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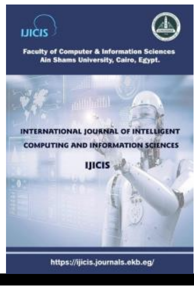

EMG SIGNAL CLASSIFICATION FOR NEUROMUSCULAR DISORDERS DIAGNOSIS USING TQWT AND BAGGING

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Abstract: *Electromyography (EMG) is a technique used to assess and record the electrical activity produced by skeletal muscles. This information can be used to diagnose muscle disorders, such as myopathy and Amyotrophic Lateral Sclerosis (ALS). In this study, we made a significant contribution to the field by proposing an automated method for classifying EMG signals that is more accurate than previous methods. Our method uses tunable-Q factor wavelet transform (TQWT) to decompose the EMG signal into its constituent components. These components are then used to calculate seven features that characterize the signal which are Interquartile Range (IQR), Mean Absolute Value (MAV), Mode, Kurtosis, Standard Deviation, Ratio of the absolute mean value , and Skewness. The features are then used to train a Bagging ensemble classifier. We evaluated our method on a dataset of EMG signals from healthy people, patients with myopathy, and patients with ALS. Our method achieved an accuracy of 99% in classifying the EMG signals. Our results suggest that the proposed method is a promising approach for diagnosing muscle disorders using EMG. This method could be used to improve the early diagnosis and treatment of these disorders.*

Keywords: *EMG signal, ALS, Myopathy, TQWT, Bagging classifier*

1. Introduction

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A depolarizing cell in human body organ can produce an electrical activity that form biomedical signals. The electrical activity generated in skeletal muscle fibers is recorded and analyzed by electromyography (EMG) technique. EMG signals have many applications in the biomedical field. Major areas of research include clinical and biomedical engineering in the area of diagnosis. An EMG is the sum of the action potentials from muscle fibers recorded using skin electrodes. The higher the EMG signal, the more action potentials are recorded and the more muscles that contract. The acquisition of the Motor Unit Action Potentials (MUAPs) in an EMG examination would provide critical information for the diagnosis of neuromuscular disorders. EMG can be used to evaluate the condition of muscles as well as the nervous system that controls them. The EMG signal is a complex signal that is dependent on the anatomical and physiological characteristics of muscles [1].

As the EMG signal travels through different tissues, it generates noise. Furthermore, if the EMG detector is placed on a particularly deep surface, it can pick up signals from different engine units, causing the signals to interact. In biomedical engineering, EMG signals have become a remarkable necessity. Until now, many studies and efforts have been made in this field to improve algorithms and develop old methodologies. Techniques for reducing noise and obtaining accurate EMG signals are also under development. Clinical settings, as well as prosthetic and rehabilitation applications, make extensive use of EMG signals [2].

EMG signals can be discovered, decomposed, processed, and classified using advanced techniques. Many software programs can collect signals from individual patients and effectively and efficiently describe the signal and its nature [3].

Finding and diagnosing neuromuscular disorders was previously difficult for their clinical counselling analysis. The skeleton muscles are composed of thousands of muscle fibers that are connected to the axon or motor neuron that generates electrical activity in the muscles.

Recent advances in signal processing and mathematical models have been used to improve EMG signal evaluation and detection. This entails the application of artificial intelligence and a variety of mathematical techniques. The parametric extraction from EMG signals is a critical step in determining the feature vector. Feature selection guides the selection of the best feature for classification, which is dependent on a number of processes. As a result, feature extraction is critical in diagnostic systems for classification. Nerve cell damage in the brain and spinal cord can cause a neurological disease (Amyotrophic Lateral Sclerosis (ALS)) which can be characterized by motor neuron disorders.

The EMG signal of this disease can be diagnosed depending on the motor unit. This motor unit is a set of motor neurons and muscle fibers. Muscle activities can be controlled by the signal transferred from the upper motor neurons in the brain to the lower motor neurons in the spinal cord [4].

Many researchers were concerned about the role of EMG in assessing muscle activity in ALS and myopathy (MYO), because ALS is commonly associated with muscle atrophy and significantly affects the neuron, causing serious damage to both the nervous and respiratory systems, whilst MYO begins to affect the skeletal fiber muscle, leading to inflammation [5-7]. Finally, the information from the classification stage is presented as control commands [8]. Classifier performance is affected by EMG variations caused by different muscle contractions, which can be controlled using machine learning techniques and feature extraction.

Oscilloscopes were traditionally used by neurophysiologists and medical professionals to access Motor Unit Action Potentials (MUAP) information from their shapes and patterns. However, MUAPs from different motor neurons overlap, creating an interference pattern that makes detecting individual MUAP shapes difficult. As a result, a number of computer-based EMG signal analysis algorithms [9] have been developed.

The success of feature extraction methods and classifiers determines classification accuracy. This is presented by the researchers in order to improve the efficacy of the extracted features used in characterizing EMG signals for classification.

We propose a bagging ensemble classifier based on the TQWT for diagnosing ALS, myopathy, and healthy EMG signals in this paper.

TQWT is applied to the EMG signal in the proposed technique, and features are extracted and used for EMG signal classification, as shown in Figure 1. To evaluate the efficiency of the classifier framework used in the classification of EMG signals, it was compared to other classifiers that use EMG signals.

The organization of the other sections is described as following: Section 2 discusses the dataset used in the implementation, while section 3 explains the methodology. Both results and conclusion are presented in sections 4 and 5 respectively.

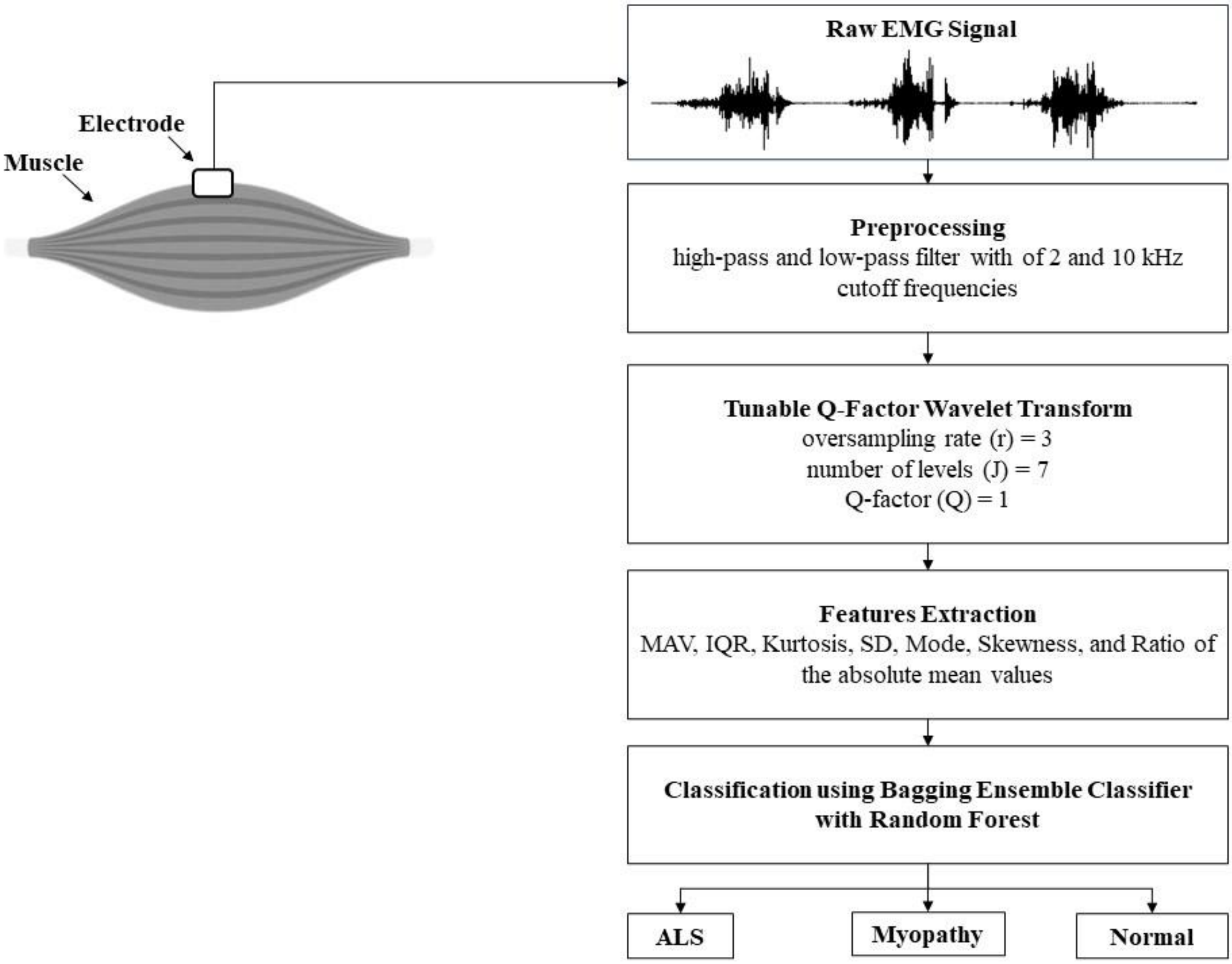

Figure. 1: An overview of the proposed method for classifying EMG signals

2. Literature Review

Tunable-Q wavelet transform (TQWT) was utilized by Subasi and Yaman (2021) to extract features from the raw EMG, and the Random Subspace ensemble classifier was used to categorize the EMG signals. Thus, with k-fold cross validation, the suggested Random Subspace ensemble classifier model with TQWT feature extraction showed promising results. The effectiveness of the Random Subspace ensemble classifier model for the identification of neuromuscular illnesses was demonstrated by experimental data. The SVM and ANN with Random Subspace ensemble approach had a 99% accuracy rate, according to the results. [10]

A method to automatically categorize EMG data as normal, neurogenic, or myopathic was put out by Subasi (2012). Additionally, he evaluated the classification accuracy of EMG data using classifiers based on multilayer perceptron neural networks (MLPNN), dynamic fuzzy neural networks (DFNN), and adaptive neuro-fuzzy inference systems (ANFIS). Different outcomes were found through investigation of the soft computing methodologies with regard to the effects of characteristics on the classification of EMG signals. According to the comparison research, the ANFIS modeling was superior to the DFNN and MLPNN in at least three ways: it had a slightly higher recognition rate, was less sensitive to overtraining, and consistently produced reliable results. [11]

With the help of higher order statistics, Cherifi et al. (2023) used a variety of techniques to extract features from the raw EMG signal in the time and time-frequency domain using DWT, WPD, and a combination of the two, with or without preprocessing and for varying levels of decomposition from level 3 to 10. With Bayesian optimization of the hyperparameters, they used optimized ensemble trees and optimized SVM classifiers. The EMG lab dataset, which is open to the public, was used for the studies. They found that utilizing DWT at level 9 without any preprocessing and the linear SVM classifier produced good training results, with testing accuracy of 78.35%. The results obtained show how well the suggested technique performs in precisely classifying the EMG signals. The classifier ensemble trees failed to distinguish between those with ALS and healthy people, according to the authors. [12]

In order to help in the identification of neuromuscular illnesses, Jose et al. (2020) presented the creation and validation of an accurate automatic diagnostic method to classify intramuscular EMG (iEMG) signals into categories of healthy, myopathy, or neuropathy. This study uses the lifting wavelet transform (LWT) to breakdown an iEMG signal into a group of "disjoint" down-sampled signals. The LWT coefficients in the subbands' Higuchi's fractal dimensions (FDs) were calculated. Each down-sampled signal's one-dimensional local binary pattern and the FDs of the LWT subband coefficients were combined. The class labels of the down-sampled signals were then calculated using a multilayer perceptron neural network (MLPNN). In order to help in the identification of neuromuscular illnesses, Jose et al. (2020) presented the creation and validation of an accurate automatic diagnostic method to classify intramuscular EMG (iEMG) signals into categories of healthy, myopathy, or neuropathy. This study uses the lifting wavelet transform (LWT) to breakdown an iEMG signal into a group of "disjoint" down-sampled signals. The LWT coefficients in the sub-bands' Higuchi's fractal dimensions (FDs) were calculated. Each down-sampled signal's one-dimensional local binary pattern and the FDs of the LWT sub-band coefficients were combined. The class labels of the down-sampled signals were then calculated using a multilayer perceptron neural network (MLPNN). [13]

Deep models have gained a lot of traction recently thanks to their outstanding performance across a wide range of classification issues. Deep networks require specialized hardware and have tremendous computational complexity. A hand-modeled feature selection strategy is suggested in (Baygin et al., 2022) as a solution to this issue (without lowering classification ability). A brand-new shape-based local feature extractor that makes use of the frustum's geometric form was introduced. A frustum pattern was used to create textural elements. Additionally, this model featured statistical features that had been retrieved. Low-level features were obtained after fusing textures and statistics features to create a hybrid feature extraction phase. TQWT was utilized to produce high level features. The hybrid feature generator that was described produced 154 feature vectors, hence the name Frustum154. This model

was able to automatically choose the right feature vectors throughout the multilevel feature synthesis phase, and it combined the suitable feature vectors to form the final feature vector. Shallow classifiers were then applied after iterative neighborhood component analysis (INCA) determined which feature vector was best. Three straightforward hand-movement sEMG datasets had been used to evaluate Frustum154. Biomedical engineering frequently used hand-movement sEMG datasets, although there were significant issues. For the described models to acquire excellent classification skill, typically one dataset was needed. Three sEMG datasets were used in this study to evaluate Frustum154's performance. The proposed model was self-organized and automatically chooses the sub-bands and features that are most useful. Its shallow classifier classification accuracy results of 98.89%, 94.94%, and 95.30% show that Frustum154 can increase classification accuracy. [14]
An innovative flexible approach for classifying EMG signals using the adjustable Q-factor wavelet transform (TQWT) was introduced by Achmamad et al. in 2020. The TQWT methodology produced a variety of sub-bands that were used to extract important energy-related information. Following this, the calculated features were chosen using the filter selection (FS) method. The efficiency of the feature selection stage led to improvements in classification performance as well as a decrease in the classification algorithm's computing time. For automated diagnosis, the chosen feature subsets were fed into different classifier algorithms, including k-nearest neighbor (k-NN), least squares support vector machine (LS-SVM), and random forest (RF). In comparison to LS-SVM and RF, the experimental results indicate that the k-NN classifier provides better classification measures. A 10-fold cross-validation method was used to assess the categorization task's robustness. [15]

In the present work, we introduce a classification model implemented on a big dataset using TQWT in contribution with bagging ensemble classifier with random forest for achieving massive accuracy.

3. Description of Dataset

In this work, we employed EMG signals provided by EMGLAB database [16]. Table 1 shows the database selected for healthy people of six males and four females aged between (21- 37).

Table 1 Database of the selected sample

	ALS		Myopathy		Normal	
Age	35 - 67 years		19 - 63 years		21 - 37 years	
No. of individuals	8	4 women	7	5 women	10	4 women
		4 men		2 men		6 men
Condition	Five participants died within a few years of being diagnosed with the disease.				no history of neuromuscular disease	
Sampling rate and duration	23437.5 Hz, 11.2 seconds					
Sampling points	262500					

Selected samples have not been prescribed before of neurological diseases. Table 1 also shows another EMG signals database of Myopathy patients aged 19 to 63 years of 5 males and 2 females, as well as ALS patients aged 35 to 67 years of 4 males and 4 females. Muscle's EMG signal was acquired such that data was collected from five distant places using concentric needle electrode. Three different depths with constant and low voluntary contraction levels of the muscle were selected to set and place the electrode in the muscle. A 16-bit resolution digitizer was used to digitize the EMG data at a sampling frequency of 23437.5 Hz.

1st order- Butterworth zero-phase distortion digital high-pass filter, 3 dB limit, and 50 Hz was used to filter the recorded EMG data to reduce low-frequency baseline movements.

Furthermore, and before analysis, a high-pass and low-pass filter with of 2 and 10 kHz cutoff frequencies was used filter the signals.

The brachial biceps muscles were the most frequently examined in all three groups. For this, they become the focus of the work. The EMG raw patterns of Myopathy, ALS, and normal cases from EMGLAB dataset are presented in Figure 2.

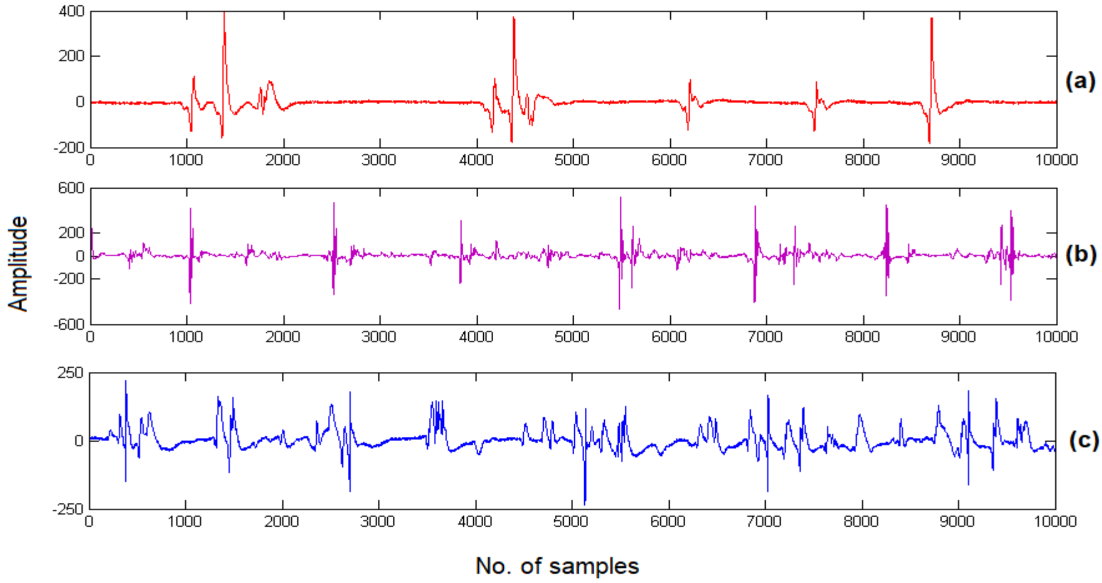

Figure. 2: EMG raw patterns of (a) ALS (b) Myopathy (c) Normal subjects [16]

4. Methodology

4.1. Tunable Q Factor Wavelet Transform (TQWT)

In recent years, TQWT has become a very common technique for analyzing biomedical signals. This approach was developed by Selesnick [17]. TQWT allows the user to specify a Q-factor to produce a wavelet Multi Resolution Analysis (MRA). Among discrete-time wavelet transforms techniques, TQWT has proven its simplicity and efficiency in tuning the parameters required to reconstruct the signals ([18]). Applying radix-2 Fast Fourier Transforms (FFTs) can increase the efficiency of TQWT implementation. Like fractional spline wavelet transform, TQWT depends on non-rational transfer functions filters to divide the signal energy into high and low pass sub-bands. The parameters r (oversampling rate/redundancy), J (number of levels), and Q (Q-factor) measure TQWT's efficiency in signal decomposition. In the present work, the best performance was achieved using the parameters r = 3, J = 7, and Q = 1.

4.2. Features Extraction

The EMG signals are decomposed into sub-bands by TQWT. Statistical features such as Mean Absolute Values (MAV), Interquartile Range (IQR), Kurtosis, Standard Deviation (SD), mode, skewness, and ratio of absolute mean values are then determined from the sub-bands to classify EMG signals for the different cases.

The mean absolute value μ was calculated by Eq. (1),

$$\mu = \frac{1}{L}\sum_{j=0}^{L}\left|x_j\right| \tag{1}$$

Where L is the dataset length, $x_j$is the j^{th} sample amplitude

The seconed feature, Interquartile Range IQR, was determined by Eq. (2),

$$IQR = Q_{j_2} - Q_{j_1} \tag{2}$$

Where Q_{j_1} and Q_{j_2} are the 25^{th} and 75^{th} percentile of thedata respectively.

Kurtosis K can be obtained by Eq. (3),

$$K = \frac{1}{L}\sum_{j=0}^{L}\frac{\left(x_j - \mu\right)^4}{\sigma^4} \tag{3}$$

Where σ is the standard deviation which can be calculated by Eq. (4),

$$\sigma = \sqrt{\frac{\sum_{j=0}^{L}\left(x_j - \mu\right)^2}{L}} \tag{4}$$

The statistical feature of the "Mode" is represented by the number of observations of a value which is the most occurring in the total dataset.

The Skewness φ is related to the the total length of the dataset L, thej^{th} sample amplitude x_j, the mean value μ, and the standard deviation σ by Eq. (5),

$$\varphi = \frac{1}{L}\sum_{j=0}^{L}\frac{\left(x_j - \mu\right)^3}{\sigma^3} \tag{5}$$

The last statistical feature, ratio of the absolute mean values α can be determined by Eq. (6),

$$\alpha = \frac{\sum_{j=0}^{L}|x_j|}{\sum_{j=0}^{L}|y_j|} \quad (6)$$

Where $\boldsymbol{y_j}$ is the adjacent sample amplitude to $\boldsymbol{x_j}$.

4.3. Method of Classification

For classifying the EMG signal dataset, we recommended applying Bagging Ensemble Classifier with Random Forest. The bagging (bootstrap aggregation) algorithm combines basic ensemble modeling approaches by creating and aggregating base models. In the model creation process, bootstrap samples are first used from the training set to construct the base models. Then, classification or averaging for regression can be achieved by integrating them using unweighted voting. If the base method in this classifier is unstable, bagging is likely to outperform single models using the same base algorithm. However, this approach may not provide the best prediction performance. Stable algorithms do not require diversity, so classification performance may not be significantly improved or decreased.
In ensemble models, the aggregation of base models can effectively resolve their overfitting problem. In addition, attribute selection is not needed, as more attributes increase the probability of generating more diverse models. Bagging can provide a final model that may be superior to or at least on par with a single model when there are enough base models. The performance of bagging ensembles generally increases with the number of base models, but stabilizes beyond a certain level. At this stage, bootstrap samples can only achieve a certain level of model diversity.[19]
The Bagging Ensemble Classifier with Random Forest was evaluated by comparison with the following techniques:

4.3.1. Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) consist of groups of input and output neurons that are connected to each other by weighted connections. The weights of these connections determine the ability of the network to predict the correct class label for each input. One of the most popular ANN structures is the multilayer feed-forward network (FFN). In an FFN, the neurons are connected layer by layer, with no cross-layer or in-layer connections. When feature vectors are input to the network, each neuron in the input layer corresponds to a component of the feature vector. The activation function then activates the input neurons. The labels are provided by the output/last layer, since each neuron in this layer either represents a label or an element of a label vector. The activation function that governs the functional units represented by the neurons in both the hidden and output layers is often the sigmoid function [20]. In this work, an ANN with a rectified linear unit activation function was applied with 100 hidden layers, a constant learning rate of 0.001, and a maximum number of iterations of 200.

4.3.2. Random Forests (RF)

Random forest (RF) is a machine learning algorithm that consists of a group of independent decision trees. To generate an individual decision tree in the ensemble, RF randomly selects a subset of attributes at every node to identify the split. In the classification process, each tree in the classifier predicts a class. The dominant class (the final prediction) is returned by the model [20]. In this work, RF was applied with 80 estimators and the "gini" function was used to measure the quality of a split.

4.3.3. K-Nearest Neighbor (KNN)

In k-nearest neighbors (KNN), the training set is used instead of a training process. KNN relies on the similarity of tuples in the input and output spaces as its main learning concept. [20].
If an unrecognized tuple exists, it can be recognized based on its closest tuples in the training set. The closeness of tuples is typically measured using the Euclidean distance. The unrecognized tuple can be classified into the majority class among its k-nearest neighbors, and the average value of the k-nearest neighbors can be used for regression [21] .
In this work, KNN was applied with a number of neighbors of 5 and a uniform weight function was used in prediction. This means that all points in each neighborhood are weighted equally.

4.3.4. Support Vector Machine (SVM)

Support vector machines (SVMs) are a classification approach that can be used to classify linear and nonlinear data. The initial training set can be transformed into a higher dimension using a nonlinear mapping. In this higher dimension, an optimum separation hyperplane is searched for using margins and support vectors. A decision boundary is a hyperplane that discriminates one class of tuples from the others. This hyperplane is used to split the data into two classes, in case of using an appropriate nonlinear mapping providing a high enough dimension.
For this reason, SVMs can accurately predict complex nonlinear decision boundaries. Studies have found that SVMs are resistant to overfitting compared to other techniques [21]. In this work, one-vs-rest SVM with radial basis kernel function was used.

4.3.5. Naïve Bayes (NB)

Naive Bayes (NB) is a simple learning approach that assumes the features are conditionally independent. Both Maximal-A-Posterior (MAP) rules and Bayes' theorem are the main concepts of NB. It can categorize binary data as well as multi-class data. The most important benefits of this approach are incremental learning, low variance, computing efficiency, robustness in the face of missing information, and direct prediction of posterior probabilities [22].

4.3.6. Classification and Regression Tree (CART)

Classification and Regression Tree (CART) was proposed by Breiman in 1984. CART is a decision tree algorithm that recursively partitions the data space into subsets, with a simple prediction model for data fitting in each subset. CART can separate outliers in a separate node and adjust in time. CART is reliable in handling complex structured data because it can rely on one parameter, making it a challenging classification technique [23]. In this work, the “gini” function was used to measure the quality of a split.

5. Results and Discussion

In this study, we used EMG signals to diagnose neuromuscular diseases. First, we divided the EMG signal into frames of length 8192, resulting in 1051 ALS instances, 960 myopathic instances, 1600 control instances, and a total of 3611 instances for classification.
True Positives (TP) and True Negatives (TN) indicate correct classifications. False Positives (FP) occur when the expected output is negative but the classifier predicts it to be positive. False Negatives (FN)

occur when the expected output is positive but the classifier predicts it to be negative. These metrics were used to evaluate the statistics.
Each frame is decomposed into sub-bands using the TQWT method. This allows us to obtain useful statistical features for classifying signals in each sub-band. The extracted features include kurtosis, IQR, mode, MAV, skewness, standard deviation, and ratio.
We determined the classifier recall, precision, F-measure, and accuracy to evaluate the classifier's performance and reliability. The classifier recall and precision can be evaluated using Eqs. (7) and (8), respectively.

$$\boldsymbol{recall} = \frac{\boldsymbol{TP}}{(\boldsymbol{TP}+\boldsymbol{FN})} \qquad (\mathbf{7})$$

$$\boldsymbol{precision} = \frac{\boldsymbol{TP}}{(\boldsymbol{TP}+\boldsymbol{FP})} \qquad (\mathbf{8})$$

F-measure can be obtained by Eq. (9)

$$\boldsymbol{F-Measure} = \frac{(\mathbf{2}*\boldsymbol{TP})}{(\mathbf{2}*\boldsymbol{TP}+\boldsymbol{FP}+\boldsymbol{FN})} \qquad (\mathbf{9})$$

The total accuracy can be determined by Eq. (10)

$$\boldsymbol{ACC} = \frac{(\boldsymbol{TP}+\boldsymbol{TN})}{(\boldsymbol{TP}+\boldsymbol{FN}+\boldsymbol{TN}+\boldsymbol{FP})}*\mathbf{100} \qquad (\mathbf{10})$$

Selecting a specific training/test set can introduce bias, which can be reduced by using the technique of 10-fold cross-validation.
Classifier results can be expressed as a percentage of the total using kappa, which ranges from 0 to 1.
Tables 2 and 3 show the performance of single and bagging classifiers for EMG signals, respectively.

Table 2 Classification results of single classifiers

	Accuracy %	F1	Kappa	Recall	Precision
RF	0.989 (+/- 0.011)	0.991 (+/- 0.011)	0.985 (+/- 0.015)	0.990 (+/- 0.012)	0.993 (+/- 0.011)
KNN	0.922 (+/- 0.023)	0.926 (+/- 0.022)	0.887 (+/- 0.048)	0.922 (+/- 0.027)	0.929 (+/- 0.027)
NB	0.624 (+/- 0.042)	0.552 (+/- 0.073)	0.378 (+/- 0.082)	0.580 (+/- 0.042)	0.669 (+/- 0.080)
ANN	0.894 (+/- 0.056)	0.865 (+/- 0.077)	0.836 (+/- 0.090)	0.897 (+/- 0.068)	0.913 (+/- 0.057)
DT	0.945 (+/- 0.022)	0.947 (+/- 0.034)	0.916 (+/- 0.048)	0.944 (+/- 0.024)	0.936 (+/- 0.030)
SVM	0.759 (+/- 0.032)	0.756 (+/- 0.045)	0.620 (+/- 0.060)	0.738 (+/- 0.049)	0.796 (+/- 0.048)

Table 3 Classification results of bagging ensemble classifiers

	Accuracy %	F1	Kappa	Recall	Precision
RF	0.990 (+/- 0.015)	0.989 (+/- 0.008)	0.984 (+/- 0.014)	0.988 (+/- 0.016)	0.991 (+/- 0.007)
KNN	0.925 (+/- 0.022)	0.926 (+/- 0.025)	0.886 (+/- 0.030)	0.921 (+/- 0.028)	0.930 (+/- 0.031)
NB	0.624 (+/- 0.042)	0.552 (+/- 0.073)	0.378 (+/- 0.082)	0.580 (+/- 0.042)	0.669 (+/- 0.080)
ANN	0.940 (+/- 0.024)	0.936 (+/- 0.024)	0.907 (+/- 0.033)	0.939 (+/- 0.030)	0.941 (+/- 0.030)

DT	0.975 (+/- 0.013)	0.977 (+/- 0.016)	0.958 (+/- 0.022)	0.971 (+/- 0.027)	0.977 (+/- 0.017)
SVM	0.757 (+/- 0.030)	0.758 (+/- 0.036)	0.617 (+/- 0.067)	0.735 (+/- 0.029)	0.795 (+/- 0.063)

Table 2 shows the performance of single classifiers. RF achieved the best performance with an accuracy of 98.9%. Table 3 shows the performance of bagging ensemble methods. Bagging ensemble methods improved the performance of most classifiers, with RF again achieving the best performance with a success rate of 99%.

6. Conclusion

This work proposes a technique for classifying myopathy, healthy, and amyotrophic lateral sclerosis (ALS) EMG signals using tunable Q-factor wavelet transform (TQWT) based features and bagging ensemble classifier technique. TQWT decomposes the EMG signals into high and low frequency sub-bands. After seven levels of decomposition, statistical features are calculated from TQWT coefficients to reduce the dimension and eliminate unnecessary features. The classification performance of the extracted features is evaluated using single and bagging ensemble classifiers. Bagging ensemble classifier achieved better classification performance than single classifiers. The proposed technique can be easily implemented in any computer-based diagnosis system.

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