Classification of Electromyography Signal of Diabetes using Artificial Neural Networks

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***Abstract*—Diabetes is one of the most chronic diseases, with an increasing number of sufferers yearly. It can lead to several serious complications, including diabetic peripheral neuropathy (DPN). DPN must be recognized early to receive appropriate treatment and prevent disease exacerbation. However, due to the rapid development of machine learning classification, like in the health science sector, it is very easy to identify DPN in the early stages. Therefore, the aim of this study is to develop a new method for detecting neuropathy based on the myoelectric signal among diabetes patients at a low cost with utilizing one of the machine learning techniques, the artificial neural network (ANN). To that aim, muscle sensor V3 is used to record the activity of the anterior tibialis muscle. Then, the representative time domain features which is mean absolute value (MAV), root mean square (RMS), variance (VAR), and standard deviation (SD) used to evaluate fatigue. During neural network training, a different number of hidden neurons were used, and it was found that using seven hidden neurons showed a high accuracy of 98.6%. Thus, this work indicates the potential of a low-cost system for classifying healthy and diabetic individuals using an ANN algorithm.**

***Keywords*—Electromyography; diabetic neuropathy; classification; machine learning; artificial neural networks**

I. Introduction

According to the statistics, diabetes is one of the most common chronic diseases, with an increase in patients yearly [1]. It can lead to many serious complications, including diabetic peripheral neuropathy (DPN), a neuromuscular disease affecting up to half of all people with diabetes [2]. DPN can damage the nerves and blood vessels in the feet and legs, resulting in plantar foot ulcers, motor unit loss, and muscle volume reduction [3]. Furthermore, the peripheral nervous system, which transports currents to specific areas of the body to control muscle activity, will be disrupted by this disease. Early identification of DPN is important for people with diabetes to maintain a high quality of life by adopting a healthy lifestyle, such as eating healthy food, being active every day, and stopping smoking [4].

Electromyography (EMG) has been designed as the standard gold examination to diagnose DPN and determine nerve distribution and severity [5]. Some disadvantages of EMG include the complexity of data processing and the expense of the equipment [6]. Not many hospitals routinely do EMG analysis because commercially available equipment costs range from € 15.000 to € 20.000 [7].

Today, inexpensive and simple electrical sEMG (such as muscle sensor V3) can capture biological signals, resulting in affordable EMG equipment. As an example, Toro et al.[8], study to design of a low-cost sEMG system that allows for assessing when fatigue appears in a muscle. The author used low-cost sEMG sensors, an Arduino board, and a PC. The study proves the feasibility of a low-cost system to detect muscle fatigue reliably.

Meanwhile, the EMG signals generated by a healthy person differ from those generated by an individual with damaged muscle fibre or nerve groups. However, it is nearly impossible to discern the signals with the naked eye because they appear almost identical [9]. Classification techniques are one of the suitable alternative solutions for this problem in analysis and decision-making [10]. Automated EMG evaluation using artificial neural networks (ANNs) has become increasingly common in recent years due to the ability of these networks to analyze large amounts of multidimensional data and the strong capabilities of these networks for field recognition and classification [11].

An artificial neural network is a supervised classification technique replicating biological neurons' connection structure [12]. It comprises many interconnected neurons working together to solve problems [13].

In this study, the ANN algorithm used develops a new method for detecting neuropathy among diabetes patients at a low cost. The performance of this system is evaluated by taking actual signals from non-diabetic subjects (healthy) and diabetics. However, due to time constraints in finding suitable subjects, this study uses an increasingly popular way to overcome the issues of data availability is to use synthetic data [14]–[16]. The synthetic data was implemented by adding random noise to the original signals [17].

II. Related Work

Researchers have compared the performance of the k-nearest neighbors algorithm (KNN) and ANN to classify and diagnose diseases [18]. Compared to KNN, ANN produces variable outcomes, but ANN has a higher accuracy of 80.86% compared to KNN accuracy is 77.24%.

In [19], an EMG signal-based authentication algorithm is proposed to compensate for personal certification methods' weaknesses. The pattern identification rates for the SVM and KNN algorithms were 90%. However, the results for personal authentication were just 64%. However, individual authentication using ANN demonstrated a relatively high accuracy of 81.6%.

In [20] study compares a Support Vector Machine (SVM) to a hybrid of SVM and the ANN system as the best binary classification system for determining who has diabetes. The accuracy determined using an SVM was 77%, and when applying the ANN system, the accuracy was 87%. The results of this study show that this model, which is a mix of the SVM and the ANN, is more accurate than the SVM model.

Berina et al. [21] use machine learning techniques in the classification of diabetes and cardiovascular diseases (CVD) using Artificial Neural Networks (ANNs) and Bayesian Networks (BNs). ANN shows a greater chance of obtaining more precise results regarding the classification of CVD and diabetes. The author [22] employs artificial neural networks to determine a person's likelihood of having diabetes. The accuracy of predicting whether a person has diabetes was 87.3% after training the ANN model, which resulted in an average error function of the neural network of 0.01 and this value.

Previous studies have shown that ANNs perform well compared to other neural networks. In this study, ANN is trained with Scaled Conjugate Gradient (SCG) to perform better with a high accuracy percentage. One advantage of SCG is that it requires less time because it avoids computationally expensive linear searches [23].

III. METHODOLOGY

A. Subject

Twenty volunteer subjects were enrolled: ten healthy control (non-diabetes) subjects aged (mean ± SD) 61.9 ± 6.5 years and ten diabetes subjects aged (mean ± SD) 64.1 ± 8.3 years with duration of diabetes (mean ± SD) 17.1 ± 12.1 years. The data of subjects are shown in Table I.

The inclusion criteria were non-diabetics (healthy), and diabetic subjects were male and female gender and aged 18 to 65. In this study, the exclusion criteria for subjects with a bad general health state were; stroke, Parkinson's disease, legs with (ulcer, gout, and disability), peripheral nervous system history, and severe muscular atrophy in lower limbs because that could interfere with electromyographic recording activity [24], [25].

TABLE I. DEMOGRAPHIC DATA FOR THE SUBJECTS

	Healthy	**Diabetics**
Male/Female	5/5	5/5
Age (Years)	61.9 ± 6.5	64.1 ± 8.3
BMI (kg/m^2)	26.2	29.9
Duration of Diabetes (Years)	-	17.1 ± 12.1
HbA1c (%)	-	9.7

B. Low Cost Hardware Implementation

- Muscle Sensor V3

Fig. 1 shows the Muscle Sensor V3 that is used to record electrical potentials produced by contracting muscles. This sensor process the raw signal when records because its sequence is constructed of an instrumentation amplifier, rectifier, analog filter circuits, and an end amplifier circuit [26]. After recording the signal, the sensor amplifies and processes the complex electrical activity of a muscle before converting it to a simple analog signal that is easily read by a microcontroller Arduino) to convert it into a digital signal [27].

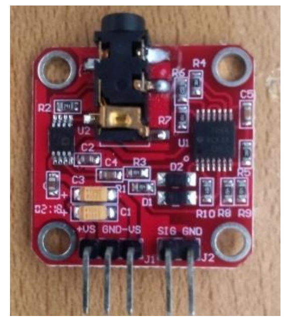


Fig. 1. Muscle Sensor v3.

- Electrode Pads

Gel electrodes are used with muscle sensor v3 to capture data. The electrode is replaced when to record for another subjects, to get the higher quality EMG signal, maintain cleanliness, and prevent the spreading of infectious diseases. This electrode has three colors, red, green and yellow as in Fig. 2, —the red electrode is (ground), the yellow electrode (reference) and the green color electrode is (the EMG signal electrode) [28].

Fig. 2. Ag/AgCl Disposable Electrode.

- Arduino Uno

Fig. 3 shows Arduino UNO with ATmega328P-based microcontroller board. It contains 14 input/output digital pins (of which six can be used as PWM outputs). Arduino UNO is used to convert analog to digital output due to the signal produced by muscle sensor v3. Muscle sensor v3 output was interfaced with an Arduino UNO microcontroller to record the signal on a laptop operating in battery mode for signal processing and classification [29]. Data will save and upload to Matlab workspace for extraction and classification [30].

Fig. 3. Arduino Uno.

C. Electrode Location

The placement of muscle EMG electrodes on muscles is based on the SENIAM (Surface Electromyography for the Non-Invasive Assessment of Muscles) group guideline [32], [33]. The anterior tibialis muscle was selected to record the data because it is the most medial muscle in the lower leg and the strongest dorsiflexor movement of the leg. As in Fig. 4, the electrode is located on the anterior tibialis muscle at 1/3 of the distance between the end of the fibula and the end of the medial malleolus. Yellow electrode placed on an inactive body section, such as the bony portion, in this study is attached to the knee. Before placing electrodes, the skin's surface must be cleaned to lower its resistance.

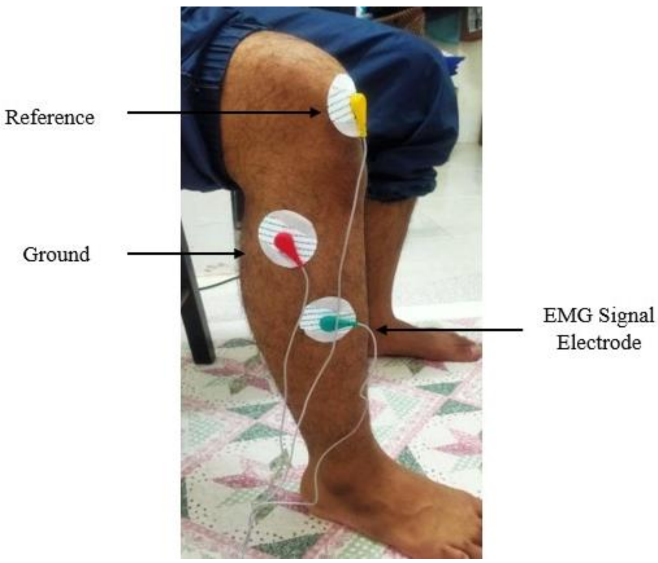
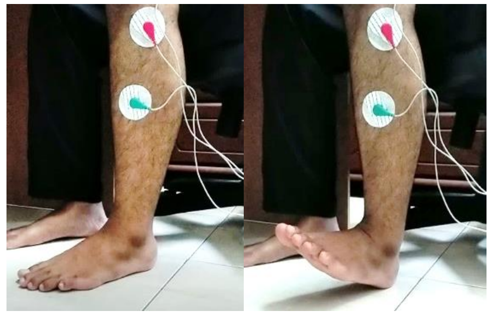


Fig. 4. Electrode Location on Tibialis Anterior Muscle.

D. Experiment Procedure

The subject is sitting on the chair and at rest for a period of five minutes after electrode placements. After five minutes, the subject is asked to slowly lift the toes and the forefoot towards the shin, digging the heel into the floor (dorsiflexion). The toes will be raised as high as they can for one minute (hold) and then slowly lower to the floor, as in Fig. 5. This method makes TA muscle contraction while minimizing the subject's movement without requiring the subject to walk.



(a) (b)

Fig. 5. Normal Foot Position on the Floor, (b) Foot Position During Dorsiflexion.

E. Data Collection

EMG signals were obtained from 20 subjects of different gender and ages. A total of 20 recordings samples were taken from every 20 subjects. Then, the EMG data load to Matlab workspace for synthetic data process before feature extraction. The synthetic data is repeated four times for each original sample. As a result, the original 20 samples produce 80 synthetic data and make the total for the classification procedure 100 samples (20 original and 80 synthetics).

F. Feature Extraction

The most common features for the time domain are Root Mean Square (RMS), Mean Absolute Value (MAV), Standard Deviation (STD), and Variance (VAR), which were used for this study [31]–[33]. This makes 100 samples of data divided into four characteristics for classification input (4x100).

The equations are used to determine the value of the features:

Mean Absolute Value (MAV) [34]: The mean absolute value and the moving average rectified value (ARV) are probably similar. Expression is given below.

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

Root Mean Square (RMS) [34]: This is a measurement of the square root of the input signal, expressed as:

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \quad (2)$$

Variance (VAR) [34]: If the variable signal is squared and then divided by the mean value, then the variance is identified, which is stated as:

$$VAR = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \bar{x})^2 \quad (3)$$

Standard Deviation (SD) [34]: Using the following expression, the threshold level of muscular contraction activity is determined:

$$SD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(x_n - \bar{x})^2} \quad (4)$$

N represents the data length for each feature, while x_n represents the EMG signal in a segment or the value for each feature.

G. Classification

The classification used Matlab (nprtool) to solve a pattern-recognition classification problem. In this tool, an input layer, hidden layers, and an output layer make up a feedforward neural network. Scaled backpropagation of the conjugate gradient (trainscg) used to train the network. This study used default settings and parameters bt Matlab because possible to set the parameters and settings manually except for the number of hidden neurons.

A feedforward neural network load with the sample data (4x100) as inputs and binary numbers 10 for healthy and 01 for people with diabetes as outputs (2x100). At the same time, different hidden layers and training functions were tested as affected factors were tested with (1-10) hidden neurons.

ANN requires three data sets for the inputs and outputs of the system: training, validation, and testing. It required 30% (15 % for validation and 15% for testing), leaving 70 % for training. 100 samples were divided into 70 samples for training, 15 for testing, and 15 for validations.

IV. Result and Discussion

This section discusses the evaluation of the results and performance of the proposed model. An ANN was created to distinguish between diabetics and healthy subjects using Matlab. After training, the network gives a confusion matrix to indicate the correctness network. The confusion matrix is constructed to compare classification during the training, testing, and validation processes.

The confusion matrix provides details about the distribution for each output class, and then it uses color coding: green for accurate classification and red for inaccurate classification. Four confusion matrices are shown, one for each stage, namely the training, validation, testing processes, and overall classification, as shown in Fig. 6.

Fig. 6. Result from the Confusion Matrix.

The performance of ANN is tested with the different number of hidden neurons (1-10) used during training. Matlab nnstart toolbox was utilized during training and development of the neural network. Based on the results, using seven hidden neurons shows the highest overall accuracy archive with 98.6% as shown in Table II.

TABLE II. Classification Performance of Diabetics and Healthy Subjects

No Hidden Layer	Training (%)	Testing (%)	Validation (%)	Overall (%)
1	92.9	95.2	76.2	90.7
2	92.9	90.5	100	93.6
3	85.7	85.7	90.5	86.4
4	94.9	85.7	81.0	91.4
5	96.9	100	95.2	97.1
6	94.9	81.0	85.7	91.4
7	99.0	95.2	100	98.6
8	94.9	90.5	90.5	93.6
9	93.9	100	100	95.7
10	91.8	85.7	81.0	89.3

The result showed that the number of hidden neurons was significant in characterizing the network's performance, which should not be too large or too small [35]. If there are more hidden units than needed, the network may not work well because it will take longer to process everything, affecting backpropagation in the long run. If less than the required number of hidden units is made, some information may lose, and the prediction may not be right [36].

The obtained network will be less complex since the number of neurons in hidden layers is fixed correctly without any least significant neurons. It will be more accurate because backpropagation is used to adjust the weight after each change is made to the network [37]. With the help of the backpropagation algorithm, the network with the best training gives the best results. Besides, the selection of scaled conjugate gradient backpropagation technique also helps the best result. In [38] study results prove that scaled conjugate gradient backpropagation is the most effective choice than other backpropagation algorithms that give high accuracy.

Table III shows performance comparison between this study and other works. This comparison is based on the study that does the classification signal from the self-study data collection on diabetic or neuropathy patients.

TABLE III. A Comparison between this Study and Previous

Reference	Classifier Method	Accuracy
Ahmed et al [9]	SVM ANN	70% 85%
Yousfat et al. [39]	-	93%
Bhusari et al. [32]	KNN	70%
This Study	ANN	98.6%

V. Conclusion and Recommendation

This paper shows the performance of low-cost EMG acquisition boards using artificial neural networks (ANN) in proposing an approach for detecting diabetes neuropathy. Based on the results, the highest accuracy is 98.6% when trained with the SCG algorithm. According to the recorded EMG data, the ANN is an effective way to classify these two classes of subjects. This system can assist in the correct initial detection of diabetic neuropathy so that appropriate treatment will be given.

For future work, with more time and funds, more samples can be measured for model validation. With a larger sample size, a more accurate system is likely to be studied, thus allowing higher accuracy in classifying neuropathic pain to be carried out. High accuracy results also indicate opportunities to develop a system not only to know neuropathy pain but also to know the severity of neuropathy faced by diabetic patients.

Acknowledgment

This work was supported by the Research Management Centre UTHM, Malaysia under the Fundamental Research Grant Scheme (TIER 1 (Grant Code: Q017)).

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