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Prediction and Analysis of Muscular Paralysis Disease Using Daubechies Wavelet Approach

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***Abstract* - Genetic advancements have shown that ALS is not a single entity but consists of a collection of syndromes in which the motor neurons degenerate. Together with these multiple genetic etiologies, there is a broad variability in the disease's clinical manifestations in terms of the age of symptom onset, site of onset, rate and pattern of progression, and cognitive involvement. In this paper, prediction of human paralysis is done based on extraction of features from the ALS dataset samples. The classification has been carried by two different Machine Learning based algorithms i.e., Gradient Boosting (GB), and neural Network (NN). The standard data set such as ALS has been used for this purpose. The classifier model has used 80% data as a training set and the remaining 20% of data as the test set. The result shows that GB and NN perform better with an accuracy of 98%. Based on the desired accuracy, this classification model serves better compared with existing models.**

***Keywords:* Features, Daubechies Wavelet, Gradient Boosting, Neural Network, ALS Signal**

I. INTRODUCTION

The EMG signals are highly complex and non-linear signal and used in prediction diagnosis of neurological and neuromuscular problems [1]. Due to complex nature of EMG signals many times even experienced researchers are failed to provide enough information about these signals. EMG signals involve a great deal of information about the nervous system with anatomical and psychological properties of muscles. It is a record of electrical potentials generated by muscles cell [4]. There are numerous neuromuscular disorders that influence the spinal cord, nerves, or muscles. Early finding and diagnosis of these diseases by clinical examination is crucial for their management as well. In the previous literatures Fast Fourier Transform (FFT) was used for analysis of EMG signals, but FFT suffers from large noise sensitivity [5]. Parametric power spectrum methods suchas autoregressive (AR), reduces the spectral loss problems and gives better frequency resolution [5]. Since EMG signals are non-stationary; the parametric methods are not suitable for frequency decomposition of these signals.

Another method is Short Time Fourier Transform (STFT) which provides resolution in short window of time for all frequencies. FFT, AR, STFT do not have timeand frequency resolution at same time [7]. To extract the features of EMG signals and toovercome the problems of STFT, AR, FFT, a power-full tool that is Wavelet Transformcan be applied to extract the wavelet coefficients of discrete time signals. This procedure makes use of multi-rate signal-processing techniques [4, 13]. Artificial Neural Networks (ANN) has been used in great number of medical diagnostic decision support system applications because of the belief that these have great predictive power. Many authors have shown that combining the prediction of several models often results in a prediction accuracy that is higher than that of individual models [4, 10]. From the large number of neuromuscular diseases, we have selected ALS for our study, as their consistency of clinical appearance is more than other EMG diseases. Amyotrophic Lateral Sclerosis (ALS) is part of this study. ALS is a progressive nervous system disease that affects nerve cells in the brain and spinal cord, causing loss of muscle control.

Genetic advancements have shown that ALS is not a single entity but consists of a collection of syndromes in which the motor neurons degenerate. Together with these multiple genetic etiologies, there is a broad variability in the disease's clinical manifestations in terms of the age of symptom onset, site of onset, rate and pattern of progression, and cognitive involvement.

Electromyography (EMG) is a procedure that measures the electrical activity inmuscle using needle electrodes or surface electrodes. Any disruption in the motor system, whether in the spinal cord, the motor neurons, the muscle, or the neuromuscular junctions, can cause changes in the characteristics of these electrical signals [15]. The aim of our work is to select the relevant features that have an influence on the neuromuscular disorder classification performance.

II. LITERATURE REVIEW

The various pre-processing stages such as Detection and classification of EMG signals play a prominent role because it allows a more sophisticated evaluation method to differentiate between different neuromuscular diseases [1]. In this research article, a brief reviews on different features extraction and classification techniques have been presented. The Wavelet Transform (WT), Principal Component Analysis (PCA), and Independent Component Analysis (ICA) are considered. Further, the different techniques to classify EMG data such as probabilistic neural network (PNN), Support Vector Machine (SVM), Artificial Neural Networks (ANN), etc are also considered. The neuromuscular disease classifications from EMG signals are proposed based on different combination of features extraction methods and types of classifiers. The combined technique i.e., WT and SVM improves the classification accuracy than other combinations such as DWT with ANN, ICA with MLPN, PCA with ANN and DWT with PNN. Researchers strive hard to find better method for classification of biomedical signals especially for De-noising and feature extraction keeping accuracy as significant factor [2].

An efficient machine learning method for EMG classification by applying de-noising, feature extraction and classifier is presented in this paper. The Multiscale Principal Component analysis for de-noising, the D.W.T for feature extraction and the decision tree algorithms for classification are examined and developed a framework which automatically classify the signals into either myopathic or ALS or normal. A Comparative analysis with sensitivity, specificity, accuracy, F-measure and area under ROC curve (AUC) parameter is presented. A Machine learning strategy for precise detection of Neuro-muscular disorders and classification of captured raw EMG signals to automatically either neuropathy, myopathy, or absence of disease [3]. Hilbert Transform approach is used to decompose each signal into amplitude or frequency modulated sub-bands. Automatic Prediction of muscular and neuromuscular disorders from raw electromyography (EMG) is an interesting topic for researchers [4].

In this paper, a unique method to classify the non-stationary EMG signal based on DWT is presented. It is very essential to select the appropriate mother wavelet and its related decomposition in DWT-based EMG signal analysis. This works starts by considering the decomposing a raw EMG signal into various sub-bands followed by extraction of statistical features from each of these sub-bands. Analysis has been carried out with the help of six wavelet families. The sym14 mother wavelet with the 8th optimal wavelet decomposition shows its significant performance.

The computational time of this proposed automated prediction of neuromuscular disorders shows better results as per the simulation results as presented in this paper and it is more reliable on par with the real-time prediction. The captured raw EMG signal from multi-channel has been represented with unconstrained sets of the mother wavelet of DWT, the classifications of these EMG signal are carried out using support vector machine approach [5]. SVM method for classification is being applied for different hand movements from different locations. The combined DWT and SVM techniques yield better accuracy in this proposed approach and suits for real-time implementation. The various neuromuscular disorders information is extracted from motor action potentials. In this paper, classification of EMG signal based on variants of machine learning were used and a comparative analysis is done with these variants for accuracy [6]. The developed models work such that classification of the EMG signals into either normal, ALS is automated. Further, as a outcome of comparative analysis; the fuzzy support vector machines_ (FSVM) modelling gives better performance than its counterpart with respect to recognition rate which is high; overtraining exhibits insensitivity; and consistent outputs shows its reliability. The combined effect of these models i.e., wavelet transform (DWT) and FSVM throws high performance and same has been quantified. As an outcome of these research; the proposed model provides a reliable classification of EMG signals, and also helps in accurate prediction of neuromuscular disorders. The efficient methods of analyzing EMG signals with discrete wavelet Transform (DWT) techniques gives accurate results through patterns of the signals and the performance is being analyzed rigorously [7]. The experimental results exhibit that a root mean square difference (RMSD) value for the denoising and quality of reconstruction of the SEMG signal. Further, the obtained result shows that the best mother wavelets for tolerance of noise are second order of samlets and bior6.8. Results inferred that bior6.8 suitable for the classification and analysis of SEMG signals of different arm motions results in a classification accuracy of 88.90%. Two schemes for neuromuscular disease classification from EMG signals are proposed based on DWT features [8].

In the first scheme, a few high energy DWT coefficients along with the maximum value are extracted in a frame-by-frame manner from the given EMG data. Instead of considering only such local information obtained from a single frame, we propose to utilize global statistics which is obtained based on information collected from some consecutive frames. In the second scheme, motor unit action potentials (MUAPs) are first extracted from the EMG data via template matching based decomposition technique. It is well known that not all MUAPs obtained via decomposition are capable of uniquely representing a class.

Thus, a novel idea of selecting a dominant MUAP, based on energy criterion, is proposed and instead of all MUAPs, only the dominant MUAP is used for the classification. A feature extraction scheme based on some statistical properties of the DWT coefficients of dominant MUAPs is proposed. To classification, the K-nearest neighborhood (KNN) classifier is employed. Extensive analysis is performed on clinical EMG database for the classification of neuromuscular diseases, and it is found that the proposed methods provide a very satisfactory performance in terms of specificity, sensitivity, and overall classification accuracy.

In this paper an analysis of surface electromyogram (SEMG) signals has been investigated through Wavelet Transforms [9]. The pre-processing of SEMG signals carried out in steps, firstly; the acquired signal has been decomposed using wavelet transform technique; secondly; these decomposed coefficients are analyzed by threshold methods, and, finally, as a last step the reconstruction has been done. Further Daubechies wavelets are used for effective removal of noise from the original SEMGs carried out. Among all wavelet transform, the db4 shows better results. The experimental Results indicates that at Daubechies wavelet families (db4) were more suitable for the analysis of SEMG signals with respect to upper limb motions, and an accuracy of 88.90% was achieved. EMG signal analysis of using wavelet transform is the prominent signal processing tools [10]. Wavelet Transform technique is widely used in the EMG recognition system also. In this paper, an investigation has been carried out for extraction of the EMG from multiple-level wavelet decomposition of the EMG signal such as 1-D & 2-D and especially with various mother wavelets to obtain the useful resolution components from the EMG signal. Noise elimination has been done during this pre-processing stage of the signals. The mean absolute value and root mean square techniques are used to extract the Useful component from EMG signal.

The ratio of Euclidean distance is calculated using the two most popular criteria i.e., standard deviation and the scatter graph. As a result of extensive experimental analysis an optimal wavelet decomposition is obtained using the seventh order of Daubechies wavelet and the fourth-level wavelet decomposition. This paper furnishes the design, optimization, and performance evaluation of artificial neural network (ANN) for the efficient classification of Electromyography (EMG) signals [11].

The raw EMG signals collected from various hand gesture/ hand motion are being processed to extract some predefined features which are inputs to the neural network. The time and as well as time frequency based extracted feature are used to train the neural network. The Levenberg-Marquardt training algorithm has been employed for the classification of EMG signals. The results show that the designed and optimized network able to classify single channel EMG signals with an average success rate of 88.4%. The various existing techniques have its own limitation such as irrelevant feature selection and reduced classification accuracy in case muscular disorder prediction [13].

In this research, the hybrid FE method is discussed for the accurate prediction of muscular disorder, and DWT is used to reduce the feature degradation. The Relief-F feature selection selects the optimal relevant features for the classification and CNN method effectively analysis the feature relation for the classification. The UCI EMG-Lower Limb Dataset is used to validate the results of the proposed CNN method along with existing techniques in terms of important parameters F-measure, accuracy, precision, recall, and error rate. Classified the muscles as normal, neurogenic, or myopathic by developing a transparent semi-supervised EMG muscle classification system [14].

According to the motor unit potentials (MUPs), the predictions were carried out by using multiple instance learning (MIL) based classifiers. The main aim of this study was to develop a fuzzy-based MIL that improves the quantitative EMG techniques' usage. The different groups of muscles included proximal and distal of both hand and leg muscles were used to validate the performance of fuzzy-based MIL by implementing the existing SVM and Random Forest in terms of accuracy, sensitivity, and specificity. In general, fuzzy model has three categories namely Takagi-Sugeno-Kang (TSK) models, Mamdani-Larsen models, and generalized fuzzy models; however, only TSK was considered due to less time consumption for de-fuzzification. The classifier performance is required to be improved for effective performance of the signal classification. Developed a regression model using the collected surface EMG signals of human lower limbs [15].

To extract the time-series EMG signals, the model calculated the joint angles of knee, hip, and ankle accurately. After this calculation, deep belief network (DBN) was developed, which contained restricted Boltzmann machines. The optimal features were extracted by encoding the multi-channel surface EMG in a low dimensional space. Finally, the optimal surface EMG features were mapped with the flexion/extension joint angles by developing a back propagation neural network. The results proved that the DBN achieved better performance than principal components analysis (PCA). However, the performance of this method was verified with six healthy patients and collected the data from normal gait datasets, where abnormal gait data were required to verify the developed method's performance.

III. PROPOSED MODEL

Amyotrophic Lateral Sclerosis is one of the most common forms of neuro degeneration in the population, accounting for approximately 6,000 deaths in the United States and 11,000 deaths in Europe annually characterized by progressive paralysis of limb and bulbar musculature, it typically leads to death within three to five years of symptom onset.

Genetic advancements have shown that ALS is not a single entity but consists of a collection of syndromes in which the motor neurons degenerate. Together with these multiple genetic etiologies, there is a broad variability in the disease's clinical manifestations in terms of the age of symptom onset, site of onset, rate and pattern of progression, and cognitive involvement.

The group with ALS consisted of 8 patients; 4 females and 4 males aged 35-67 years. All the candidate samples had clinical signs of ALS. The dataset samples of ALS and normal data of patients are used for evaluating the proposed model. The proposed model for prediction of muscular Paralysis is shown in Figure 1.

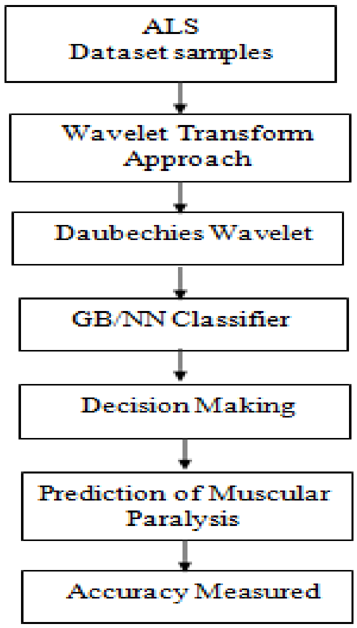

Fig. 1 Proposed Model

The Daubechies wavelet (DW) is applied to the clinical ALS dataset samples, and it is chosen due to its better frequency and time resolution in the input signals. It provides its localization ability. In addition, feature noise is minimized, and the local characteristics of the input signals are revealed by DW. The features such as mean, variance, root mean square, kurtosis and skewness of the samples are extracted for classification. To preserve the edge of the signal as well as short time windows are used to achieve the improved low- and high-frequency information, the Daubechies wavelet is well suited for the feature extraction model.

A. Wavelet Transform: Since time domain features and frequency domain features in this work gives no significant variations among ALS conditions, Wavelet transform (WT) became an effective tool to extract useful information from the EMG signal. A wide class of literatures has focused on the evaluation and investigation of an optimal feature extraction obtained from wavelet coefficients.

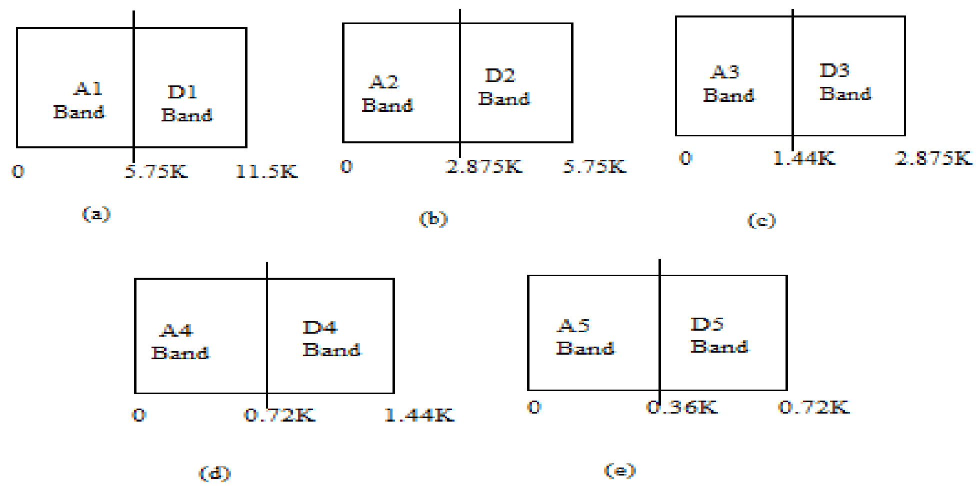

Fig. 2 Wavelet Decomposition Levels: (a) A1&D1 Bands (b) A2&D2 Bands
(c) A3 & D3 Bands (d) A4 &D4 Bands (e) A5 &D5 Bands

The selection of the Daubechies mother wavelet determines the signal representation. The coefficients derived from wavelet decomposition are too long to be used as features for classification. In this work Wavelet decomposition is achieved for five levels: Figure 2 shows the Wavelet decomposition for different bands of frequencies. The A1 Band is Approximation Band 1 and D1 is Detail Band 1. Similarly, A2, A3, A4, & A5 are Approximation Bands and D2, D3, D4, & D5 are Detail Bands. The mean value, variance, root mean square, Kurtosis of signal and Skewness of signal features of data samples were extracted to carry out the work.

1. Mean Value: The amplitude Mean value of the EMG for selected analysis interval is the most important EMG-calculation, because it is less sensitive to duration differences of analysis intervals. The mean EMG value best describes the gross innervation input of a selected muscle for a given task and works best for comparison analysis.

2. Variance: Variance of EMG signal (VAR) is good at measuring the signal power, and it can be expressed as

$$\mathrm{VAR} = \frac{1}{L-1}\sum_{i=1}^{L}(x_i)^2$$

3. Root Mean Square: Root mean square (RMS) is one of the popular features which is useful in describing the muscle information. In mathematics, RMS can be calculated using

$$\text{RMS} = \sqrt{\frac{1}{L}\sum_{i=1}^{L}(x_i)^2}$$

4. Kurtosis: Kurtosis refers to the statistical measure that describes the shape of either tail of a distribution, that is whether the distribution is heavy-tailed (presence of outliers) or light-tailed (paucity of outliers) compared to a normal distribution. In other words, it indicates whether the tail of distribution extends beyond the ±3 standard deviation of the mean or not.

$$\text{Kurtosis} = \text{Fourth Moment}/(\text{Second Moment})^2$$

5. Skewness: Skewness is a measure of symmetry in a distribution.

$$\text{Skewness} = (3 *(\text{mean}-\text{median}))/\text{standard deviation}$$

The 12 features are extracted from samples of clinical ALS dataset, optimal features are selected using Daubechies wavelet for the prediction of disease, mean absolute value, Waveform length, zero crossing, Root mean square and Log detector, kurtosis and skewness of the samples are extracted for classification for prediction of disease. In this work, the data of ALS is considered for experimentation. Features are extracted from the Data and are tabulated and represented using chart graphs in section 4.

B. MUAP Analysis

1. The EMG signals were recorded under usual conditions for MUAP analysis. The recordings were made at low (just above threshold) voluntary and constant level of contraction.
2. Visual and audio feedback was used to monitor the signal quality. A standard concentric needle electrode was used.
3. The EMG signals were recorded from five places in the muscle at three levels of insertion (deep, medium, low).
4. The high and low pass filters of the EMG amplifier were set at 2 Hz and 10 kHz.

The time domain analysis provides the information about the variation in the amplitude of EMG signal with time. But for most of the biomedical signals the frequency information is very much essential to understand the nature and characteristics of the signal. The frequency distribution of signal in spectrum will enable in understanding the physiological system in normal and pathological condition.

IV. RESULTS AND DISCUSSION

The ALS dataset is used for prediction of muscular paralysis using discrete wavelet transform, hybrid features and f-selection features approaches to carry out the work. After Wavelet decomposition the features are extracted, and results are tabulated. The GB and NN are used for classification process. The features are extracted for ALS Data with wavelet decomposition. The results are tabulated and indicated with chart graphs. The Average values, Maximum values, and Minimum values Bands are tabulated, and indicated using chart graphs.

A. Gradient Boosting Classifier: It builds in forward stage-wise fashion; it allows for the optimization of arbitrary differentiable loss functions. In each stage classes regression trees are fit on the negative gradient of the binomial or multinomial deviance loss function. Binary classification is a special case where only a single regression tree is induced.

B. Neural Network: A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. In this sense, neural networks refer to systems of neurons, either organic or artificial in nature.

TABLE I RESPONSE OF GB AND NN CLASSIFIERS FOR DIFFERENT TEST SAMPLE SIZE

SYM3	**Test Size=0.4**		**Test Size=0.3**		**Test Size=0.2**		**Test Size=0.1**	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
GB	0.7603	0.9733	0.7707	0.9742	0.7457	0.9791	0.772	0.9773
NN	0.6734	0.9246	0.6717	0.9295	0.6634	0.9322	0.6563	0.9062

TABLE II RESPONSE OF GB AND NN CLASSIFIERS FOR DIFFERENT TEST SAMPLE SIZE

SYM2	**Test Size=0.4**		**Test Size=0.3**		**Test Size=0.2**		**Test Size=0.1**	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
GB	0.7651	0.9714	0.7592	0.9742	0.7565	0.9754	0.7662	0.9774
NN	0.6685	0.9305	0.6609	0.9327	0.6547	0.9357	0.6754	0.9366

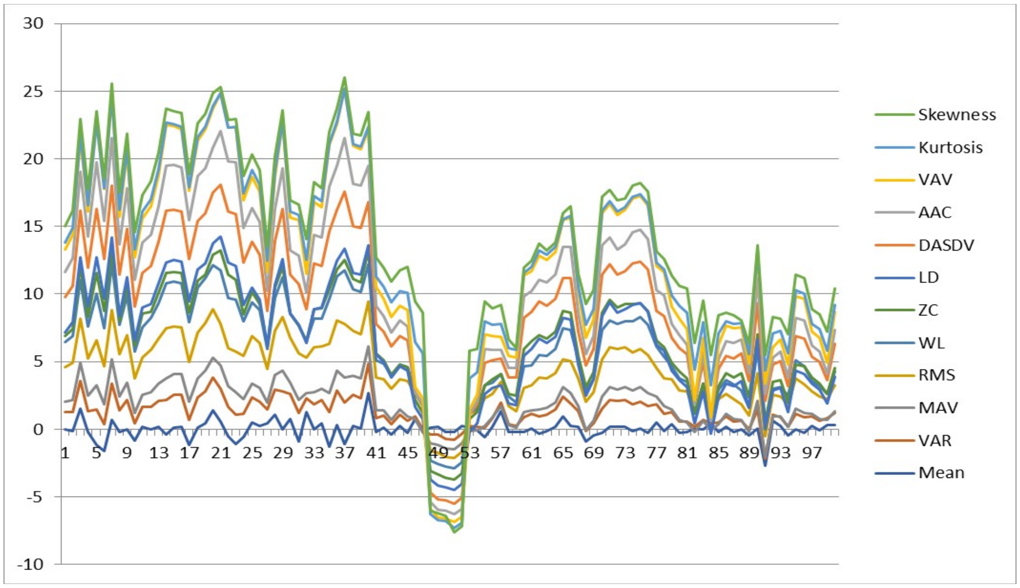

Fig. 3 Features extracted for Approximation band D5 with Daubechies wavelet of the order 1 for ALS Data

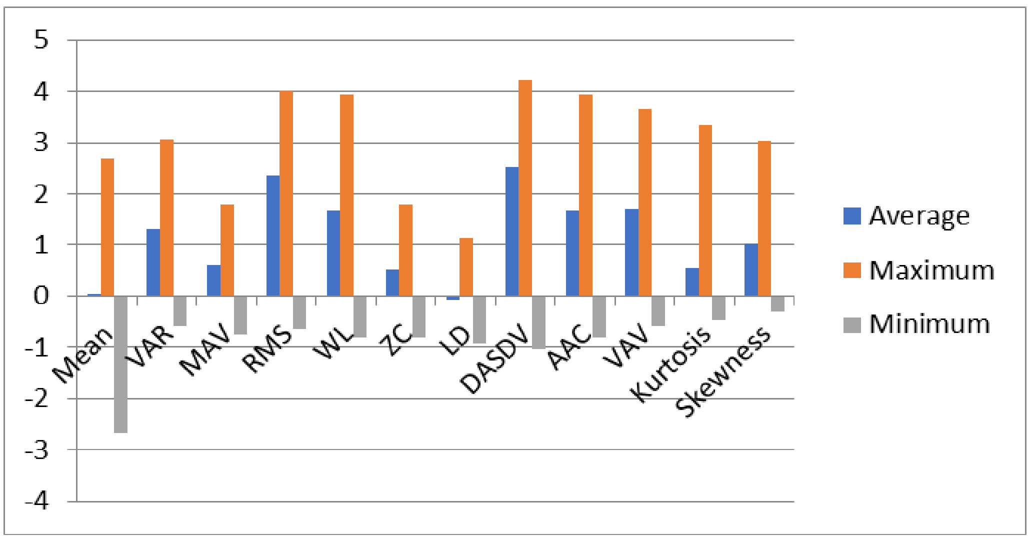

Fig. 4 Average, Maximum, & Minimum values of features extracted for Approximation band D5 with Daubechies wavelet of the order1 for ALS Data

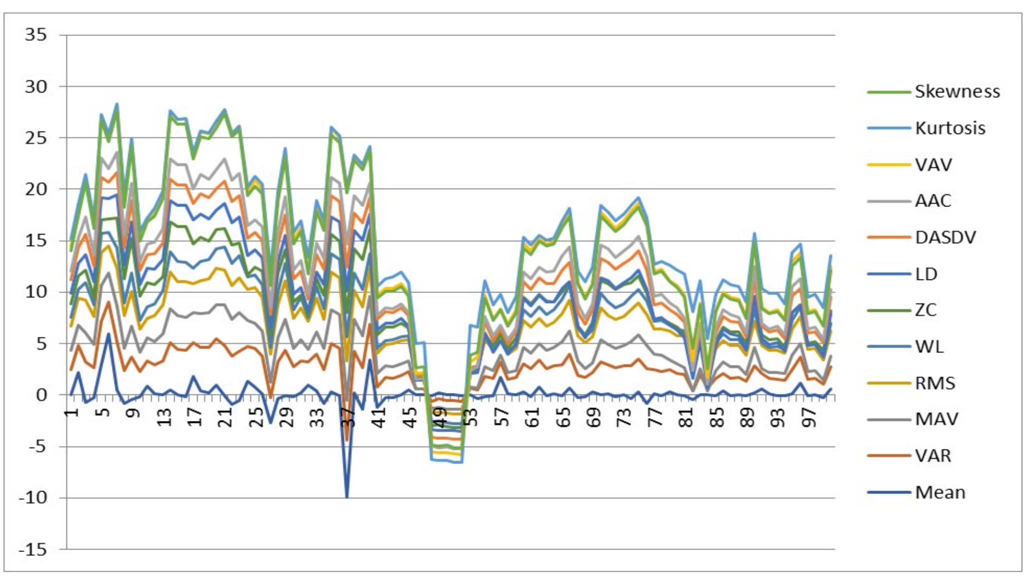

Fig. 5 Features extracted for Approximation band D4 with Daubechies wavelet of the order 1 for ALS Data

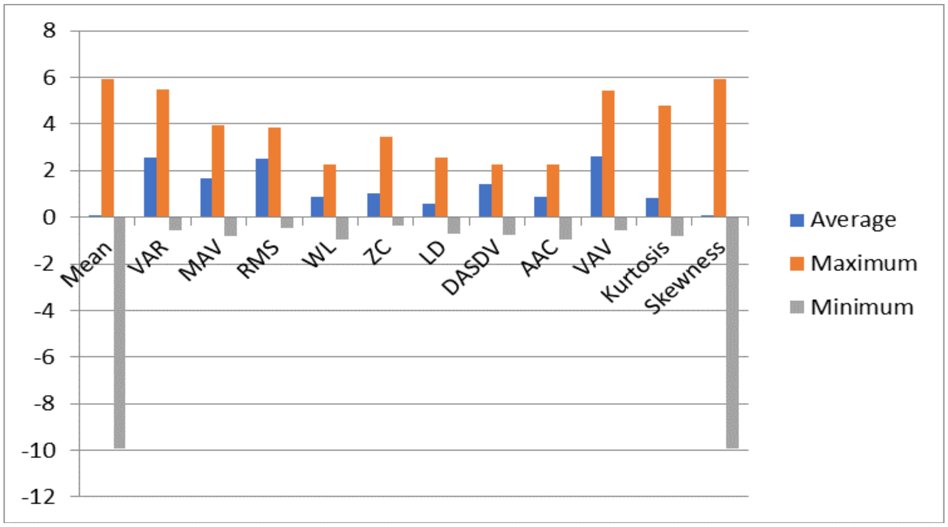

Fig. 6 Average, Maximum, & Minimum values of features extracted for Approximation band D4 with Daubechies wavelet of the order1 for ALS Data

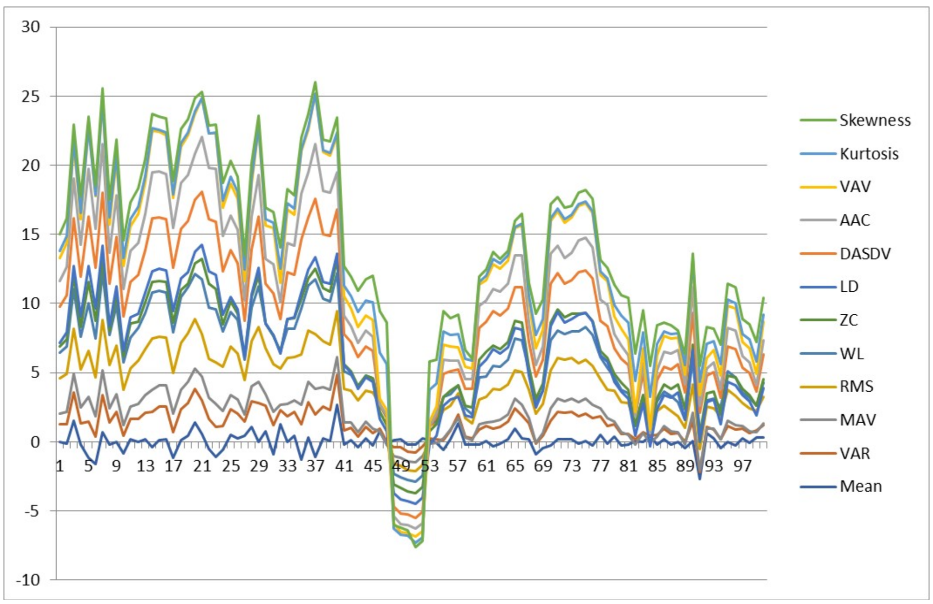

Fig. 7 Features extracted for Approximation band D3 with Daubechies wavelet of the order 1 for ALS Data

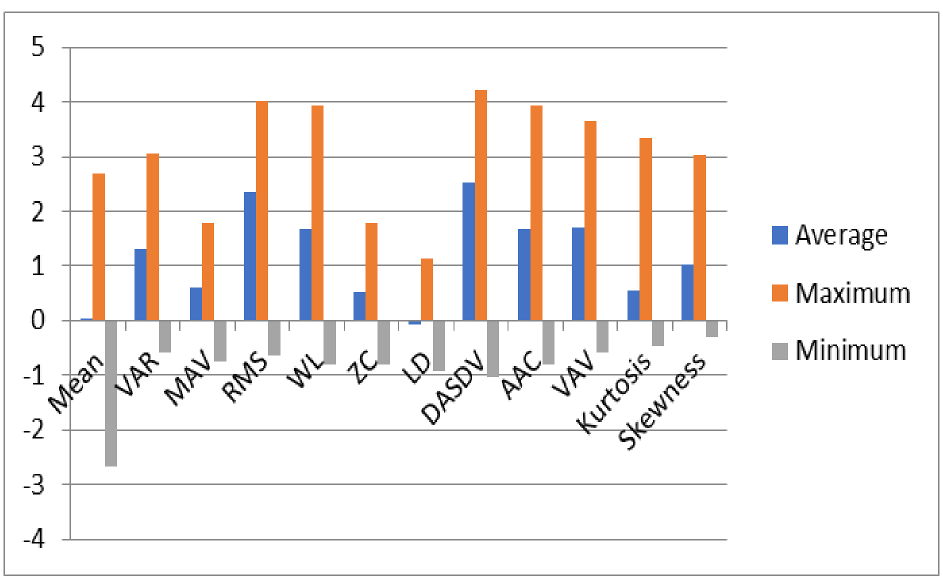

Fig. 8 Average, Maximum, & Minimum values of features extracted for Approximation band D3with Daubechies wavelet of the order 1 for ALS Data

Fig. 9 Features extracted for Approximation band D2 with Daubechies wavelet of the order 1 for ALS Data

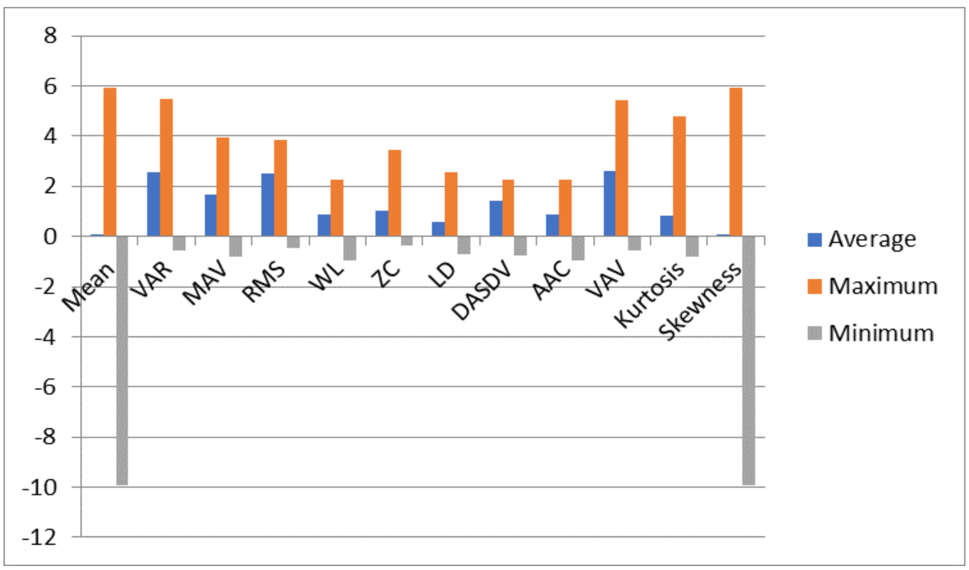

Fig. 10 Average, Maximum, & Minimum values of features extracted for Approximation band D2 with Daubechies wavelet of the order 1 for ALS Data

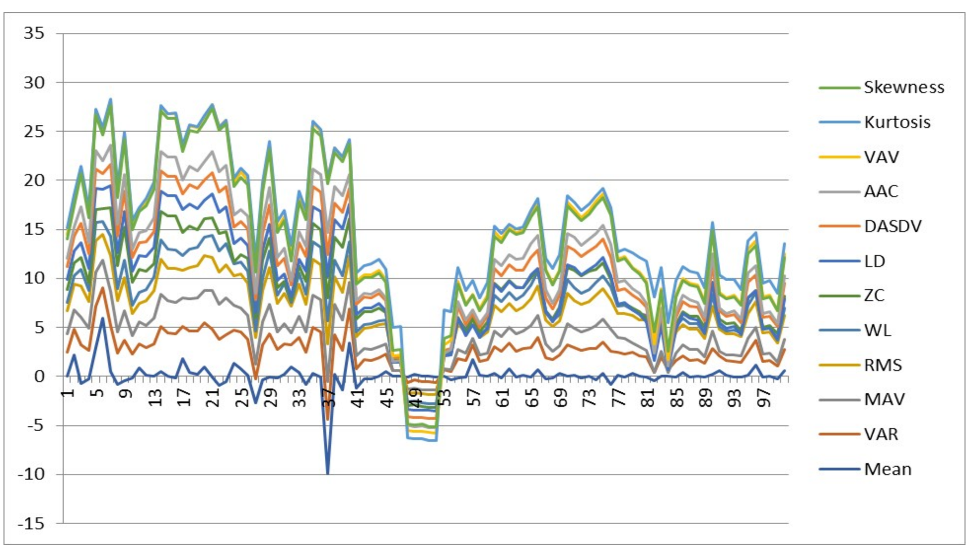

Fig. 11 Features extracted for Approximation band D1 with Daubechies wavelet of the order 1 for ALS Data

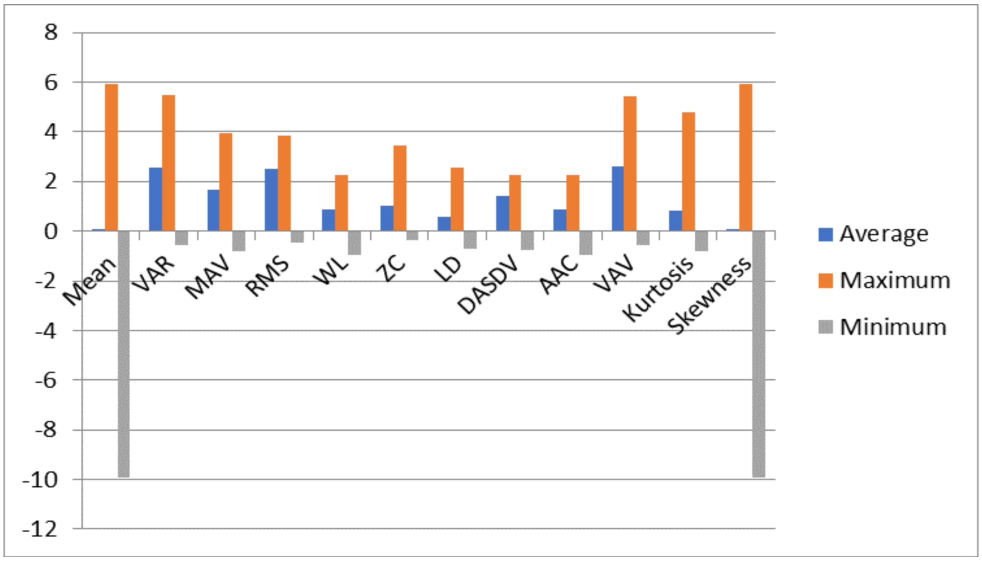

Fig. 12 Average, Maximum, & Minimum values of features extracted for Approximation band D1 with Daubechies wavelet of the order 1 for ALS Data

The extracted features from the Daubechies wavelet and test features for the different test sizes of ALS samples are classified using Gradient Boosting and NN classifiers. The response for the different size samples is tabulated in 3 and 4 respectively. Based on the results obtained, the accuracy of the model recorded up to 98% and claimed that the results were better compared to the existing model.

V. CONCLUSION AND FUTURE SCOPE

In this paper, the required features are extracted using Daubechies wavelet technique. The features such as mean absolute value, Waveform length, zero crossing, Root mean square and Log detector, kurtosis and skewness of the samples are extracted for classification for prediction of human muscular disease. The GB and NN classifiers are used for classification. The proposed model is tested on the clinical ALS dataset based on two classifiers. The model responded with a better accuracy of 98% compared to the other models. Further, the model can be tested for different datasets and various transform domain techniques to address the medical issue of human paralysis.

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