International Journal of Membrane Science and Technology, 2023, Vol. 10, No. 1, pp 801-811

Machine Learning Technique to Classify EMG Signal for Diabetes Person

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Abstract: Diabetes can cause a disease known as diabetic peripheral neuropathy (DPN), which affects the blood vessels and nerves in the legs and feet. This condition can result in plantar foot ulcers and muscular weakness. Detecting DPN early stage is crucial so patients can receive early treatment before their disease worsens. Most technology that detects this disease is usually expensive, like an Electromyography machine (EMG). But, with the increasing popularity of machine learning classification in the health sciences, DPN can be identified early by producing a low-cost equipment. This study aimed to develop a low-cost surface EMG (sEMG) system to detect electrical activity in the lower limb muscles and classify healthy and diabetic subjects during muscle fatigue using K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN) as two methods of machine learning technique. This study used Muscle Sensor V3 as sEMG to record the signal and extract using time domain feature extraction before classification. In KNN, 1–10 values (K) are used, while in ANN, 1–10 values of the number of hidden neurons are used to compare the classification performance. The result shows that ANN is suitable compared to KNN with the method used in this study. ANN algorithm performs better using four hidden neurons with an accuracy of 100% for the training and testing process. The study can conclude that this low-cost sEMG system, with the help of ANN, can effectively classify two subjects (healthy and diabetic) according to the EMG data obtained. This system can help to identify any diabetes neuropathy at an early stage and able to prevent lower limb complications related to the disease.

Keywords: Electromyography, Diabetic Neuropathy, Machine Learning, Classification.

1. INTRODUCTION

Diabetes is one of the chronic diseases with the highest growth rate [1]. DPN is a serious condition that affects up to half of the patients with diabetes [2]. Plantar foot ulcers, decreased muscle volume, and loss of motor units are serious consequences of DPN [3]. This disease may also affect the peripheral nervous system's ability to transmit nerve impulses to various body parts to control skeletal muscle function. Therefore, DPN must detected early stage so that people who have diabetes can enhance their life quality via exercise and diet changes [4].

Electromyography (EMG) has been established as the standard gold test for detecting DPN and determining its severity [5]. EMG is a technique used to assess muscle condition by recording and analysing electrical activity from skeletal muscles. Electrical activity originates from the stimulation of nerve cells called motor neurons that cause muscles to contract or tighten. EMG uses electrodes to record this electrical activity to translate these signals into graphs, sounds, or numerical values. The signals produced by EMG can provide information about muscle strength and weakness [6]. However, the disadvantages of EMG are the difficulty of processing data and the expense of the equipment [7].

More recently, low-cost EMG devices have been available to develop simple electrical sEMGs (such as muscle V3 sensors) that can record biological signals. Examples of research into this topic include that conducted by Toro et al.[8], investigated where to create a cheap sEMG device to detect fatigue signs. The authors used an inexpensive EMG sensor and Arduino board to collect data on EMG activity. Successful detection of muscular fatigue at a cheap cost has been demonstrated in the study.

However, the EMG signal produced by a healthy individual differs from that produced by someone with muscle fiber or nerve group damage. Therefore, it is challenging to distinguish the signals from the naked eye, as they look almost identical [9]. According to this challenge, classification techniques are one of the appropriate alternatives [10].

Moreover, the rapid development of classification techniques based on machine learning in the health science industry makes the process of DPN detection in its early phase very simple.

Machine Learning is a scientific and systematic field investigating the development, analysis, and use of general-purpose algorithms that can learn from model datasets. These algorithms function by simulating a model utilising input dataset known as example sets or test sets and then employing the model's outputs to generate additional forecasts, predictions, or judgments in various application areas [11].

In this study, machine learning was used to develop a low-cost sEMG system to identify neuropathy in diabetic patients at an early stage. Due to the prevalence of machine learning, ANN and KNN are used in the classification; in this study, both are used to compare the classification performance of the methods used. The classification performance uses data recorded and extracted from healthy and diabetic participants as input to the classification dataset.

2. PREVIOUS STUDY

Five feature were extracted from the EMG signal and classified using an ANN in a study to improve pattern detection accuracy [12]. The result found that ANN-based individual authentication had an 81.6% success rate. Similarly, Anjaneya et al. [13] employed a neural network to classify data using frequency and time domains which are waveform length, zero crossing, root mean square, EMG variance, amplitude, mean absolute value, and Williams's amplitude. This method was implemented using the MATLAB environment, and results from a simulation analysis demonstrated that the suggested method has a success rate of 97.05%.

Ahmed et al. conducted studies to differentiate between patients with neuromuscular diseases and healthy ones using EMG signals and ANN [9]. With the help of MATLAB, an ANN was developed that could identify between patients and healthy individuals with accuracy 85%.

Saxena et al. [14] created a KNN-based MATLAB program to diagnose Diabetes Mellitus. Results were analysed for various values of K (3 and 5), which represented the number of nearest neighbors. The result showed that the accuracy and error rates would grow as the value of k increased. This result also similar in [15] to predict diabetes mellitus using PIMA diabetic dataset. To improve classification accuracy using amalgam KNN, this research seeks to determine the optimal value of k for PIDD. For larger k values, the suggested model achieved a 97.4% classification accuracy. A higher k value in ten-fold cross-validation improves PIDD classification accuracy.

Since ANN and KNN show good performance in the pattern recognition and classification results, in this study, these two algorithms were used to compare which algorithm is suitable to be used in this study in classifying diabetic and healthy subjects.

3. METHODOLOGY

A. Block Diagram

The study's setup is shown in a block diagram (see Fig.1) for a more systematic approach. Initially, the EMG signal generated by the contraction (dorsiflexion) was collected using an electrode placed on the anterior tibialis muscles. Then, the detected signal is amplified, rectified, and smoothed by muscle sensor V3[16], [17]. Then, the signal was transformed into a digital signal using Arduino before being sent to the computer for feature extraction. The feature extraction process extracts an adequate number for an easy classification process. After the feature extraction, classification is performed using KNN and ANN algorithms. The EMG signal was analysed and classified into one of two classes, either diabetic or healthy.

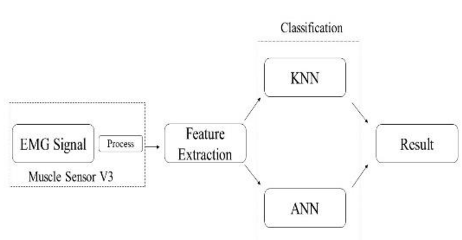

Fig. 1 Block diagram of the study

B. Subjects

Due to the ongoing outbreak of Coronavirus illness (COVID-19), the community remains on high alert. In addition, the limited time made it difficult to identify many more individuals who met the required criteria.

The inclusion criteria subjects in this study were diabetics and healthy participants, and males and females between the ages of 18 and 65.

The subjects with significant muscle atrophy in lower limbs, legs with (gout, ulcer and impairment), Parkinson's disease, stroke, and peripheral nervous system history were among the exclusion criteria for participants with poor general health. The exclusion is made because it could affect actual signal diabetes disease when recording electromyographic activity [18].

Forty volunteer subjects were enrolled: twenty non-diabetic individuals served as the healthy control group 51.7 ± 6.3 years and twenty people with diabetes aged 63.8 ± 8.1 years. The duration for someone has diabetes is 15.1 ± 12.1 years. The samples are from the community directly in the Kemaman district, Terengganu.

C. Hardware Component

- Musle Sensor V3

Muscle Sensor V3, as in Fig. 2, functions as EMG to detect muscle contracts' electrical potentials. The rectifier, analogue filter, instrumentation amplifier and end amplifier are the key component of the circuit in the sensor [19]. Firstly, the sensor detects the signal and then is amplified and converted to transform from a complicated muscle electrical activity (analog signal) into a digital signal. The signal transform into a form that can be read by a microcontroller's analog-to-digital converter (ADC) [20].

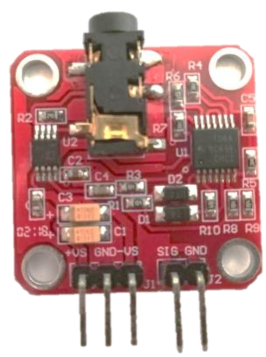

Fig 2. Muscle sensor v3

- Arduino UNO

Arduino boards as in Fig. 3 built with an Atmel microcontroller (ATmega328P) inside have an ADC. ADC allows for the reading of a wide variety of analog input data. In this study Arduino that was interfaced with the output of a muscle sensor v3 to transformed analog-to-digital signal [21]. The signal was then transferred to excel and been uploaded to MATLAB for extraction and classification [22].

Fig 3. Arduino UNO

- Electrode Pads

EMG signals from human muscles are recorded using electrode pads, as in Fig.4 [23]. The electrodes come in three colours: red colour as the ground, yellow colour as the reference point, and green colour as EMG signals [24]. Electrode location on muscles is optimised according to recommendations made by the SENIAM group [25], [26].

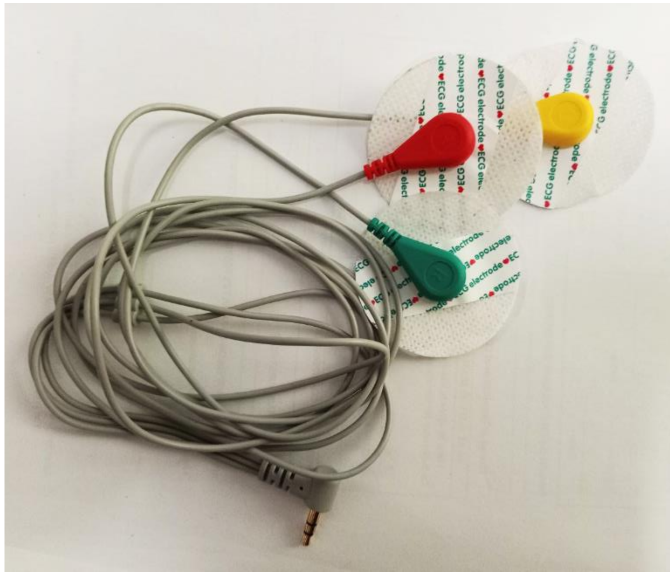

Fig 4. Electrode pads

The anterior tibialis is the muscle that is the most active in dorsiflexion because it is the muscle that is the most medially located in the lower leg; it was chosen to capture data in this study. Electrodes were placed as shown in Fig. 5; the green electrode was placed at the lateral malleolus end, and the red electrode was placed about a third of the way between the fibula distal end and the tibia's proximal end. As an inert bone, the knee was chosen to house the yellow electrode [24].

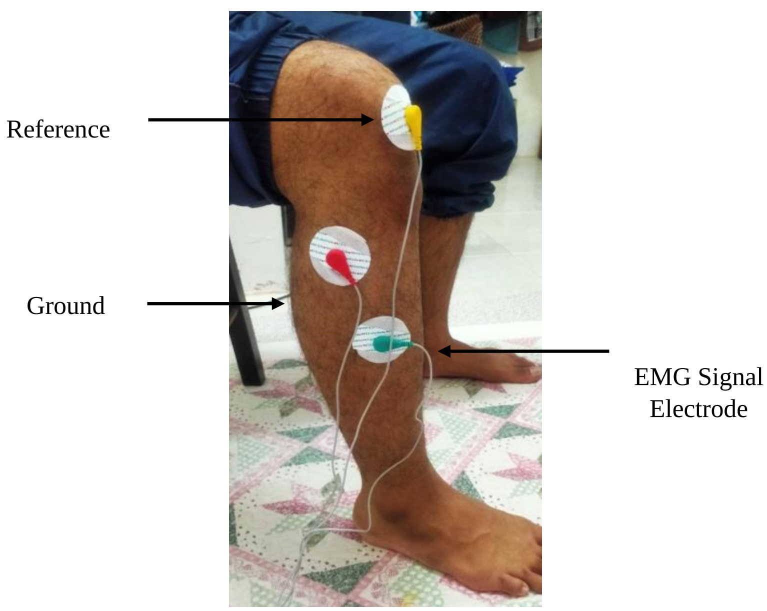

Fig 5. Electrode Location on Tibialis Anterior Muscle

D. Dorsiflexion Protocol

Fig. 6 shows subjects were asked to push their heels down on the ground while progressively bringing their toes toward their shins (dorsiflexion) and holding for one minute. The toes were held at the highest feasible height and lowered gradually to the floor after one minute.

(a) (b)

Fig 6. Condition foot; (a) Normal, (b) Dorsiflexion

E. Collection Data

Forty recordings samples were collected from each of the 40 participants. But, 40 samples are may not be sufficient for to classification problem especially for ANN [27], [28].

Therefore, the sample through a synthetic data procedure before feature extraction after being loaded into the Matlab workspace for classification.

F. Synthetic Data

The signal-to-noise ratio (SNR) must be carefully selected to reflect the original accurately. The noise will affect the signal's characteristics if the SNR is low enough [29]. Thus, 30 dB SNR was chosen because of these factors.

Noise voltage (Vattn) is the dB attenuated voltage from the SNR, and the noise array (Vnoise) was formed by multiplying random white Gaussian noise (Wnoise). In the former, the SNR dB input was used to calculate the noise voltage [30].

Vsynt, the synthetic EEG, was derived by combining the original EEG (VEEG) with the generated noise (Vnoise). The relationship is defined by (Eq. 1) and (Eq. 2).

$$V_{noise} = W_{noise} \, \mathrm{X} \, V_{attn} \qquad (1)$$

$$Vsynt = V_{EMG} + V_{noise} \qquad (2)$$

Synthetic data is data that has been created in a computer rather than collected from the physical world. Synthetic data is frequently used to train machine learning models when collected data is unavailable or difficult to collect. The actual data is used to generate synthetic data to overcome its inherent limitations. According to [31], white Gaussian noise was employed for the technique. For each sample data, the synthetic data is reproduced twice. Hence, the actual 40 samples generate 80 synthetic data, totaling 120 samples for the classification algorithm (40 actual and 80 synthetics).

G. Feature Extraction

Through feature extraction, EMG signal data is converted into a form that may be used to implement numerical features while still maintaining the quality of the original data set. The highest classification accuracy was found when time-domain properties were chosen as the best features for EMG and EOG [32]. Variance, Mean Absolute Value, Standard Deviation, and Root Mean Square are the most often used features for the time domain, which were applied in this study [33].

The formulas used to calculate the features are shown below:

N is the sample data length and Xn is the value for each data

a. Mean Absolute Value (MAV) [34]: In most cases, the rectified moving average and the mean absolute value are very similar to one another. An equation (Eq. 3) can be written as follows:

$$MAV\ (\bar{x}) = \frac{1}{N}\sum_{n=1}^{N} x_n \tag{3}$$

b. Root Mean Square (RMS) [34]: The root mean square of the sample can process as Eq. (4):

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \tag{4}$$

c. Variance (VAR) [34]: When calculating the variance, first square the signal and then divide it by the mean, as shown in Eq. (5):

$$VAR = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \bar{x})^2 \tag{5}$$

d. Standard Deviation (SD) [34]: The formula for calculating the standard deviation is in Eq. (6) below. It involves taking the square root of the variance.

$$SD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(x_n - \bar{x})^2} \tag{6}$$

H. Classification Machine Learning

In this study, 20% for testing and 80% for training were sufficient for the analysis [81]. Typically, the data used for testing were referred to as the validation data set [35]. Input data is four input features (MAV, RMS, VAR and SD) with 120 (4x120) and the target classes (1x120), i.e. 2 (healthy) and 1 (diabetes).

The k-NN classification was performed by the function *knnclassify*. This function denotes *k* to the numbers of nearest neighbors used in the system. The algorithm applied the value of *k* was set from 1 to 10.

In this study, the ANN was trained using Feed-forward networks and the Scaled Conjugate Gradient function *trainscg*. During training, 1 to 10 hidden neurons are utilised to evaluate the classification performance of the ANN.

Accuracy was employed to measure the performance of algorithms since they are more prevalent in the medical profession [15]. The calculation of accuracy requires a confusion matrix. The actual class in the confusion matrix is the class established by angiography and exists in the dataset. The class that is predicted using algorithms is called the predicted class. Table 1 below shows the design of the confusion matrix.

Table 1 Confusion matrix

	Positive Predict	Negative Predict
Positive Actual	True Positive	False Positive
Negative Actual	False Negative	True Negative

According to Confusion Matrix, Accuracy are calculated as follows:

a. Accuracy [36]: To calculate accuracy, take the sum of all correctly classified samples (true, positive and negative) and divide it by the total number of samples as in Eq. (7).

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \qquad (7)$$

4. RESULT AND DISCUSSION

Table 2 shows the accuracy classification for training and testing for ANN and KNN. The ANN model showed the best performance compared to the KNN model.

The work presents highly effective processing referring to the method in the previous studies, including feature selection to classify EMG data-based interfaces. In this study, feature extraction is used as input to a more accurate classifier, as used by previous studies [12]. This shows the importance of choosing the input variable when creating a classifier [37].

Table 2 (a) show the k-value trained between 1 and 10 to obtain the best possible. 100% training and testing result when value k=1. The accuracy decreases whenever that value of k is increased. When k is set to 1, the nearest neighbour of each sample is itself. Consequently, the prediction relies on the category of the input sample. However, setting k = 1 is not advised since it leads to overfitting, when the model simply memorises the training data but fails to perform well when applied to new data it has not previously seen [38]. A different result in another study used KNN classification, Gupta et al. examined a prediction model to determine whether a given individual has diabetes [39]. All possible k values between 1 and 60 are explored. According to the studies conducted, the optimal value of K is 45. Mangathayaru et al. also found that k=13 shows a high accuracy whenever used KNN for classification [40]. The previous study showed large values of k provide a better result. This indicates that the KNN classifier is incompatible with classifying EMG data's time-domain features due to its inconsistent performance, making the KNN classifier unable to classify correctly [41]. In short, this means the KNN is unsuitable for this study method.

Table 2 (b) demonstrates that the ANN classifier achieves good performance, with 100% for training and testing accuracy with four hidden neurons. The results indicated that the best number of hidden neurons for a given network's performance lies between a small value and a large value [42]. More neuron units than necessary might slow down the network and adversely impact backpropagation [43]. If it just contains a few hidden neurons, it is possible to make significant training errors due to underfitting. On the other hand, overfitting can significantly increase training errors if it contains many hidden neurons [44]. Table 3 shows the confusion matrix for the ANN used to classify diabetes and healthy classes using four hidden neurons.

Table 2 Comparison accuracy for (a) KNN and (b) ANN

(a)

K	Train (%)	Test (%)
1	100	100
2	95	100
3	96	95
4	91	90
5	91	95
6	91	90
7	91	90
8	86	80
9	86	80
10	85	80

(b)

N	Train (%)	Test (%)
1	95	95
2	99	95
3	100	98
4	100	100
5	100	98
6	98	95
7	97	95
8	96	95
9	98	95
10	96	95

Table 3 The result of the confusion matrix for ANN with 100% accuracy (a) Training and (b) Testing

(a)

Class	Healthy	Diabetes
Healthy	50	0
Diabetes	0	46

(b)

Class	Healthy	Diabetes
Healthy	10	0
Diabetes	0	14

This indicates that the ANN performs better in complex input data with more features than KNN. For example, many input-output patterns in the real world are non-linear and complex; hence ANN's ability to train and simulate such patterns is helpful. Moreover, the weight of an ANN may be fine-tuned after each change using backpropagation, leading to greater precision [45]. In this study, the classification training uses the *'trainscg'* function to optimise weights and biases using a scaled conjugate gradient in one of the methods to get better performance and results. The research conducted by Khadse et al. shows that scaled conjugate gradient backpropagation is better than other backpropagation algorithms in terms of performance and accuracy [46].

Table 3 show the comparison from previous study and this study result.

Table 3 Comparison result of previous study to this study

Author	Method	Accuracy
Saxena et al. [14]	KNN	75.00%
Ahmed et al.[9]	ANN	85.00%
Shin et al.[12]	ANN	81.60%
Anjaneya et al.[13]	ANN	97.05%
Nirmaladevi et al. [15]	KNN	97.60%
This study	ANN	100.00%

5. CONCLUSION AND RECOMMENDATION

This study has successfully distinguished healthy and diabetic groups using machine learning techniques. In addition, ANN shows good performance in classification in combined feature extraction. Therefore, the results of this study suggest that ANN is a useful method to differentiate between healthy and diabetic subjects. It may also help develop low-cost sEMG systems for the early diagnosis of neuropathy in diabetes patients.

However, more samples need to be tested for further studies to validate this model. A more accurate system can be obtained with a higher sample set, allowing a more accurate classification of neuropathic disease. Therefore, to increase the study sample, time, funds, and cooperation from outside parties such as hospitals are important in producing this model perfectly. For further study, this model can be upgraded with the identification feature for identifying the severity of the neurological disease.

Acknowledgement

This research was made possible thanks to funding from the Fundamental Research Grant Scheme (Code: Q017)) administered by the Research Management Centre at Universiti Tun Hussein Onn Malaysia.

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DOI: https://doi.org/10.15379/ijmst.v10i1.2665