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A HYBRID ELM-WAVELET TECHNIQUE FOR THE CLASSIFICATION AND DIAGNOSIS OF NEUROMUSCULAR DISORDER USING EMG SIGNAL

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ABSTRACT

Electromyogram (EMG) signal classification plays a major role in the diagnosis of neuromuscular disorder. The Motor Unit Action Potentials (MUAPs) in an electromyographic signal is one, which offers a significant source of information to evaluate the neuromuscular disorders. Neuromuscular diseases are the one that affect the control of muscular and nervous system. The proposed method employs a technique called Extreme Learning Machine (ELM) for the classification of EMG signal into healthy, myopathy or neuropathy. Discrete Wavelet Transform (DWT) / Wavelet Packet Transform (WPT) are the methods used for feature extraction individually. The performance of ELM together with DWT (ELM-DWT) and ELM with WPT (ELM-WPT) are compared with each other and it is found that the time complexity and number of feature vectors in ELM-WPT is reduced. The number of features is minimal in ELM-WPT compared with the ELM-DWT. The performance of ELM is evaluated using the confusion matrix and in terms of specificity, sensitivity, computational time and classification accuracy. The learning phase of ELM is completed in less than a second. The classification accuracy of ELM-WPT is 100%. The obtained result indicates that proposed ELM is very effective in the diagnosis of neuromuscular disorders.

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KEY WORDS

Electromyogram (EMG); Motor Unit Action Potentials (MUAPs); Extreme Learning Machine (ELM); Discrete Wavelet Transform (DWT); Wavelet Packet Transform (WPT).

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INTRODUCTION

The human skeletal muscular system consists of the nervous system and the muscular system, which together form the neuromuscular system. The disorders which originate in the nervous system, in the neuromuscular junctions, and in the muscle fibers are known as neuromuscular disorders. It has different degrees of severity ranging from minor loss of strength to amputation due to neuron or muscle death [1].Proper diagnosis of the disorder is of vital importance so that more focused treatment can be administered in the early stage [2]. Electromyography (EMG) signal is used for diagnosing patients with neuromuscular disorders. Pathological changes in the structure of motor units cause neuromuscular disorders, which can be classified into muscular (myopathy) and neuronal disorders (neuropathy) [3]. In myopathic disorders, the duration and the area to amplitude ratio of the action potential is reduced whereas in case of neuropathic disorder the duration and the area to amplitude ratio of the action potential is increased. In order to compensate low amplitude in myopathic disorder, a larger number of motor units are hired at lower than the normal levels of muscular contraction. In neurogenic disorder, the excited motor neurons are decreased in number and in order to keep a certain force of contraction, the available motor neuron must fire at higher rate than normal to balance the motor neuron loss. For an effective computerized EMG signal classification, an efficient treatment of EMG signals must be carried out [4]. The principle of this diagnostic system involves extraction of features from the acquired raw EMG signal which in turn helps in the diagnosis of neuromuscular disorder [1]. In this study, statistical features of Discrete Wavelet Transform (DWT) and Wavelet Packet Transform (WPT) have been used as a comparative study to characterize the EMG signal pattern in the diagnosis of neuromuscular disorder. These statistical features give major differences between healthy, myopathic and neurogenic signals and are useful for disease classification. The extracted statistical features are used as inputs to the ELM classifier. ELM is an efficient learning algorithm which performs well in classification application. This algorithm provides excellent performance at extremely fast learning speed [5]. ELM is an extensively used learning method that is capable of directly approximating nonlinear mappings by input data and provides models for a number of natural and artificial problems [6].

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Englehart et al. [7] used the feature sets based on Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Wavelet Packet Transform (WPT) as an effective representation for EMG classification. The best performance is exhibited when using a combination of WPT, Principal Component Analysis (PCA), Linear Discrinminant Analysis (LDA), yielding an average classification error of 6.25%. Christodoulou and Pattichis [8] applied two different pattern recognition techniques for the classification of MUAPs. They compared the performance of two algorithms namely i) Artificial Neural Network (ANN) technique based on unsupervised learning, by means of a revised version of the Self-Organizing Feature Maps (SOFM) algorithm and Learning Vector Quantization (LVQ) ii) a statistical pattern recognition technique based on the Euclidean distance. It was found that the performance of ANN technique was better with the success rate of 97.6%. The advantage of this technique is that the learning is achieved in one epoch for both SOFM and LVQ algorithms. A key issue in LVQ is the choice of an appropriate measure of distance or similarity for training and classification. Subasi et al. [9] described the use of Autoregressive (AR) model with Wavelet Neural Network (WNN) to classify the EMG signals. They compared the performance of Feed forward Error Back Propagation Artificial Neural Network (FEBANN) and WNN based classifiers. The WNN performs better than FEBANN with a classification accuracy of 90.7%. The computational speed of WNN is faster when compared with Back Propagation Neural Network (BPNN). But the issue in this method is due to the unavailability of structured method to determine the optimum level of WNN factors, it is set by trial and error [10]. Katsis et al [11] proposed a novel method for the classification of MUAP's from the intramuscular EMG signals and obtained MUAPs classification accuracy of 86%. Abdulhmit Subasi [4] introduced the fuzzy based technique, ANFIS (Adaptive Neuro Fuzzy Inference System) for EMG signal classification and compared its performance with Multi Layer Perceptron Neural Network (MLPNN) and Dynamic Fuzzy Neural Network (DFNN). Among the three methods, it was reported that ANFIS performed better with an accuracy of 95%. In [1] Abdulhamit Subasi introduced PSO-SVM to improve the EMG signal classification and succeeded with the classification accuracy of 97.41%. Huang et al. [5] illustrated a new learning algorithm called Extreme Learning Machine (ELM) for Single-hidden Layer Feed forward Neural networks (SLFNs) which randomly chooses hidden nodes and analytically determines the output weights of SLFNs. Zong et al. [12] used ELM classifier to recognize the face and compared the result with that of SVM. It was reported that the recognition accuracy and training time of ELM was better than SVM with less optimization constraint. Liang et al. [13] used ELM to classify five mental tasks from different subjects using electroencephalogram (EEG) signals and compared the results with BPNN and SVM. It was found that ELM performed better than the other two techniques.

Neuromuscular disorders are those that affect the brain, spinal cord, nerves and muscles causing muscular weakness or muscle tissue wasting. During initial stages of the disease, pathological changes in the EMG signals are not much predominant which causes difficulty in the diagnosis of neuromuscular disorder. In such cases wavelet transforms can be used to characterize the localized frequency content of each MUP [4, 14, 15].

MATERIALS AND METHODS

Feature extraction methods

In the proposed method, ELM is used to classify the EMG signals as shown in Fig.1 and consists of three steps:

- The EMG signal is decomposed either using Discrete Wavelet Transform (DWT) or Wavelet Packet Transform (WPT) into different frequency bands.
- Statistical features are extracted from these sub-bands to represent each EMG signal.
- An unknown EMG signal is classified as Healthy or Myopathic or Neurogenic using the soft computing technique (ELM).

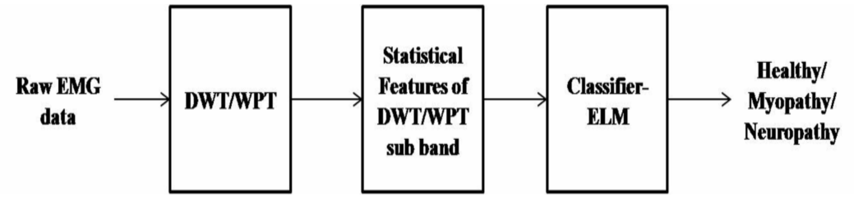

Fig: 1. Block diagram of the proposed method

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This research work makes use of 30 EMG data collected from various subjects for analysis. Fig. 2 shows a sample of healthy, neuropathy EMG data.

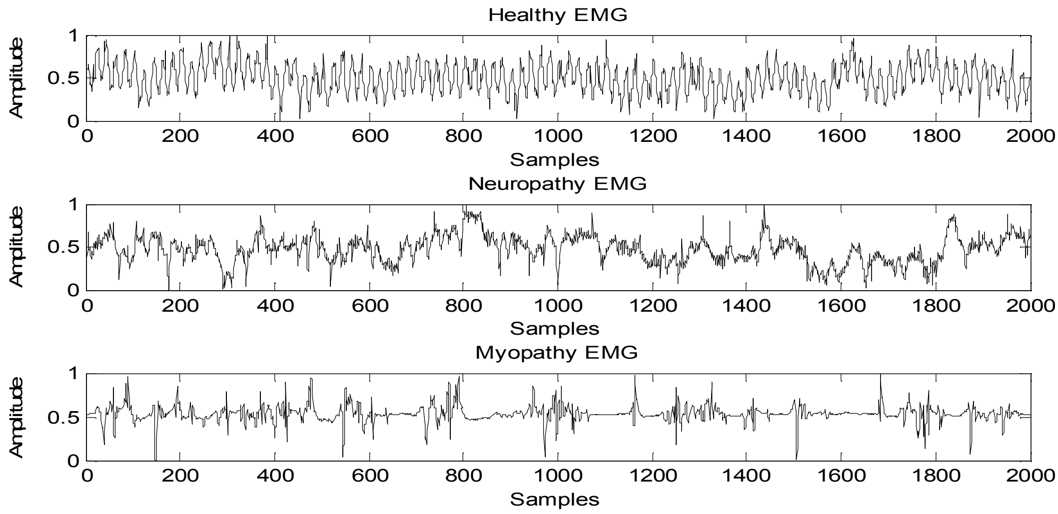

Fig: 2. Healthy, neuropathy and myopathy EMG data.

The choice of features of raw signals is very important for the accomplishment of any signal classification system. WT is one of the most capable methods to extract features from the EMG signals [4]. In this research work, WPT and DWT are used for feature extraction individually, from the EMG signal and their performances are compared with each other.

A) Feature extraction using discrete wavelet transform

The Wavelet transform (WT) is the one which provides both the time and frequency information at the same time. The wavelet transform decomposes a signal into a set of basic functions called wavelets that are obtained by dilations, contractions and shifts of an exclusive function called wavelet prototype translations [16, 17, 18, 19]. The wavelet transform in which the wavelets are sampled at discrete intervals is known as DWT [20]. As the time domain signal is passed through various high pass and low pass filters, the output of either is taken and the process is repeated. This process is known as decomposition. This continues until the signal decomposed to a pre-defined level. Thus, cluster of signals correspond to the same signal, but all related to different frequency bands. Lower and higher frequencies are better resolved in frequency and time respectively [4].

Repeated low-pass and high-pass filtering of the time domain signal results in the decomposition of the signal into different frequency bands. The down-sampled outputs of first high-pass and low-pass filters provide the detail, D1 and the approximation, A1 information respectively. The outputs of the high-pass and low-pass filters, are sub-sampled by 2. As the result of decomposition, the time resolution is halved and the frequency resolution is doubled, because the frequency band of the signal now spans only half the previous frequency band, successfully reducing the uncertainty in the frequency by half. The above procedure is also known as the sub-band coding which can be repeated for further decomposition. At each level, the filtering and sub-sampling results in half the number of samples and half the frequency band spanned. The first approximation A1 is further decomposed and this process is continued. In this research work, Daubechies 4 (DB4) wavelet filter is used for decomposition and reconstruction [4].

To represent the time-frequency distribution of the EMG signals, the following statistical features are used:

Mean values of the coefficients in each sub-band: The mean indicates the average value of a signal and is given by Equation (1)

$$\mu_{di} = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (1)$$

where x_i represents the corresponding coefficient; N denotes the total number of coefficients.

Variance of the wavelet coefficients in each sub-band: Variance indicates how far/close the data points are to the mean value of the coefficients and is computed as in Equation(2)

$$\mathrm{Var}(x_i) = E[x_i^2] - [E[x_i]]^2 \qquad (2)$$

Skewness of the coefficients in each sub-band: Skewness is a measure of extent to which the probability distribution of a real valued random variable leans to one side of the mean. The skewness value may be positive or negative and is given in Equation (3).

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$$Skewness = \mu_3 / \sigma^3 \quad (3)$$

where μ_3 is third moment about mean; σ is the standard deviation.

Entropy of the coefficients in each sub-band. Entropy is a numerical measure of the randomness of a signal. Then entropy is given by Equation (4)

$$H(X) = \sum_{i=1}^{n} p(x_i)\log_b p(x_i) \quad (4)$$

where X is the random variable with n outcomes $\{X_1, X_2, X_3, \dots, X_n\}$.

Standard Deviation of the coefficients in each sub-band: The standard deviation (σ) shows how much variation or dispersion from the average exists. A large value of σ indicates that the data points are far from the mean and a small value of σ indicates that they are clustered closely around the mean. σ is calculated using the Equation (5)

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \quad (5)$$

where μ is the mean, x_i denotes the corresponding coefficient.

Ratio of absolute mean values of adjacent sub-band: It denotes the ratio of the mean values of the adjacent sub-bands which is given by the Equation (6)

$$Ratio = \mu_{di} / \mu_{di+1} \quad (6)$$

where μ_{di} represents the absolute mean of a coefficient, μ_{di+1} is the absolute mean value of its adjacent coefficient.

Two sets of features, feature set 1(F1) and feature set 2 (F2) are used as input to ELM-DWT individually. F1 is the one, which is used in the existing method [1] .To compare the performance of the proposed method with the existing method; F1 is included in the present work. F1 comprises of features such as mean of absolute values of coefficient in each sub-band, standard deviation of the wavelet coefficient in each sub-band, ratio of absolute mean values of adjacent sub-bands and F2 comprises mean, variance, skewness and entropy of the wavelet coefficient in each sub-band.

Thus by extracting 6 different values for mean and standard deviation, 5 different values for ratio of absolute mean values of adjacent sub-band, a total of 17 features are extracted for F1. Similarly, by extracting 6 different values for mean, variance, skewness and entropy of the coefficients in each sub-band, a sum of 24 features are extracted in case of F2. These features are calculated from the frequency bands D1, D2, D3, D4, D5 and A5 of DWT and then used as input to ELM classifier.

B) Feature extraction using wavelet packet transform (WPT)

In DWT decomposition, a signal is decomposed into two frequency bands such as lower frequency band (approximation coefficients) and higher frequency band (detail coefficients) and the low frequency band is used for further decomposition, thus it gives a left recursive binary tree structure. In case of Wavelet packet Transform (WPT), a balanced binary tree structure is generated since both lower and higher frequency bands are decomposed into two sub-bands. It helps to divide the high frequency side into smaller bands which cannot be achieved by using DWT [21]. In our analysis, Daubechies 2 (db2) family of wavelet packets is implemented as the mother wavelet. As a result of 3 level decompositions, 8(2^3) feature vectors are extracted from each signal frame and are used as input to ELM classifier for the classification of the EMG signals. The feature extracted from the wavelet packet is energy feature and it is given by Equation (7)

$$E = \sum_i |x_i|^2 \quad (7)$$

where x_i denotes the wavelet packet coefficient.

Classifier- extreme learning machine

Guang-Bin Huang introduced ELM which is a Single-hidden Layer Feed forward Neural network (SLFN) with at most L hidden nodes and with almost any nonlinear activation function can exactly learn L distinct observations. SLFNs can be considered as a linear system after the input weights and the hidden layer biases are chosen randomly. The output weights (linking the hidden layer to the output layer) of SLFNs can be analytically determined through simple generalized inverse operation of the hidden layer output matrices. ELM can approximate any target continuous function and classify any disjoint regions [5]

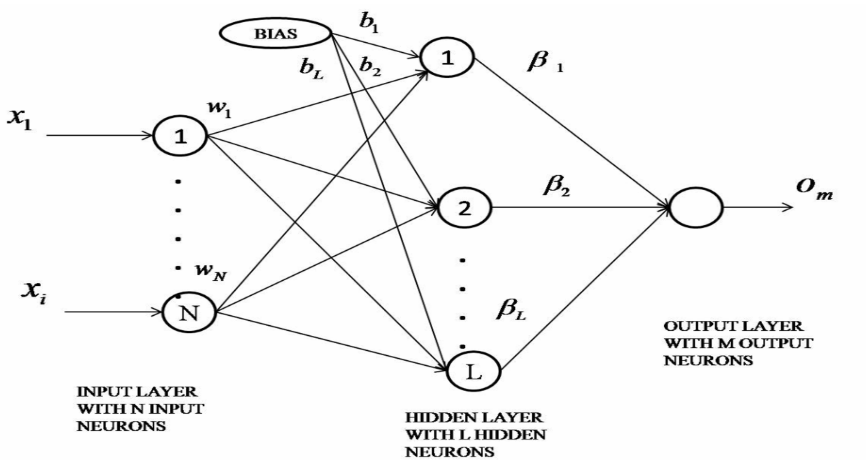

Fig: 3. ELM Architecture.

Fig: 3 shows the ELM architecture which consists of single hidden layer. The number of input neuron corresponds to the number of input features. The number of hidden neurons is equal to or greater than the input neurons. The number of output neuron is equal to the number of classes. For N arbitrary distinct samples (x_i, t_i) where $x_i = [x_{i1}, x_{i2} \ldots\ldots x_{in}]^T$ and $t_i = [t_{i1}, t_{i2} \ldots\ldots t_{in}]^T$, standard SLFNs with L hidden nodes and activation function $g(x)$ are mathematically modeled as in Equation (8)

$$\sum_{j=1}^{L} \beta_j g_j(x_i) = \sum_{j=1}^{L} \beta_j g_j(w_j . x_i + b_j) = o_j \text{ where } i=1,2, \ldots N \qquad (8)$$

Where $w_j = [w_{j1}, w_{j2} \ldots\ldots w_{jL}]^T$ is the weight vector connecting the j^{th} hidden node and the input nodes, $\beta_j = [\beta_{j1}, \beta_{j2} \ldots\ldots \beta_{jm}]^T$ is the weight vector connecting the j^{th} hidden node and the output nodes, and b_j is the threshold of the j^{th} hidden node. $wj.xi$ denotes the inner product of w_j and X_i. That standard SLFNs with L hidden nodes with activation function g(x) can approximate these N samples with zero error means

i.e., $\sum_{j}^{L} = 1 \| o_j - t_j \| = 0$ and there exist w_j and β_j such that

$$\sum_{j=1}^{L} \beta_j g(w_j . x_i + b_j) = t_j \; j = 1,2,3, \ldots L \qquad (9)$$

The Equation (9) can be written compactly as shown in Equation (10)

$$T = \beta H \qquad (10)$$

Where H, β, T are given in Equation(11), Equation (15) and Equation (16)

$$H(w_1, \ldots\ldots, w_L, b_1, \ldots\ldots, b_L, x_1, \ldots\ldots, x_N) = \begin{bmatrix} g(w_1.x_1 + b_1) & \cdots & g(w_L.x_1 + b_L) \\ \vdots & \ddots & \vdots \\ g(w_1.x_N + b_1) & \cdots & g(w_L.x_N + b_L) \end{bmatrix} \qquad (11)$$

$g(w_j, x_i, b_j)$ is the activation function and it may be Unipolar sigmoid, Bipolar sigmoid or Gaussian . H is called the hidden layer output matrix of the neural network; the j^{th} column of H is the j^{th} hidden node output with respect to inputs $x_1, x_2 \ldots\ldots x_N$ [5].

Unipolar sigmoid activation function is calculated using the formula as given in Equation (12)

$$g(w_j, x_i, b_j) = 1 / 1 + e^{(-((w_j * x_i) + b_j) * \lambda)} \qquad (12)$$

Bipolar sigmoid activation function is represented as in Equation (13)

$$g(w_j, x_i, b_j) = \frac{1 - e^{(-((w_j * x_i) + b_j) * \lambda)}}{1 + e^{(-((w_j * x_i) + b_j) * \lambda)}} \qquad (13)$$

Gaussian function is calculated using the Equation (14)

$$g(w_j, x_i, b_j) = e^{(-b_j * \| x_i - w_j \|)} \qquad (14)$$

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where λ is the learning rate whose range is 0-1.

$$\beta = \begin{bmatrix} \beta_1^T \\ \beta_2^T \\ \cdot \\ \vdots \\ \cdot \\ \beta_L^T \end{bmatrix}_{L \times m} \quad (15)$$

$$T = \begin{bmatrix} t_1^T \\ t_2^T \\ \cdot \\ \vdots \\ \cdot \\ t_N^T \end{bmatrix}_{N \times m} \quad (16)$$

RESULT AND DISCUSSION

Data acquisition

EMG data are collected from 15 healthy subjects (fourteen females and one male) with ages ranging from 22 to 42 years, 1 myopathy subject (male) with age 75 and 11 neuropathy subjects (seven males and four females) with ages ranging from 55 to 65. The signal was acquired by placing 3 electrodes on the biceps using Labview software and DAQ with a sampling rate of 1 KHz and 16 bit resolution. In addition, 1 healthy, 1 myopathy and 1 neuropathy EMG data are obtained from physionet [22].

Selection of Wavelet and level of decomposition plays a very important role in the extraction of features. In the existing method mentioned [1], four statistical features namely Mean of the absolute values of the coefficients, Average power of the wavelet coefficients in each sub-band, Standard deviation of the coefficients from each sub-band and Ratio of the absolute mean values of adjacent sub-bands were the features extracted for classification using PSO-SVM classifier and it resulted in a classification accuracy of 97.41%.

In the proposed method, ELM uses the features extracted through DWT and WPT separately for the classification of EMG signal. The performance of the methods ELM-DWT and ELM-WPT are compared with each other.

ELM-DWT

The performance of ELM-DWT is evaluated for two sets of features F1 and F2 as mentioned in section 2.1. In order to compare the proposed method with the existing method, the first feature set F1(17 features) is classified using ELM which yielded a classification accuracy of 100%.The number of feature vectors used in the proposed method is 17, whereas 23 feature vectors were used in the work mentioned in [1] . As the number of features used for classification reduces, the computational time reduces. Hence classification with limited number of features is advantageous. The performance of the proposed method is also evaluated with second feature set F2 (24 features), which again yielded a classification rate of 100%.

ELM-WPT

In this method, EMG signal is decomposed into 3 levels using Wavelet Packet Transform (WPT) with Daubechies order 2 (db2) wavelet. Thus $2^3 = 8$ numbers of packets are obtained. Wavelet packet energy feature is computed for each packet. Thus a total of 8 feature vectors have been extracted using WPT and classified using ELM which again yielded a classification accuracy of 100%.Though both methods ELM-DWT and ELM-WPT yielded a result of 100%, the latter method is computationally efficient because of its ability to classify with a limited number of features.

Theoretically the number of nodes in the hidden layer of the classifier is equal to or greater than the number of input nodes. If the number is too small, ELM may not reflect the relationship between input data and output value. On the contrary, a large number may create such a complex network that might lead to a very large output error caused by

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over-fitting of the training sample. The parameters used for ELM-DWT and ELM-WPT are shown in **Table– 1**. The activation function used in the classifier may be Unipolar sigmoid or Bipolar sigmoid or Gaussian. The activation function for which ELM yielded 100% classification accuracy is shown in **Table– 2**. From the collected EMG data, 5 data (2 healthy, 1 myopathic and 2 neurogenic) are used for training and 25 data (14 healthy, 1 myopathic and 10 neurogenic) are used for testing.

Table: 1. Parameters used in ELM

Parameter	ELM-WPT	ELM-DWT	
		Feature set 1	Feature Set 2
Number of Input node	8	17	24
Number of Hidden node	8	20	30
Number of Output node	3	3	3
Learning Rate	0.001	0.001	0.001

Table: 2. Various activation functions used in ELM

Method		Unipolar Sigmoid	Bipolar Sigmoid	Gaussian function
ELM-WPT		×	×	×
ELM-DWT	Feature Set1			×
	Feature Set2	×		

The classification accuracy of the ELM classifier is 100 % each. Irrespective of the number of training data sets, ELM performs well and guarantees an accuracy of 100%.Classification results of the ELM are visualized using confusion matrix [23]. The confusion matrix showing the classification results of ELM is shown in **Table–3**.

Table: 3. Confusion matrix of ELM classifier

Output/desired	Result (Healthy)	Result (Myopathy)	Result (Neuropathy)
Result (Healthy)	14	0	0
Result (Myopathy)	0	1	0
Result (Neuropathy)	0	0	10

DISCUSSION

The computation of the following parameters showed the test performance of ELM:

Specificity: Number of correctly classified healthy subjects/ number of total healthy subjects

Sensitivity (myopathy): Number of correctly classified subjects suffering from myopathy/number of total subjects suffering from myopathy.

Sensitivity (neuropathy): Number of correctly classified subjects suffering from neuropathy disorder/number of total subjects suffering from neuropathy disorder.

Classification accuracy: number of correctly classified subjects/ number of total subjects.

$$\text{Classification accuracy} = \sum {}^{D_c}/_{N} \qquad (17)$$

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where, Dc is the diagonal elements of the confusion matrix, N is the total number of training/testing samples. The values of these parameters are tabulated in **Table–4**. The ELM classified healthy subjects, myopathy subjects and subjects suffering from neuropathy with the accuracy of 100%. Table .4 shows the classification success rate obtained for 30 EMG recordings.

Table: 4. Comparison of ELM-WPT and ELM-DWT models for EMG signal classification

Statistical Parameters	ELM-WPT	ELM-DWT	
		Feature set 1	Feature Set 2
Computational Time (sec)	12.678	14.522	17.427
Specificity	1	1	1
Sensitivity (neuropathy)	1	1	1
Sensitivity (myopathy)	1	1	1
Classification Accuracy (%)	100	100	100

CONCLUSION

Electromyography plays an important role in clinical neurological diagnosis, to indicate the location and type of abnormality or expose disorders that are clinically uncertain. The classification of neuromuscular disorders is essential for correct diagnosis. The proposed method, Extreme Learning Machine (ELM) is a simple and effective algorithm for single-hidden layer feed forward neural networks (SLFN) which automatically classifies the EMG signal into healthy, myopathic or neuropathic. For any classification application, feature extraction is necessary and in this research work DWT, WPT are the two used individually. The proposed techniques ELM-DWT and ELM-WPT are found to be best when compared with the existing techniques in terms of classification accuracy and number of feature vectors. Among the proposed techniques, ELM-WPT excels ELM-DWT in terms of computational time and number of features. The learning speed of ELM is extremely fast. From the simulation result, it can be seen that the learning phase of ELM is completed in less than a second. The ELM appears to be suitable in applications which require fast prediction and response capability. For any type of activation function, the classification accuracy of ELM-WPT is 100%.

CONFLICT OF INTEREST

Authors declare no conflict of interest.

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