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Analysis and Classification of Muscular Paralysis Disease using Electromyography Signal with Machine Learning

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ABSTRACT

Electrical activity of the muscles is characterized by Electromyography (EMG) signals. The EMG signal analysis form the basis for the diagnosis of muscular paralysis. The EMG signals from amyotrophic lateral sclerosis (ALS), and Myopathy are considered to analyze the paralysis. The statistical analysis of EMG signals from ALS, Myopathy, and Normal conditions, aid in the analysis and classification of paralysis. This work intends to analyze and classify the paralysis and normal conditions using EMG features extracted in time and frequency domains. Twelve statistical features are extracted from the EMG signals considered. Machine Learning techniques and deep learning techniques (DLT) are employed to perform the classification. multi-layer perceptron (MLP), support vector machine (SVM), random forest (RF), gradient boosting (GB), and nearest neighbor (NN) classifier models are used for the classification. The accuracy of the classifiers is calculated. The accuracy values obtained are 72% for MLP, 73% for SVM, 72% for RF, 71% for GB, and 69% for NN. The performance accuracy is better in SVM compared to other classifiers.

Keywords: ALS, EMG, GB Classifier, MLP Classifier, Myopathy, NN Classifier, RF Classifier, SVM Classifier.

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INTRODUCTION

Paralysis describes the loss of muscular activity. Muscular activity comprises the muscles' ability to move or work. Damage in the nervous system is one of the causes for paralysis. Paralysis may also result from stroke, nerve injury, amyotrophic lateral sclerosis(ALS), myopathy, multiple sclerosis, cerebral palsy, parkinson's disease, poliomyelitis, peripheral neuropathy, and Guillain-Barre syndrome.[1]

Paralysis can be temporary or permanent. It can be localized or generalized and be unilateral or bilateral. Muscle tone variation is caused by paralysis. Paralysis may lead to flaccidity, flabbiness of the muscles or muscle spasticity. The symptoms accompanying paralysis are pain, numbness, tingling, balance problems, speech difficulty, and altered vision. Paralysis may cause sores, deep vein thrombosis, osteoporosis, and many more.

This work is aimed to analyze the paralysis by considering the EMG signals from ALS, Myopathy, and Normal conditions. Statistical features are extracted in time and frequency domains from the EMG signals. These features are used to perform the classification of Paralysis and Normal conditions.

The neurons in the brain and spinal cord, are affected by ALS, resulting in loss of motor function, muscle weakness, and paralysis.[2] The muscle tissues affected by any disease is termed as myopathy. This causes spasms, inflammation, tetany, weakness and paralysis.[3]

In the present work, the features extracted from ALS, Myopathy, and Normal conditions are considered for the classification. Classification is performed using MLP, SVM, RF, GB, and NN classifier models.

The electrical impulses originating in the brain control muscular activity. These impulses are carried to specific body locations through the peripheral nervous system. Muscular activity is impaired by neuromuscular diseases (NMDs).[4]

The neuromuscular disease ALS is caused due to motor neuron disorders. ALS will in turn lead to failure of the respiratory system, loss of brain control over muscles, weakness, and paralysis.[5]

Injury or infection in the muscle leads to myopathy. Myopathy describes the disorder of the muscles.[6] Clinical care can be provided with early diagnosis. EMG is one of the

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measures in diagnosing neuromuscular diseases by viewing the abnormalities associated with the EMG signals.

LITERATURE REVIEW

The EMG signal analysis can be accomplished through several methodologies and application of several algorithms.[7] The advancements in methods are applicable for EMG signal detection, decomposition, processing, and classification. The short-time Fourier Transform Ranking (STFT-ranking) feature, used to determine multichannel EMG signals, became a novel feature extraction method.[8] To recognize human motion patterns, multichannel EMG signals are majorly used. The various muscle contractions cause variation in the EMG signals and affect pattern recognition performance. To compare the performance, the novel feature and conventional features in time-domain and frequency-domain are employed during dynamic and isometric muscle contractions. Among the features employed, the STFT-Ranking feature yielded an accuracy rate exceeding 90% when the EMG signals used in the training and validation feature data sets were of the same type of muscle contraction. When STFT-ranking feature is projected onto the PCA space, it offers increased performance compared to other features employed for motion pattern recognition, as feature data from various motion patterns are more separable. The inference from the experiment is that EMG signals from similar muscle contractions, dynamic or isometric, are consistent with being used in training and validation stages. In rehabilitation, this methodology can be potentially applicable.

The electrical representation of neuromuscular activation is indicated by EMG signal, from which physiological process can be accessible. To design a knowledge-based expert system for disease diagnosis, the root of the feature mean square, spectrogram, kurtosis, entropy and power extracted from EMG signals can be used. These features are considered for ALS, representing myopathy and neuropathy.[9] The force generated in the muscles produce movements and aid in interacting with a working environment. The muscle force results from a biomechanical phenomenon. The EMG classification is challenging because EMG signal is non-stationary in nature. The features root mean square, spectrogram, kurtosis, entropy and power are extracted from ALS EMG signals during isometric contraction. The obtained classification accuracy is satisfactory for designing EMG signal classifier for various clinical diagnostic applications.

A novel method is used to detect individual motor unit action potentials (MUAPs) originating from intramuscular activity. The automatic MUAP classification is achieved for normal, or myopathy, neuropathy classes.[10] This method detects the template MUAP clusters and classifies into the normal, or neuropathic, myopathy class. The method includes preprocessing of EMG, MUAP detection and clustering, and MUAP classification. The method is validated using EMG data and collected MUAPs. The accuracy for MUAP clustering is 93, 95, and 92% for normal, myopathy and neuropathy, respectively. The 91% of superimposed MUAPs are identified accurately. The obtained accuracy for MUAP classification is about 86%.

The EMG signals from hand movements are used to perform classification.[11] The features in the classification are employed in the time domain, frequency domain, time-frequency domain and time-scale domain. Using EMG signals in prosthetic device control, neuromuscular disease identification is widely observed. EMG signals can also be used for human-computer interaction (HCI) systems. The article describes the detection of different predefined hand motions (left, right, up and down). The classification is performed using an artificial neural network (ANN). The neural network is trained by Levenberg-Marquardt training algorithm and is of back propagation type. The EMG signals are preprocessed before feature extraction. The extracted features in the time and frequency domain are used in the classification process. The classifier model is trained with the normalized feature set with the supervised learning method. The results show that this approach can classify the hand motions from the EMG signals with a success rate of 88.4%.

For the classification of MUAPs, a two-stage classifier is developed.[12] The superimposed MUAPs detection and decomposing MUAPs in to their constituents are performed automatically. The classification is performed using ANN according to their pathology. The needle EMG signals are considered for detecting and classifying individual MUAPs. The method includes the automatic decomposition of MUAPs, and a two-stage feature-based classifier, which classifies the normal, or neuropathic, myopathy conditions. The method involves preprocessing of EMG, MUAP clustering and detection of superimposed MUAPs, feature extraction, and MUAP classification. The Radial Basis Function, Artificial Neural Networks and Decision Trees are employed in the method. The interpretation for the classification is provided with minimal use of tuned parameters. The method is validated using real EMG, and collected MUAPs. The success rate for MUAP clustering is 96%, while the accuracy for MUAP classification is about 89%.

The classification of MUAPs from the neural network classifier, using time-domain and AR parameters is described.[13] For diagnosing neuromuscular disorders, the shapes of MUAPs, become an important source of information. The information from EMG can be extracted by identifying the MUAPs, clustering of MUAPs with similar shapes, MUAPs clusters feature extraction and MUAPs classification. The data-driven segmentation algorithm is used for MUAPs identification, and clustering of MUAPs are achieved using the statistical pattern recognition technique. Time domain and Autoregressive (AR) features are extracted. MUAPs classification is accomplished by using neural network (NN) classifier. Twelve EMG signals from three normal, five myopathy and four motor neuron disease conditions are considered. The success rate for the segmentation technique is 95.90% and for the statistical technique is 93.13%. The classification accuracy of NN is 66.72% with time-domain parameters and 75.06 % with AR

parameters.

From the related works, it is inferred that the features extracted from EMG signals can be used to analyze and classify the data.

METHODOLOGY

In this work, the 12 statistical features of EMG are considered for analysis and classification of paralysis disease. The major characteristics of the biomedical signals are continuous in nature. The graphical representation of these signals concerning some function of the time parameter is required to analyze these time-series signals. The general plot will be with amplitude along the time. Almost all signals in their natural form are in the time domain. Hence the signals are represented with a time-amplitude plot.

The analysis of EMG signal in the time domain gives information regarding variation in the amplitude concerning time. For the majority of the biomedical signals, the analysis in the frequency domain is very useful in finding the nature and characteristics of the signal. The frequency components of the biomedical signal explain the physiological system condition, describing the normal or pathological condition.

Database Used

The dataset[14] consists of EMG signals recorded from needle electrodes at five different locations in the muscles. The electrode insertion levels is low, medium, and deep. The EMG signals sampling frequency is selected to 23.435 kHz. EMG recordings are taken from Biceps brachii and medial vastus muscles. For normal subjects, EMG is recorded from Biceps brachii muscle. EMG is recorded from Biceps brachii and medial vastus muscles for myopathy and ALS subjects. EMG signal filtering is achieved using filters with 2 Hz and 10 kHz cutoff frequencies. The EMG signals in the dataset are recorded from a group of patients with myopathy, a controlled normal subjects group, and a group of patients with ALS. Four females and six males aged between 21 to 37 years are in the control group.

Two females and Five males between 19 to 63 years of age are in the group of patients with myopathy. Four females and Four males aged between 35 to 67 years are in the group of patients with ALS. In the dataset EMG data samples of normal class is 300, EMG data samples of myopathy are 315, and EMG data samples of ALS is 332. All EMG data samples are recorded for the duration 11.2 seconds.

Features considered are mean value, variance, mean absolute value, root mean square, waveform length, zero crossing, log detector, difference absolute standard deviation value, average amplitude change, variance absolute value, kurtosis of signal, and skewness of signal.

- *Mean Value:* The amplitude Mean value of the EMG for selected analysis intervals. The mean EMG value gives the gross innervation input of a selected muscle for a specified task and works.
- *Variance:* Variance of EMG signal (VAR) give the signal power.

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

- *Mean Absolute Value:* Mean absolute value (MAV) is the average of the summation of absolute value of signal.

$$MAV = \frac{1}{L}\sum_{i=1}^{L}|x_i|$$

- *Root Mean Square:* Root mean square (RMS) describe the muscle information.

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

- *Waveform Length:* Wavelength (WL) can be calculated by simplifying the cumulative length of waveform summation.

$$WL = \sum_{i=2}^{L}|x_i - x_{i-1}|$$

- *Zero Crossing:* Zero Crossing (ZC) measures the frequency information.

$$ZC = \sum_{i=1}^{L-1} f(x_i)$$

Where,

- $p = \begin{cases} 1, & \text{if } \{(x_i > 0 \& x_{i+1} < 0) | (x_i < 0 \& x_{i+1} > 0)\} \& |x_i - x_{i+1}| \geq T \\ 0, & \text{otherwise} \end{cases}$

Where x is the wavelet coefficient, T is the threshold value and L is the length.

- *Log Detector:* Log Detector (LD) estimates the exerted force.

$$LD = \exp\left(\frac{1}{L}\sum_{i=1}^{L}\log(|x_i|)\right)$$

- *Difference Absolute Standard Deviation Value:* Difference Absolute Standard Deviation Value (DASDV) can be expressed as in Equation:

$$DASDV = \sqrt{\frac{\sum_{i=1}^{L-1}(x_{i+1} - x_i)^2}{L-1}}$$

- *Average Amplitude Change:* Average Amplitude Change (AAC) can be formulated as in Equation:

$$AAC = \frac{1}{L}\sum_{i=1}^{L-1}|x_{i+1} - x_i|$$

- *Variance Absolute Value:* Variance Absolute Value can be expressed as in Equation:

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

- *Kurtosis:* Kurtosis describes the shape of tails of a distribution to know the presence of outliers.

  Kurtosis = Fourth Moment / (Second Moment)^2

- *Skewness:* Skewness is a measure of symmetry in distribution.

  Skewness=(3 *(mean-median)) / standard deviation

Figure 1 shows the block diagram representation of the method employed. Each EMG data sample is recorded for 11.2 secs duration. The amplitude of the EMG ranges from -5

mv to +5 mv. The sampling frequency of the EMG is 23.435 kHz. For feature extraction, 300.37 msec rectangular windows with overlap of 99.84 msec is used. 11.20 secs data yield 110 segments from the window technique. Each segment consists of sample size of 7040 sample values and an overlapping sample size of 2340 sample values. The dataset is used to extract the features in the time and frequency domains. Twelve statistical features are considered in work. FFT algorithm is employed to convert time-domain data into corresponding frequency domain representation. The frequency-domain features are extracted with the application of window technique. The 300.37 msec rectangular window with sample size of 7040 sample values and overlap of 99.84 msec with sample size of 2340 sample values is considered.

The features obtained are used for classification. The classification is performed using MLP, SVM, RF, GB, and NN classifiers.The classification is performed with test sample sizes of 40, 30, 20 and 10%, and training sample sizes of 60, 70, 80, and 90%, respectively. The classification is achieved in the segment level and sample level. The accuracy of the classification is calculated for each classifier model.

Multilayer perceptron classifier relies on neural networks (MPCNN) for classification. SVMs are a set of supervised learning techniques for classification, regression and outlier detection purposes. The kernel trick technique is used in SVMs. Random forest classifier contains (RFC) decision trees on various subsets of the data and performs the averaging to enhance the prediction accuracy. Gradient boosting classifier (GBC) uses set of machine learning algorithms by combining weak learning models to develop a good predictive model. Neural Network consists of a series of algorithms that recognize the relationships in the data set by mimicking the human brain operation. Neural networks refer to computing systems consisting of interconnected nodes similar to neurons in the human brain. The ML and DL techniques are employed for the classification.

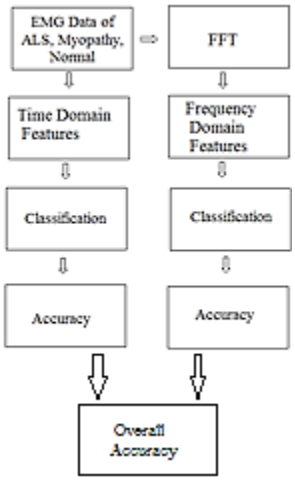

Figure 1: EMG Feature extraction and classification.

RESULTS AND DISCUSSION

The dataset consists of EMG of ALS, Myopathy, and Normal subjects is used for analysis and classification of muscular paralysis. The EMG features are extracted in the time domain and frequency domain. The MLP, SVM, RF, GB, and NN classifiers are used for classification.

The results are tabulated and indicated with chart graphs.

Table 1 shows the average values of EMG features in frequency domain for ALS, myopathy, and normal Data. The values indicate the majority of the amplitudes of features computed. The values describe the signal nature in paralysis in terms of ALS and myopathy concerning normal conditions. The values obtained are greater for paralysis compared to normal conditions. Since absolute values are obtained due to FFT application, no zero crossings are found in the signals.

Figure 2 represents the chart graph of average values of EMG features in frequency domain for ALS, myopathy, and normal Data.

Table 2 shows the average values of EMG features in time domain for ALS, myopathy, and normal Data. The values

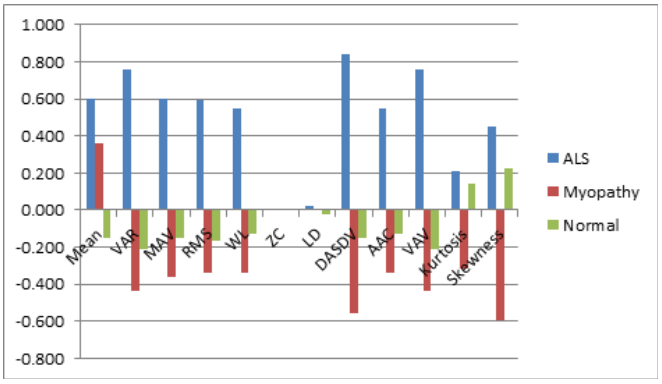

Figure 2: Column chart of Frequency Domain EMG Features - Average Values for ALS, Myopathy, and Normal Data

Table 1: Frequency domain EMG features - average values for ALS, myopathy, and normal data

	Mean	*VAR*	*MAV*	*RMS*	*WL*	*ZC*	*LD*	*DASDV*	*AAC*	*VAV*	*Kurtosis*	*Skewness*
ALS	0.603	0.762	0.603	0.591	0.551	0.000	0.026	0.839	0.551	0.762	0.208	0.447
Myopathy	0.364	-0.435	-0.364	-0.337	-0.337	0.000	0.000	-0.554	-0.337	-0.435	-0.314	-0.593
Normal	-0.147	-0.211	-0.147	-0.164	-0.129	0.000	-0.023	-0.154	-0.129	-0.211	0.146	0.227

Table 2: Time domain EMG features - average values for ALS, myopathy, and normal data

	Mean	*VAR*	*MAV*	*RMS*	*WL*	*ZC*	*LD*	*DASDV*	*AAC*	*VAV*	*Kurtosis*	*Skewness*
ALS	0.006	0.757	0.735	0.815	0.199	-0.105	0.521	0.137	0.199	0.794	-0.031	0.017
Myopathy	0.000	-0.432	-0.599	-0.399	-0.222	0.166	-0.574	0.005	-0.222	-0.418	0.195	0.073
Normal	-0.005	-0.210	-0.017	-0.295	0.058	-0.081	0.143	-0.124	0.058	-0.257	-0.176	-0.090

indicate the majority of the amplitudes of features computed. These values describe the signal nature in ALS, myopathy, and normal condition.

Figure 3 represents the chart graph of average values of EMG features in time domain for ALS, Myopathy, and Normal Data.

Table 3 shows the frequency domain values of EMG Features for ALS data. The range of values lies between minimum to the corresponding maximum value, with the majority of the values indicated by average value.

Figure 4 represents the frequency domain values of EMG Features for ALS data. The maximum, minimum, and average values of the features are indicated in the chart graph.

Table 4 shows the frequency domain values of EMG Features for Myopathy data. The range of values lies between minimum to the corresponding maximum value, with majority of the values indicated by average value.

Figure 5 represents the frequency domain values of EMG Features for Myopathy data. The maximum, minimum, and average values of the features are indicated in the chart graph.

Table 5 shows the frequency domain values of EMG Features for Normal data. The range of values lies between minimum to corresponding maximum value, with majority of the values indicated by average value.

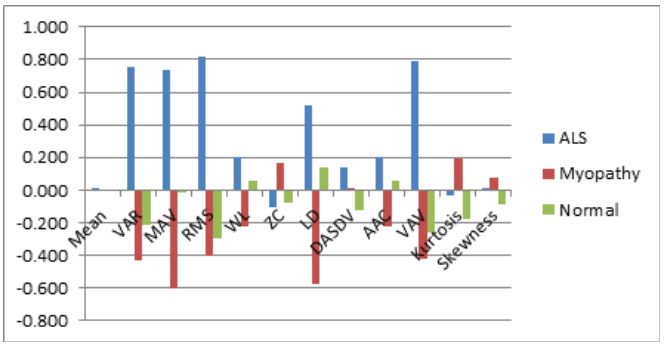

Figure 3: Column chart of Time Domain EMG Features -Average Values for ALS, Myopathy, and Normal Data

Figure 6 represents the frequency domain values of EMG Features for Normal data. The maximum, minimum, and average values of the features are indicated in the chart graph. Table 6 shows the time domain values of EMG Features for ALS data. The range of values lies between minimum to

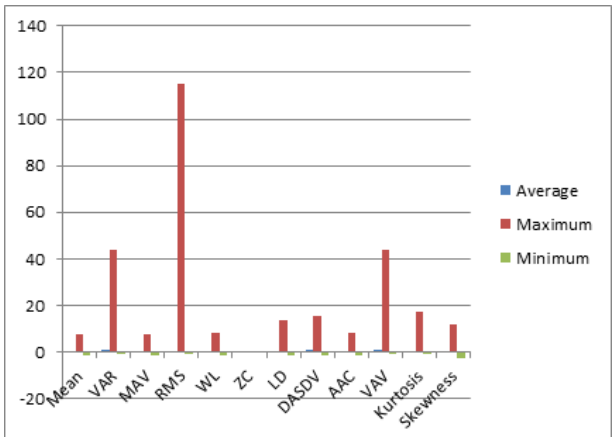

Figure 4: Column chart of frequency-domain EMG features-values for ALS data

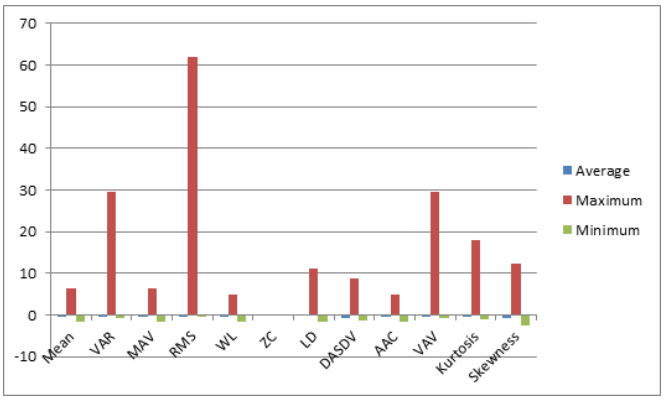

Figure 5: Column chart of frequency domain EMG features -values for myopathy Data

Table 3: Frequency domain EMG features -values for ALS data

	Mean	*VAR*	*MAV*	*RMS*	*WL*	*ZC*	*LD*	*DASDV*	*AAC*	*VAV*	*Kurtosis*	*Skewness*
Average	0.603	0.762	0.603	0.591	0.551	0.000	0.026	0.839	0.551	0.762	0.208	0.447
Maximum	7.848	44.005	7.848	114.971	8.062	0.000	13.499	15.207	8.062	44.005	16.997	11.675
Minimum	-1.563	-0.648	-1.563	-0.466	-1.515	0.000	-1.337	-1.364	-1.515	-0.648	-0.918	-2.382

Table 4: Frequency domain EMG features -values for myopathy data

	Mean	*VAR*	*MAV*	*RMS*	*WL*	*ZC*	*LD*	*DASDV*	*AAC*	*VAV*	*Kurtosis*	*Skewness*
Average	-0.364	-0.435	-0.364	-0.337	-0.337	0.000	0.000	-0.554	-0.337	-0.435	-0.314	-0.593
Maximum	6.410	29.657	6.410	61.863	5.022	0.000	11.182	8.780	5.022	29.657	17.933	12.331
Minimum	-1.647	-0.648	-1.647	-0.466	-1.586	0.000	-1.623	-1.380	-1.586	-0.648	-0.973	-2.526

Table 5: Frequency-domain EMG features-values for normal data

	Mean	*VAR*	*MAV*	*RMS*	*WL*	*ZC*	*LD*	*DASDV*	*AAC*	*VAV*	*Kurtosis*	*Skewness*
Average	-0.147	-0.211	-0.147	-0.164	-0.129	0.000	-0.023	-0.154	-0.129	-0.211	0.146	0.227
Maximum	5.046	6.791	5.046	9.027	5.063	0.000	9.180	3.411	5.063	6.791	119.078	38.729
Minimum	-1.755	-0.648	-1.755	-0.466	-1.691	0.000	-2.058	-1.406	-1.691	-0.648	-0.883	-2.048

the corresponding maximum value, with most of the values indicated by average value.

Figure 7 represents the time domain values of EMG Features for ALS data. The maximum, minimum, and average values of the features are indicated in the chart graph.

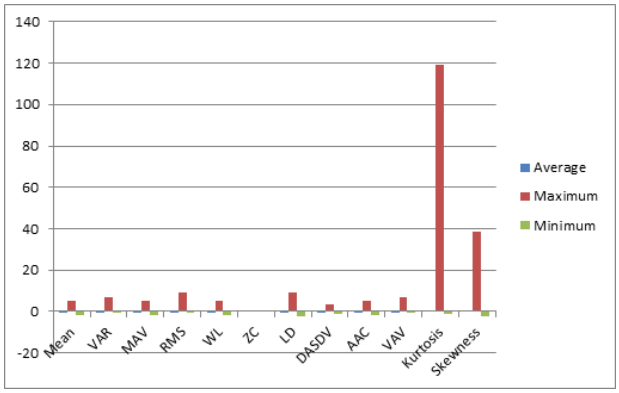

Figure 6: Column chart of frequency domain EMG features -values for normal data

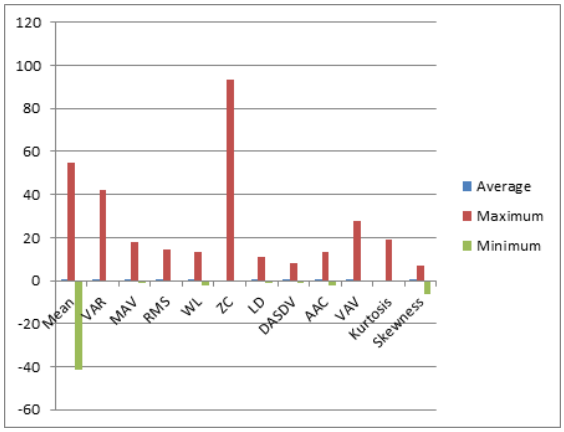

Figure 7: Column chart of time domain EMG features -values for ALS data

Table 7 shows the time domain values of EMG Features for Myopathy data. The range of values lies between minimum to corresponding maximum value, with majority of the values indicated by average value.

Figure 8 represents the time domain values of EMG Features for Myopathy data. The maximum, minimum, and average values of the features are indicated in the chart graph.

Table 8 shows the time domain values of EMG Features for Normal data. The range of values lies between minimum to corresponding maximum value, with majority of the values indicated by average value.

Figure 9 represents the time domain values of EMG Features for Normal data. The maximum, minimum, and average values of the features are indicated in the chart graph.

Table 9 gives the range of values of EMG features in the frequency domain for ALS, Myopathy, and Normal Data. The range of values in frequency domain for features VAR, MAV, RMS, WL, ZC, LD, DASDV, AAC, VAV is greater in ALS data & Myopathy data concerning normal data. The range of values in frequency domain for the features kurtosis, and Skewness is less in ALS data & Myopathy data with reference to normal data.

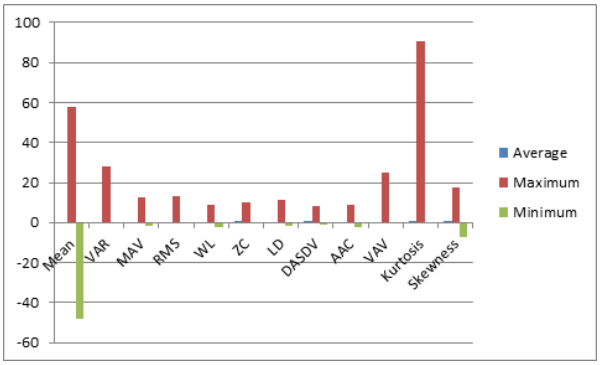

Figure 8: Column chart of time domain EMG features -values for myopathy data

Table 6: Time domain EMG features -values for ALS data

	Mean	*VAR*	*MAV*	*RMS*	*WL*	*ZC*	*LD*	*DASDV*	*AAC*	*VAV*	*Kurtosis*	*Skewness*
Average	0.006	0.757	0.735	0.815	0.199	-0.105	0.521	0.137	0.199	0.794	-0.031	0.017
Maximum	54.775	42.081	17.725	14.523	13.324	93.352	11.245	7.900	13.324	27.543	18.778	7.165
Minimum	-41.731	-0.668	-1.354	-0.714	-2.125	-0.690	-1.372	-1.019	-2.125	-0.663	-0.699	-6.278

Table 7: Time domain EMG features -values for myopathy data

	Mean	*VAR*	*MAV*	*RMS*	*WL*	*ZC*	*LD*	*DASDV*	*AAC*	*VAV*	*Kurtosis*	*Skewness*
Average	0.000	-0.432	-0.599	-0.399	-0.222	0.166	-0.574	0.005	-0.222	-0.418	0.195	0.073
Maximum	58.011	28.309	12.412	12.903	8.664	9.919	11.408	8.209	8.664	25.136	90.599	17.792
Minimum	-48.132	-0.669	-1.402	-0.715	-2.323	-0.690	-1.372	-1.128	-2.323	-0.664	-0.706	-7.217

Table 8: Time domain EMG features - values for normal data

	Mean	*VAR*	*MAV*	*RMS*	*WL*	*ZC*	*LD*	*DASDV*	*AAC*	*VAV*	*Kurtosis*	*Skewness*
Average	-0.005	-0.210	-0.017	-0.295	0.058	-0.081	0.143	-0.124	0.058	-0.257	-0.176	-0.090
Maximum	14.328	6.343	3.625	8.351	6.401	6.682	4.655	7.421	6.401	9.148	71.535	11.623
Minimum	-46.814	-0.669	-1.454	-0.715	-3.462	-0.690	-1.372	-1.316	-3.462	-0.664	-0.766	-15.401

Figure 10 represents the area chart of the range of values of EMG features in frequency domain for ALS, myopathy, and normal data.

Table 10 gives the range of values of EMG features in time domain for ALS, Myopathy, and Normal Data. The range of values of features VAR, MAV, RMS, WL, ZC, LD, DASDV, AAC, VAV is greater in ALS data and Myopathy data with reference to normal data. The range of values for the features kurtosis, and Skewness are not significant to differentiate between ALS data & Myopathy data with reference to normal data.

Figure 11 represents the Area chart of Range of Values of EMG Features in Time Domain for ALS, Myopathy, and Normal Data.

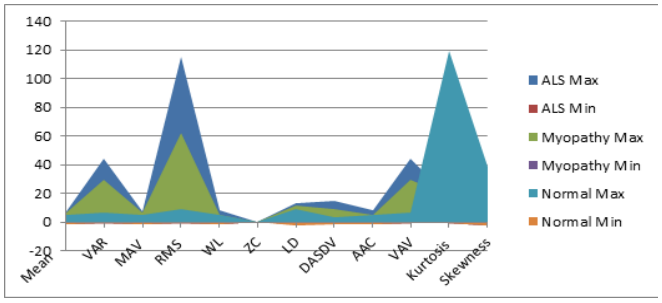

Figure 10: Area chart of frequency domain EMG features - range of values for ALS, myopathy, and normal data

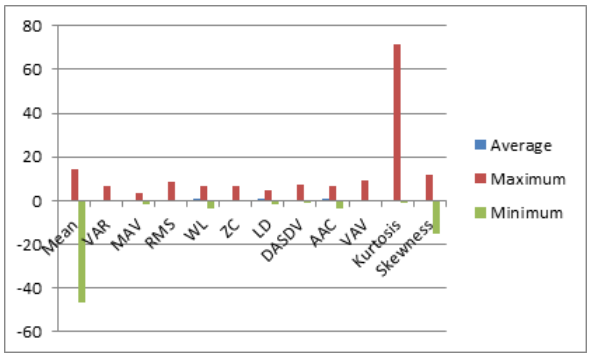

Figure 9: Column chart of time-domain EMG features-values for normal data

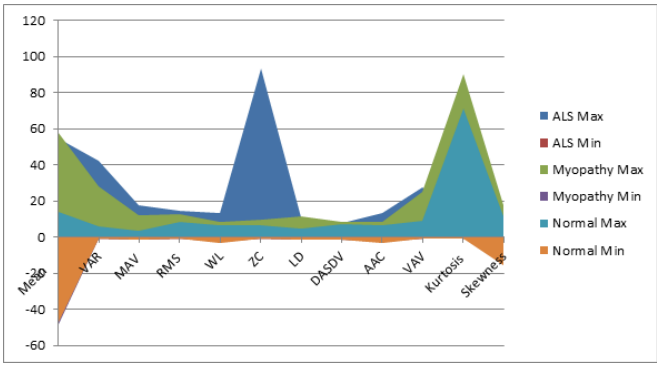

Figure 11: Area chart of time domain EMG features - range of values for ALS, myopathy, and normal data

Table 9: Frequency-domain EMG features-range of values for ALS, myopathy, and normal data

		Mean	*VAR*	*MAV*	*RMS*	*WL*	*ZC*	*LD*	*DASDV*	*AAC*	*VAV*	*Kurtosis*	*Skewness*
ALS	Max	7.848	44.005	7.848	114.971	8.062	0	13.499	15.207	8.062	44.005	16.997	11.675
	Min	-1.563	-0.648	-1.563	-0.466	-1.515	0	-1.337	-1.364	-1.515	-0.648	-0.918	-2.382
Myopathy	Max	6.41	29.657	6.41	61.863	5.022	0	11.182	8.78	5.022	29.657	17.933	12.331
	Min	-1.647	-0.648	-1.647	-0.466	-1.586	0	-1.623	-1.38	-1.586	-0.648	-0.973	-2.526
Normal	Max	5.046	6.791	5.046	9.027	5.063	0	9.18	3.411	5.063	6.791	119.078	38.729
	Min	-1.755	-0.648	-1.755	-0.466	-1.691	0	-2.058	-1.406	-1.691	-0.648	-0.883	-2.048

Table 10: Time Domain EMG Features - Range of Values for ALS, Myopathy, and Normal Data

		Mean	*VAR*	*MAV*	*RMS*	*WL*	*ZC*	*LD*	*DASDV*	*AAC*	*VAV*	*Kurtosis*	*Skewness*
ALS	Max	54.775	42.081	17.725	14.523	13.324	93.352	11.245	7.9	13.324	27.543	18.778	7.165
	Min	-41.731	-0.668	-1.354	-0.714	-2.125	-0.69	-1.372	-1.019	-2.125	-0.663	-0.699	-6.278
Myopathy	Max	58.011	28.309	12.412	12.903	8.664	9.919	11.408	8.209	8.664	25.136	90.599	17.792
	Min	-48.132	-0.669	-1.402	-0.715	-2.323	-0.69	-1.372	-1.128	-2.323	-0.664	-0.706	-7.217
Normal	Max	14.328	6.343	3.625	8.351	6.401	6.682	4.655	7.421	6.401	9.148	71.535	11.623
	Min	-46.814	-0.669	-1.454	-0.715	-3.462	-0.69	-1.372	-1.316	-3.462	-0.664	-0.766	-15.401

Table 11: Classification accuracy of Classifiers Models using Time Domain EMG Features of ALS, Myopathy, and Normal Data

Classifier	*Test size = 0.4*		*Test size = 0.3*		*Test size = 0.2*		*Test size = 0.1*	
Model	*Segment Level*	*Sample Level*	*Segment Level*	*Sample Level*	*Segment Level*	*Sample Level*	*Segment Level*	*Sample Level*
M L P	0.6894	0.7162	0.6923	0.7554	0.7272	0.765	0.6841	0.6847
S V M	0.7159	0.7493	0.711	0.7591	0.7329	0.7704	0.729	0.7717
R F	0.7166	0.752	0.7166	0.7445	0.7161	0.7431	0.7211	0.7608
G B	0.7096	0.7713	0.7014	0.7262	0.7148	0.7431	0.7191	0.7282
N N	0.6684	0.7575	0.67	0.7335	0.6766	0.7322	0.6661	0.7282

Table 12: Classification accuracy of classifiers models using frequency domain EMG features of ALS, myopathy, and normal data

Classifier	*Test size = 0.4*		*Test size = 0.3*		*Test size = 0.2*		*Test size = 0.1*	
Model	*Segment Level*	*Sample Level*	*Segment Level*	*Sample Level*	*Segment Level*	*Sample Level*	*Segment Level*	*Sample Level*
M L P	0.6993	0.7465	0.7016	0.7518	0.6846	0.7213	0.7092	0.7608
S V M	0.7166	0.7603	0.7119	0.7591	0.6987	0.7322	0.6848	0.7391
R F	0.6673	0.7217	0.6663	0.7043	0.676	0.7595	0.674	0.7173
G B	0.6552	0.7493	0.6502	0.7299	0.658	0.7158	0.6452	0.7282
N N	0.648	0.7162	0.6506	0.6897	0.6488	0.683	0.6548	0.7282

The classification is performed using Multilayer Perceptron (MLP), Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (GB), and NN classifiers models. The classification is performed with test sample sizes of 40%, 30%, 20% and 10%, and training sample sizes of 60%, 70%, 80%, and 90%, respectively. The classification is achieved in segment level and sample level. The accuracy of the classification is calculated for each classifier model.

Table 11 gives the classification accuracy for each classifier model used with time domain EMG features of ALS, Myopathy, and Normal Data. Each sample data consist of 110 segments due to window technique performed.

Table 12 gives the classification accuracy for each classifier model used with frequency domain EMG features of ALS, Myopathy, and Normal Data. Each sample data consist of 110 segments due to window technique performed.[15]

CONCLUSION

This work uses the 12 statistical features from Mean, VAR, MAV, RMS, WL, ZC, LD, DASDV, AAC, VAV, Kurtosis, and Skewness, from the EMG data are extracted in time domain and frequency domain. EMG Features values are considered for analyzing and classifying muscular paralysis disease. The average values of EMG feature in the frequency and time domain, and the range of values of EMG features in the frequency and time domain, are computed. The range of values in time and frequency domains are significant for analyzing the ALS, Myopathy conditions and, hence, the paralysis condition. The MLP, SVM, RF, GB, and NN classifiers are used for classification. The classification is performed in segment level and as well as in sample level. The overall accuracy values obtained are 72% for MLP, 73% for SVM, 72% for RF, 71% for GB, and 69% for NN using both tome domain & frequency domain EMG feature values. The performance accuracy is better in SVM classifier model compared to other classifier models. This approach can be used as diagnostic tool for muscular paralysis. The classification accuracy can be improved by using time-frequency domain EMG features through wavelet decomposition technique.

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