion	Accuracy of 92.3%
[40]	Upper limb phantom movement classification	ANN	5 transhumeral amputees participated performing 8 upper limb phantom movement	Accuracy of 60.9% to 93.0%
[41]	Shoulder Movement Classification	NN and LDA	8 healthy subjects (4 males and 4 female) performing 8 shoulder movements	Accuracy of 92%
[42]	Hand motion classification	LDA, QDA, SVM, ANN, KNN and Random Forest (RF)	8 healthy subjects (3males and 5 female)Three grasping things (mug, marker, rectangle) at three different places to observe	Accuracy of 83%
[43]	Hand movement classification	SVM, naïve bias and KNN	9 subjects walking, running, resting and open door	Accuracy more than 90%

Despite the fact that ML has been utilised for a long time, published studies have proven that it is capable of making faster and more reliable diagnoses in physiological signals.The potency may well trigger a shift way from the current used decision support methods such as SVM and Neural Network (NN), towards ML. Table 2 demonstrates that the application of ML to the analysis of an electromyographic (EMG) signal improved diagnostic accuracy. This is due to the fact that the proposed model successfully extracts unique characteristics from the EMG data. This classifier features allow the network to be trained even without big data, leading to satisfactory diagnostic results. In contrast, the automated analysis of EMG signals is more difficult due to the chaotic character of these signals. Therefore, it is more difficult for the network to learn from these signals' concealed and delicate information.

In Table 2 also shows the ML algorithm types that has been used by previous researcher works to analyse a EMG signal. Overall, SVM, KNN and LDA are most popular ML algorithm that used in diagnosis of EMG signal especially for upper limbs of our body. Apart from the algorithm, Table 2 also shows the data types used to implement the ML algorithm. SVM, KNN and LDA classifier are the most used for hand movement activity with the best accuracy compare to the other classifiers.

6.0 CONCLUSION

In this paper have been reviewed on the ML methods applied to healthcare application based on Electromyography (EMG) signals. The paper also go through the mathematical formula to decribe the ML algorithms. ML is one of the artificial intelligence that make the decisions to achieve the objective.ML algorithm is useful for identifiying patterns in observed data, build models and predict things without having explicit programmed rules and models. The learning model can be any classifier such as a KNN, LDA, NB and SVM. In this review revealed that SVM, KNN and LDA are most popular ML algorithm that used in diagnosis of EMG signal especially for upper limbs of our body because mostly the accuracy for the respective classifier shows that more than 80 to 90% accurate results.

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