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Analysis of Muscular Paralysis using EMG Signal with Wavelet Decomposition Approach

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Abstract - **Paralysis refers to temporary or permanent loss of voluntary muscle movement in a body part or region. The degree of muscle function loss determines the severity of paralysis. The muscle function is represented by electrical activity of the muscles. Electromyography is a technique concerned with the analysis of myoelectric signals. EMG allows the determination of muscular activity. EMG signal analysis is performed using the features extracted in time domain, frequency domain and time frequency domain. In this work, the EMG of Amyotrophic Lateral Sclerosis (ALS), Myopathy, and Normal conditions are considered, and the time frequency analysis has been carried out to extract the features using wavelet decomposition approach. The classification of normal and paralyzed condition is carried by four classifier models. The classifier models used are Multi-layer Perceptron (MLP), Random Forest (RF), Gradient Boosting (GB), and Nearest Neighbor (NN) models. The standard data set has been used for the purpose. The classification accuracy obtained for MLP is 80%, for RF is 75%, for GB is 79%, and for NN is 69%. MLP shows better classification performance over RF, GB, and NN Classifiers.**
Keywords: **Paralysis, Electromyography, ALS, Myopathy, Wavelettrans Form, Multi-Layer Perceptron (MLP), Random Forest (RF), Gradient Boosting (GB), Nearest Neighbor (NN)**

I. INTRODUCTION

Electromyogram (EMG) measures muscle response or electrical activity and aid in diagnosis of muscular paralysis. EMG signal is measure of electrical currents generated due to muscle fibers dynamics. EMG signal is a complicated signal controlled by the complex nervous system. EMG could be acquired by two mechanisms either through invasive or noninvasive. EMG provides valuable information about muscular contraction. The paralysis is the loss of muscle function. The paralysis is caused due to spinal cord injury, stroke, Amyotrophic Lateral Sclerosis (ALS), Myopathy, and injuries in the nervous system. The present work is carried with the analysis of EMG using time frequency domain features, and classification of normal and paralyzed condition. In this work the ALS, and Myopathy, conditions are considered for analysis of Paralysis. Amyotrophic lateral sclerosis (ALS) leads to death of motor neurons, Myopathy is a muscular disorder leads to muscular weakness.

II. RELATED WORK

A. EMG Features

First Author	EMG Data	Features	Classifiers employed	Conclusion
Christopher Spiewak [1]	Acquired from invasive and non-invasive methods.	•Mean Absolute Value (MAV) •Mean Absolute Value Slope (MAVS) •Simple Square Integral (SSI) •Variance of EMG (VAR) •Root Mean Square (RMS) •Waveform Length (WL) •Autoregressive Coefficients (AR) •Frequency Median (FMD) •Frequency Mean (FMN) •Modified Median Frequency (MMDF) •Modified Frequency Mean (MMNF)	•Neural Network (NN) •Fuzzy Logic (FL) •Bayesian Classifier (BC) •Support Vector Machine (SVM) •Linear Discriminant Analysis (LDA) •Neuro-Fuzzy Hybridization (NF)	Methods based in the time domain are used as an onset index for muscle activity with slight differences in output parameters in each method. Methods based in the frequency domain are generally used for determining muscle fatigue and motor unit recruitment •presented six different methods of classification. Each having slight differences in their strengths and weaknesses. methods of classification. Each having slight differences in their strengths and weaknesses.

Reza Bagherian Azhiri [2]	Dataset provided by Center of Intelligent Mechatronic Systems at the University of Technology at Sydney	•Integrated EMG (IEMG) •Mean Absolute Value (MAV) •Simple Square Integrated (SSI) •Root Mean Square (RMS) •Variance (VAR) •Myopulse Percentage Rate (MYOP) Waveform Length (WL) •Difference Absolute Mean Value (DAMV) •Second-Order Moment •Difference Variance Version (DVARV) •Difference absolute standard deviation value (DASDV) •Willison Amplitude (WAMP)	•ANN •ANN+NMF •SVM •KNN + SVM + Fusion •NN	•Proposed five new feature extraction functions applying on each level of wavelet transform. Enhances the accuracy up to 8% approximately and increased the accuracy to 95:5%.
Angkoon Phinyomark [3]	Surface EMG data obtained from four different datasets comprised of forty subjects (31 able-bodied subjects and 9 transradial amputees)	•Integrated Absolute Value (IAV) •Mean Absolute Value (MAV) • Root Mean Square (RMS) • Variance (VAR), •Waveform Length (WL) • Log Detector (LD) •Difference Absolute Mean Value (DAMV) • Difference Absolute Standard Deviation Value (DASDV) • Difference Variance Value (DVARV) •Mean Value Of The Square Root (MSR) •L-Scale (LS) •Maximum Fractal Length (MFL) •Detrended Fluctuation Analysis (DFA) •Sample Entropy (Sampen) •Zero Crossing (ZC) •Slope Sign Change (SSC) • Willison Amplitude (WAMP) • Median Frequency (MDF) • Mean Frequency (MNF) •Autoregressive Coefficients (AR) •Cepstrum Coefficients (CC) •Histogram (HIST)	SVM	•The results of this investigation also included a comparison of twenty-six individual features •The classification performance of all evaluated features decreased significantly ($p < 0.05$) with the reduced sampling rate. •Due to real-time constraints, however, the total response time for myoelectric control, which includes both the window size and processing delay, should not exceed 300 ms Loss of high frequency components could also degrade the classification

Inference: From the related works we can observe that the EMG features can be used to analyse the EMG Data. In many research works the time domain features, frequency domain features, and time-frequency domain features are extracted. In this work all twelve statistical features selected are computed time-frequency domain.

B. Wavelet Decomposition

First Author	EMG Data	Wavelet Decomposition	Features	Conclusion
Lukasz Wiklendt [4]	Three artificial signals and one real EMG signal recorded from smooth-muscle	MESACLIP algorithm	Spike detection based on threshold crossing	Potential problem of harmonic artifacts have now been solved with the presented mesaclip algorithm
Angkoon Phinyomark [5]	EMG signals used in this study were extracted from six daily-life upperlimb	•DWT •Four levels of wavelet decomposition •Seven mother wavelets are selected	•MAV •RMS	EMG signals that were estimated from the detail coefficients of the first level and the second level yield the improving of the class separability. It ensures that the

	movements and two forearm muscle chan	•Second and the Seventh orders of Daubechies wavelet (db2 and db7), •Forth and the Fifth orders of Coiflet wavelet (coif4 and coif5). • Fifth order of Symlets wavelet (sym5) •Fifth order of BioSplines wavelet (bior5.5). •Second order of Reverse Bior wavelet (rbio2.2).		result of the classification accuracy will be as high as possible. The suitable mother wavelet and decomposition level are the seventh order of Daubechies wavelet and the fourth decomposition levels, respectively.
Gang Wang [6]	SEMG recorded from flexor carpi radialis (FCR) and extensor carpi radialis longus (ECRL)	•Discrete Wavelet Transform (DWT) with adequate scale values. •GP Algorithm	Correlation Dimension D_C	Ability of classifying four different types of forearm movements Wavelet-based correlation dimension can catch different nervous activities Wavelet-based correlation dimension method can represent the difference of the SEMG signals relevant to different movements. Classification accuracy was 100%, when two channels of SEMG signals were used.

Inference: From the related works it is evident that Wavelet Decomposition application on EMG Data yielded better understanding of the data. The use of time-frequency domain features gives the better classification performance. Hence in the present work EMG features are extracted in time-frequency domain to obtain the better classification performance.

C. EMG Classification

First Author	EMG Data	Classifiers	Conclusion
Bushra Saeed [7]	SEMG: The Ninapro database cover 10 repetitions of 52 differenthand movements obtained from 27 intact subjects	•LDA •ANN	Non-linear ANN classifier revealed better performance results as compared to linear LDA classifier.
N Srisuwan [8]	EMG signals from five positions (channels) of speech production muscles were captured	•Nearest Mean (NM) • K-Nearest Neighbor (KNN) • Linear Bayes Normal (LBN) • Logistic Linear (LOGL) • Quadratic Bays Normal (QBN) • Fisher's Least Square Linear Discriminant (FLDA) • Support Vector Machine (SVM) •Artificial Neural network (ANN).	The FLDA classifier gave the best accuracies (90.01%)
Elamvazuthi [9]	EMG data were obtained from an EMG lab database. EMG signals were obtained from manysubjects (healthy subjects and subjects suffering from neuropathy and myopathy) with different of mean age.	Multilayer Perceptron (MLP)	Multilayer Perceptron (MLP) isuseful tool to classify the EMG signals with three different groups such as healthy, myopathy and neuropathy.
Adenike A [10]	SEMG Data from non-amputee subjects	•LDA Classifier •Quadratic Discriminant Analysis Classifier (QDA) •Multilayer Perceptron	QDA performed worse than all other classifiers pattern recognition techniques to be used for control of partial-hand prostheses

Inference: From the related works it is observed that various classifier models are used for EMG Data classification. In this work the Classification based on ML techniques are employed. The classifier models selected yield better performance with time-frequency domain features.

This work is intended to develop a method which gives better performance for classification of paralysis disease compared to existing methods. The work is carried out with EMG Data from Normal, Myopathy, and ALS Conditions. The EMG Data is referred from database of clinical signals at emglab. The statistical features are computed from the EMG data. All the features are computed in time-frequency domain, to analyze the EMG data efficiently. To extract time-frequency domain features, wavelet decomposition technique is used with Daubechieus, Symlet, and Coiflet Wavelets. The ML classifiers are used for the classification. The accuracy of the classifier models is calculated to indicate the classifier performance.

III. METHODOLOGY

To analyze the paralysis, ALS, and Myopathy conditions are considered. ALS is a progressive nervous system disease that affects nerve cells in the brain and spinal cord, causing.

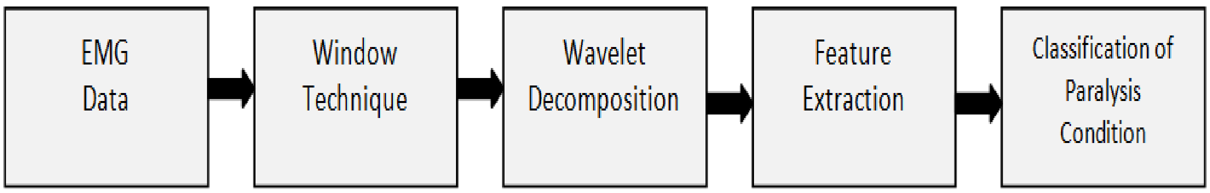

Fig 1 Classification of muscular Paralysis

Figure 1 shows the method employed in classification of paralysis condition. 300 msec rectangular window is used for extraction of features in segment level. For sample level the 11.2 sec recorded data is used for extraction of features. The EMG Data decomposition is achieved using the Daubechies wavelets of order 2 to 10, Symlet wavelets of order 2 to 10, and Coiflet wavelets of order 1 to 5. Twelve features are extracted for analysis. The features obtained are further used for classification. The MLP, RF, GB, and NN classifier models are used. The classification accuracy is measured.

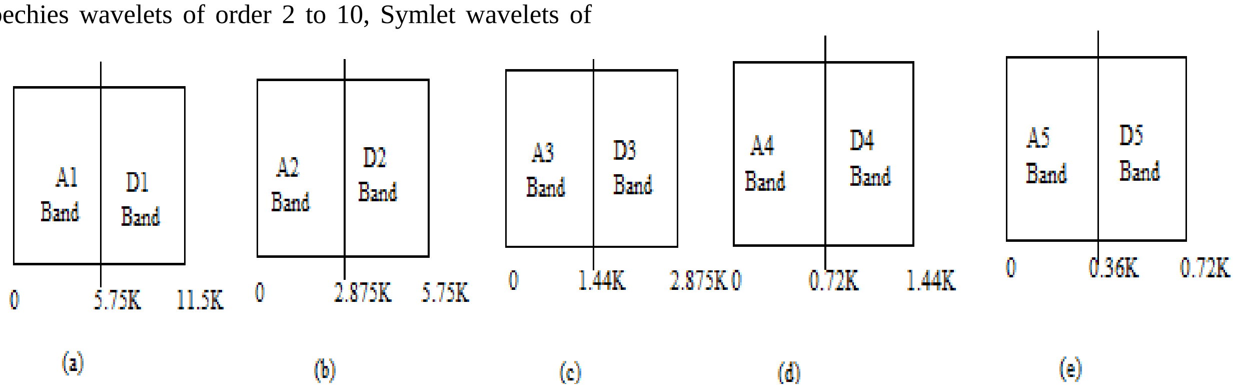

Fig. 2 Wavelet Decomposition: (a) A1 & D1 Bands. (b) A2 & D2 Bands.
(c) A3 & D3 Bands. (d) A4 &D4 Bands. (e) A5 & D5 Bands

Figure 2 shows the Wavelet decomposition for different bands of frequencies. The A1 B and is Approximation Band 1 and D1 is Detail Band 1. The Similarly, A2, A3, A4, & A5 are Approximation Bands and D2, D3, D4, & D5 are Detail Bands. The Mean, Variance, MAV, RMS, WL, ZC, LD, DASDV, AAC, VAV, Kurtosis, and Skewness are the features extracted from the Data and are used as input vectors for classifier models.

IV. RESULTS AND DISCUSSION

The ALS, and Myopathy data are used for analysis of muscular paralysis. After Wavelet decomposition the 12 features, Mean, Variance, MAV, RMS, WL, ZC, LD, DASDV, AAC, VAV, Kurtosis, and Skewness, are extracted, and these features are used in classification of paralysis and normal condition.

The classification is achieved with training sample sizes of 60%, 70%, 80%, and 90%, and test sample sizes of 40%, 30%, 20% and 10% respectively. The classification is achieved in the segment level and sample level. The accuracy of the classification is calculated for each classifier model. The results are tabulated.

Table I shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Symlet of order 10 (SYM10).

TABLE I CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING SYMLET OF ORDER 10 (SYM10)

SYM10	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7716	0.7988	0.7787	0.8102	0.8051	0.8142	0.7849	0.8043
RF	0.733	0.7768	0.7351	0.7992	0.7196	0.7431	0.7486	0.826
GB	0.7486	0.8154	0.749	0.8065	0.7619	0.8087	0.7776	0.8586
NN	0.6664	0.7134	0.6694	0.7262	0.6644	0.7267	0.6639	0.7065

TABLE II CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING SYMLET OF ORDER 9 (SYM9)

SYM9	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7829	0.8264	0.763	0.7883	0.7913	0.8415	0.7852	0.826
RF	0.7364	0.7878	0.732	0.7481	0.718	0.7431	0.744	0.8043
GB	0.7559	0.8016	0.7613	0.8138	0.751	0.8142	0.768	0.7934
NN	0.6679	0.7024	0.667	0.7226	0.6614	0.7049	-	-

Table II shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Symlet of order 9 (SYM9).

TABLE III CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING SYMLET OF ORDER 8 (SYM8)

SYM8	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7785	0.8071	0.7869	0.8248	0.7877	0.8032	0.7908	0.8478
RF	0.7322	0.7823	0.7354	0.7773	0.7242	0.754	0.7519	0.7934
GB	0.7559	0.8044	0.7651	0.8175	0.7614	0.8196	0.7793	0.8369
NN	0.6664	-	0.6677	0.7153	0.6682	0.7213	0.6696	0.6956

Table III shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Symlet of order 8 (SYM8).

TABLE IV CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING SYMLET OF ORDER 7 (SYM7)

SYM7	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7899	0.8264	0.7911	0.8102	0.7965	0.8196	0.7914	0.7934
RF	0.7364	0.7768	0.7369	0.781	0.7173	0.7322	0.746	0.7826
GB	0.7607	0.8016	0.7627	0.8138	0.7528	0.7978	0.7803	0.8152
NN	0.6642	0.7052	0.6681	0.7116	-	-	-	-

Table IV shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Symlet of order 7 (SYM7).

Table V shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Symlet of order 6 (SYM6).

TABLE V CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING SYMLET OF ORDER 6 (SYM6)

SYM6	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7802	0.8044	0.7883	0.8284	0.781	0.8087	0.7847	0.8152
RF	0.7348	0.7741	0.7367	0.781	0.7184	0.754	0.7429	0.7826
GB	0.7616	0.8154	0.7606	0.8138	0.7475	0.7923	0.775	0.826
NN	0.6629	0.6914	0.659	0.7043	0.664	0.7103	0.6615	0.7065

TABLE VI CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING SYMLET OF ORDER 5 (SYM5)

SYM5	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7905	0.8181	0.7711	0.8102	0.8044	0.8251	0.8023	0.826
RF	0.736	0.7851	0.7312	0.7664	0.7194	0.7595	0.7458	0.8043
GB	0.7621	0.7906	0.7662	0.8211	0.7564	0.7923	0.7761	0.8152
NN	0.6566	0.6914	0.6501	0.7043	0.6513	0.7049	0.658	0.7173

Table VI shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Symlet of order 5 (SYM5).

TABLE VII CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING SYMLET OF ORDER 4 (SYM4)

SYM4	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7873	0.8126	0.7814	0.8211	0.8092	0.8524	0.8196	0.826
RF	0.7387	0.7851	0.7339	0.7737	0.7169	0.7486	0.7357	0.7717
GB	0.7651	0.8016	0.7592	0.8175	0.7565	0.8032	0.7662	0.826
NN	0.6685	0.7162	0.6609	0.7116	0.6547	0.6994	0.6754	0.6956

Table VII shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Symlet of order 4 (SYM4).

TABLE VIII CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING SYMLET OF ORDER 3 (SYM3)

SYM3	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7884	0.8016	0.7859	0.8211	0.813	0.8469	0.7858	0.7934
RF	0.7326	0.7823	0.735	0.77	0.7196	0.7431	0.7456	0.8043
GB	0.7603	0.8071	0.7707	0.8138	0.7457	0.7978	0.772	0.826
NN	0.6734	0.73	0.6717	0.7262	0.6634	0.7049	0.6563	0.6739

Table VIII shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Symlet of order 3 (SYM3).

TABLE IX CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING SYMLET OF ORDER 2 (SYM2)

SYM2	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7933	0.8209	0.7938	0.8284	0.8065	0.8142	0.7893	0.826
RF	0.7557	0.8044	0.7445	0.7956	0.708	0.7322	0.7407	0.8152
GB	0.7669	0.8181	0.7619	0.8029	0.7448	0.7704	0.756	0.7934
NN	0.6755	0.7327	0.6674	0.7189	0.671	0.7267	0.6911	0.7391

Table IX shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Symlet of order 2 (SYM2).

TABLE X CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING COIFLET OF ORDER 5 (COIF5)

COIF5	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7673	0.7851	0.7816	0.8211	0.7987	0.8469	0.7945	0.8152
RF	0.7242	0.7768	0.7313	0.7664	0.7132	0.7486	0.7436	0.7826
GB	0.7553	0.7933	0.7496	0.7919	0.7514	0.8087	0.7788	0.8369
NN	0.6615	0.7052	0.6682	-	0.6664	0.7103	0.6692	0.7065

Table X shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Coiflet of order 5 (COIF5).

TABLE X CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING COIFLET OF ORDER 4 (COIF4)

COIF4	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7807	0.8292	0.779	0.8065	0.8018	0.8579	0.7865	0.8152
RF	0.7297	0.7796	0.7249	0.7664	0.7162	0.7431	0.7414	0.7826
GB	0.7605	0.8016	0.7525	0.8029	0.7439	0.7978	0.7818	0.8369
NN	0.6645	0.7079	0.6672	0.7226	0.666	0.7103	-	-

Table X shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Coiflet of order 5 (COIF5).

TABLE XI SHOWS THE CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING COIFLET OF ORDER 4 (COIF4)

COIF4	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7807	0.8292	0.779	0.8065	0.8018	0.8579	0.7865	0.8152
RF	0.7297	0.7796	0.7249	0.7664	0.7162	0.7431	0.7414	0.7826
GB	0.7605	0.8016	0.7525	0.8029	0.7439	0.7978	0.7818	0.8369
NN	0.6645	0.7079	0.6672	0.7226	0.666	0.7103	-	-

Table XI shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Coiflet of order 4 (COIF4).

TABLE XII CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING COIFLET OF ORDER 3 (COIF3)

COIF3	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7843	0.8236	0.7761	0.8065	0.8004	0.8142	0.7949	0.826
RF	0.7354	0.7823	0.736	0.781	0.7173	0.7431	0.7403	0.7826
GB	0.7631	0.8044	0.7544	0.8029	0.7497	0.8087	0.771	0.8478
NN	0.6671	-	0.6648	0.7116	0.6637	0.6939	-	-

Table XII shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Coiflet of order 3 (COIF3).

TABLE XIII CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING COIFLET OF ORDER 2 (COIF2)

COIF2	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7891	0.8154	0.7896	0.8138	0.8069	0.8251	0.7999	0.8043
RF	0.7361	0.7851	0.7358	0.7737	0.7192	0.7704	0.7403	0.8043
GB	0.7646	0.8126	0.766	0.8138	0.7583	0.8196	0.7756	0.7826
NN	0.6646	0.6997	0.6588	0.7116	0.655	0.6994	0.6738	0.6956

Table XIII shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Coiflet of order 2 (COIF2).

TABLE XIV CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING COIFLET OF ORDER 1 (COIF1)

COIF1	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7831	0.8099	0.7816	0.8065	0.8059	0.8251	0.8021	0.8369
RF	0.7511	0.8099	0.7461	0.7883	0.7142	0.7868	0.7368	0.7826
GB	0.7664	0.8071	0.7626	0.8065	0.754	0.7814	0.7432	0.7934
NN	0.6746	0.7355	0.6698	0.7189	0.6716	0.7158	0.6898	0.7391

Table XIV shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Coiflet of order 1 (COIF1).

TABLE XV CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING DAUBECHIES OF ORDER 10 (DB10)

DB10	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7763	0.8126	0.778	0.8102	0.7917	0.8251	0.7917	0.8369
RF	0.7326	0.7768	0.7253	0.7554	0.7125	0.7486	0.7355	0.8043
GB	0.7554	0.8071	0.7484	0.8065	0.7551	0.8196	0.7758	0.826
NN	0.66	0.6914	0.6603	0.708	0.6639	0.6994	0.6649	0.6956

Table XV shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Daubechies of order 10 (DB10).

TABLE XVI CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING DAUBECHIES OF ORDER 9 (DB9)

DB9	**Test Size = o.4**		**Test Size = o.3**		**Test Size = o.2**		**Test Size = o.1**	
	SegLvl	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**	**SegLvl**	**SmplLvl**
MLP	0.7725	0.8099	0.7711	0.8248	0.7959	0.8251	0.7828	0.8152
RF	0.7304	0.7796	0.7325	0.77	0.7174	0.7486	0.7533	0.7934
GB	0.7591	0.8126	0.7555	0.8211	0.7612	0.7923	0.7887	0.8478
NN	0.6661	0.7107	0.662	0.7153	0.6621	0.6939	0.6682	0.7173

Table XVI shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Daubechies of order 9 (DB9).

Table XVII shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Daubechies of order 8 (DB8).

TABLE XVII CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING DAUBECHIES OF ORDER 8 (DB8)

DB8	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7732	0.8126	0.7799	0.8065	0.8021	0.836	0.7736	0.7826
RF	0.7396	0.7851	0.7296	0.7554	0.7186	0.7486	0.7516	0.8043
GB	0.7581	0.8016	0.7575	0.8211	0.7546	0.8032	0.767	0.8152
NN	0.6608	0.7024	0.6625	0.7116	0.6654	0.6885	0.6744	0.7065

TABLE XVIII CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING DAUBECHIES OF ORDER 7 (DB7)

DB7	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7766	0.8181	0.7808	0.8102	0.8002	0.8251	0.7882	0.826
RF	0.7312	0.7878	0.7263	0.7481	0.7109	0.7486	0.7491	0.8152
GB	0.752	0.8071	0.7567	0.8211	0.7593	0.836	0.7757	0.826
NN	0.6586	0.6997	0.6606	0.7189	0.6588	0.6939	0.6695	0.7282

Table XVIII shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Daubechies of order 7 (DB7).

TABLE XIX CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING DAUBECHIES OF ORDER 6 (DB6)

DB6	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7916	0.8236	0.7864	0.8029	0.7884	0.8306	0.7883	0.8043
RF	0.7302	0.763	0.7292	0.7591	0.7287	0.7486	0.7593	0.8152
GB	0.7559	0.7961	0.7634	0.8065	0.7516	0.8032	0.7766	0.826
NN	0.6676	0.719	0.6675	0.7299	0.6698	0.7103	0.6646	0.7282

Table XIX shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Daubechies of order 6 (DB6).

TABLE XX CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING DAUBECHIES OF ORDER 5 (DB5)

DB5	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7851	0.8209	0.7936	0.8284	0.8095	0.8196	0.7936	0.7934
RF	0.7329	0.7796	0.7406	0.7846	0.7152	0.765	0.7499	0.7934
GB	0.7603	0.8071	0.7645	0.8102	0.7504	0.7814	0.7672	0.8152
NN	0.6729	0.7245	0.6703	0.7262	0.6704	0.7103	0.6796	0.7173

Table XX shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Daubechies of order 5 (DB5).

TABLE XXI CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING DAUBECHIES OF ORDER 4 (DB4)

DB4	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7666	0.7933	0.779	0.8248	0.8001	0.8142	0.7912	0.8043
RF	0.7339	0.7796	0.7397	0.7956	0.7188	0.7704	0.7363	0.7826
GB	0.7606	0.8016	0.7517	0.7956	0.7654	0.7868	0.77	0.826
NN	0.657	0.6859	0.6551	0.7007	0.6561	0.6775	0.6569	0.6847

Table XXI shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Daubechies of order 4 (DB4).

TABLE XXII CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING DAUBECHIES OF ORDER 3 (DB3)

DB3	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7882	0.8209	0.786	0.8248	0.8186	0.8469	0.7865	0.8152
RF	0.7389	0.7851	0.7336	0.781	0.7186	0.765	0.7371	0.7934
GB	0.7511	0.7878	0.7795	0.8394	0.7597	0.8087	0.7762	0.826
NN	0.6772	0.73	0.6716	0.7262	0.6632	0.7049	0.6553	0.6739

Table XXII shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Daubechies of order 3 (DB3).

The Figure 3 shows chart graph of the classifier accuracy with Symlet wavelet used for decomposition.

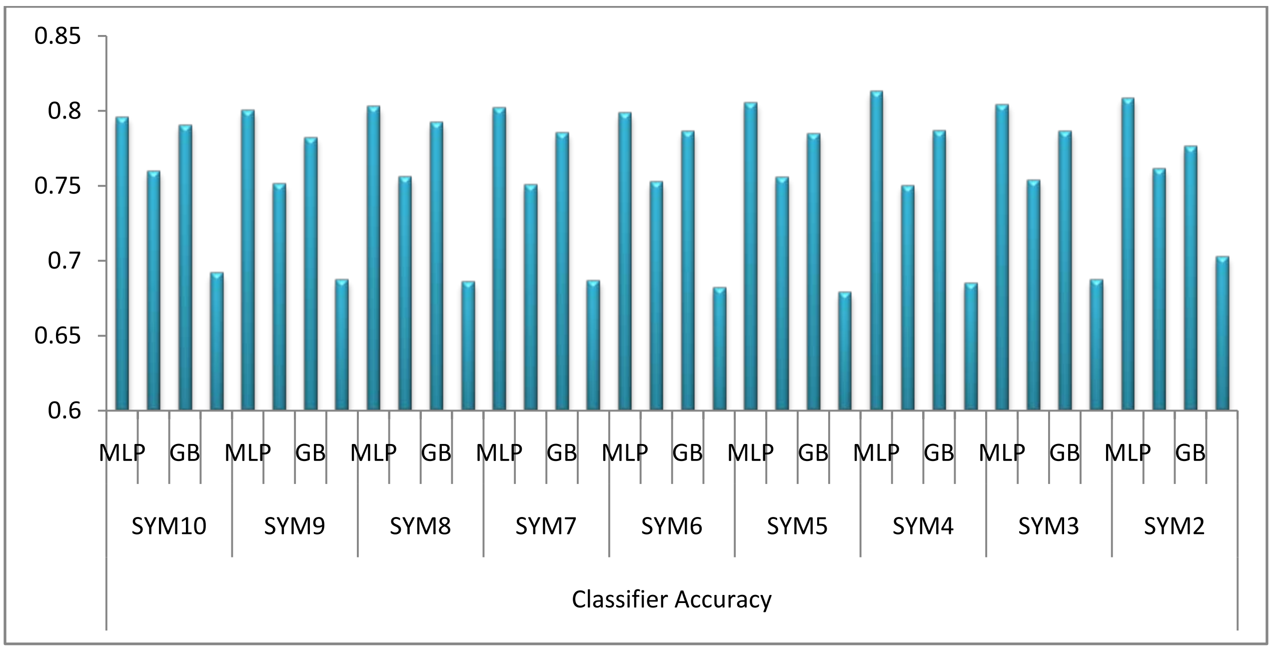

Fig. 3 Chart graph of the Classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with Symletwavelet decomposition

TABLE XXIII CLASSIFICATION ACCURACY OF CLASSIFIERS MODELS USING FEATURES OF ALS, MYOPATHY, AND NORMAL DATA WITH WAVELET DECOMPOSITION USING DAUBECHIES OF ORDER 2 (DB2)

DB2	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7793	0.8099	0.7827	0.8284	0.8073	0.8196	0.7824	0.8152
RF	0.7583	0.8099	0.739	0.7883	0.7084	0.7595	0.7368	0.7608
GB	0.773	0.8154	0.7636	0.8029	0.7484	0.7814	0.7457	0.7826
NN	0.6736	0.73	0.6656	0.7189	0.6683	0.7267	0.6886	0.7282

Table XXIII shows the classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition using Daubechies of order 2 (DB2).

The Figure 4 shows the chart graph of the classifier accuracy with Coiflet wavelet used for decomposition.

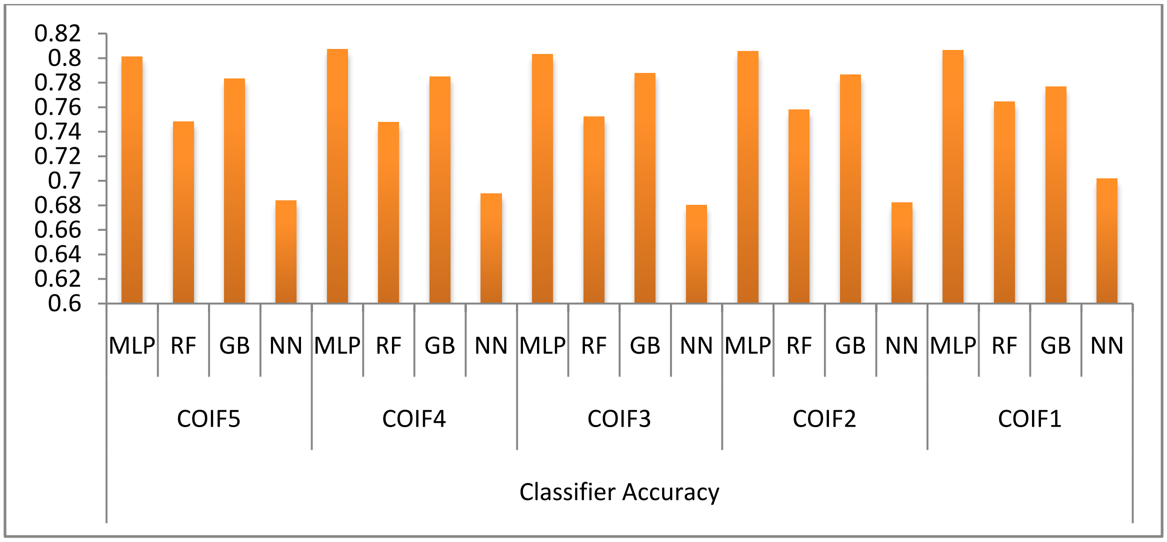

Fig. 4 Chart graph of the Classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with Coiflet wavelet decomposition

The Figure 5 shows the chart graph of the classifier accuracy with Daubechies wavelets used for decomposition.

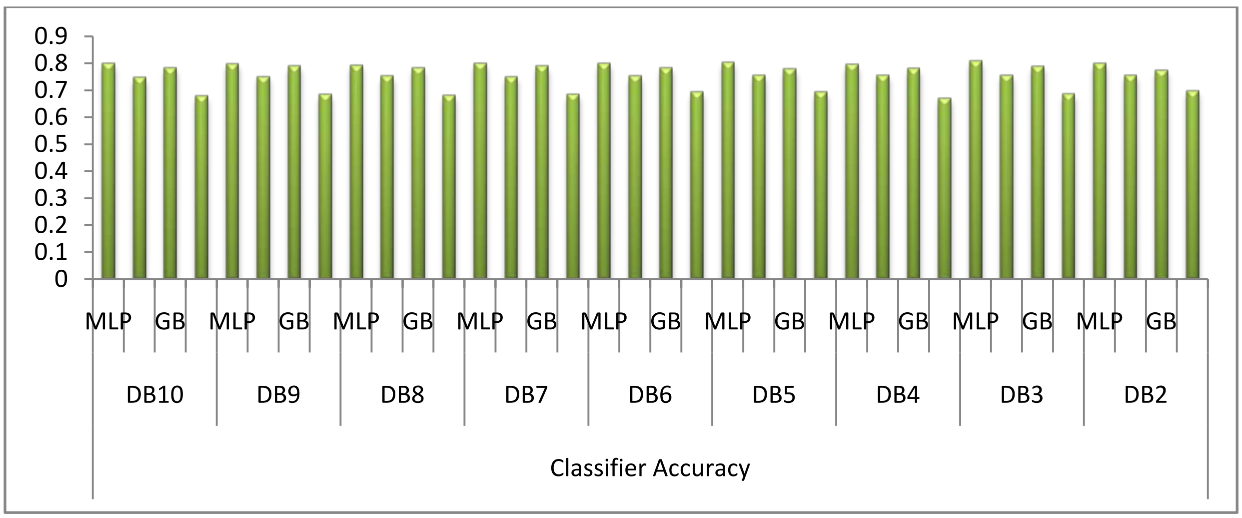

Fig. 5 Chart graph of the Classification accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with Daubechies wavelet decomposition

Figure 6 shows the chart graph of the overall accuracy of the MLP, RF, GB, & NN Classifier Models.

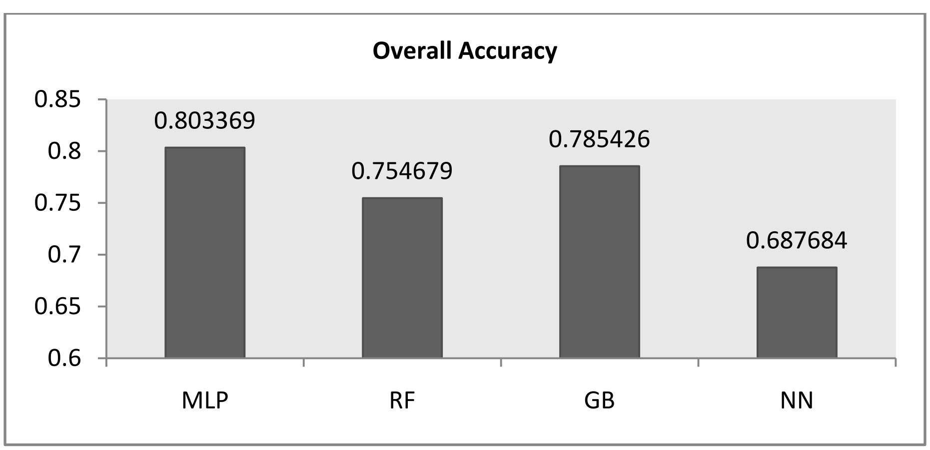

Fig. 6 Chart graph of the Overall accuracy of Classifiers Models using Features of ALS, Myopathy, and Normal Data with wavelet decomposition

V. CONCLUSION

In this work, the features Mean, VAR, MAV, RMS, WL, ZC, LD, DASDV, AAC, VAV, Kurtosis, and Skewness, from the EMG of ALS, Myopathy and Normal condition are extracted in time frequency domain. The MLP, RF, GB, and NN classifiers are used for classification. The classification is performed in segment level and in sample level. The overall accuracy values obtained are 80% for MLP, 75% for RF, 79% for GB, and 69% for NN. The performance accuracy is better in MLP classifier model compared to other classifier models. This approach can be used as diagnostic tool for paralysis.

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