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# Temporal and Spectral Analysis of EMG for Classification of Muscular Paralysis

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**ABSTRACT**

Loss of muscle function is the condition referred to as paralysis. Parts of the body may be completely paralysed or only partially. The quality of life is enhanced by the early identification of paralysis. In people with paralysis and neuromuscular diseases, EMG signals can be used to analyse muscular activation. In this study, EMG signals are analysed by feature extraction and divided into two categories: normal and paralysed. The obtained findings demonstrate that the extracted features in the suggested work perform better for EMG signal categorization. The conditions of Amyotrophic Lateral Sclerosis (ALS) and Myopathy are taken into consideration in this study to examine the paralysis state. Using time and frequency domain approaches, characteristics were retrieved from the EMG of healthy and paralysed participants. Multilayer Perceptron (MLP), Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (XGBOOST), and K-Nearest Neighbour (KNN) Classifiers are the classifier models used in the study. With time domain EMG information, classifiers like MLP, SVM, RF, XGBOOST, and KNN are used. The frequency domain EMG characteristics are applied to the MLP, RF, XGBOOST, and KNN classifiers. With time domain EMG features, MLP achieved a classification accuracy of 76.5%, SVM with 77.2%, RF with 76.1%, XGBOOST with 77.1%, and KNN with 75.8%. In comparison to classifier models employing time domain EMG information, the SVM classifier performs better. The classification accuracy for MLP, RF, XGBOOST, and KNN using frequency domain EMG features is 77.7%, 76.6%, and 75%, respectively. In comparison to other classifier models with frequency domain features, the MLP and RF classifiers perform better. Time and frequency domains of the EMG of Normal, ALS, and Myopathy diseases are investigated. It has been noted that the EMG signal and its characteristics differ significantly ($p<0.05$) between the Normal and Paralysis conditions. EMG is utilised in the current study to analyse and categorise paralysis, which helps with early diagnosis and improved treatment options.

**KEYWORDS:** Paralysis, Als, Myopathy, Emg, Time Domain Features, Frequency Domain Features, Mlp Classifier, Svm Classifier Rf Classifier, Xgboost Classifier, Knn Classifier.

## I. INTRODUCTION

A neuromuscular condition known as paralysis defines the loss of muscle function. One or more bodily areas have a decrease of muscle function. Damage to the nervous system causes paralysis [1].

The assessment of muscle and nerve damage leads to the diagnosis of paralysis. Electromyographic (EMG) signals are analysed to determine how well the muscles and nerves are working. Assessment can also be done with the help of additional testing modalities like MRI, CT, or X-rays. EMG is used to perform the nerve function test. A nerve function test evaluates how the muscles react when they are stimulated. [2].

The quality of life is improved by medical interventions, physical therapy, mobility aids, and management techniques.The identification of impaired muscle actions is made possible through analysis of the paralysed state, which also results in better treatment alternatives.

A visual representation of muscle electrical activity is called an electromyogram. An electromyography is a device used to capture the electrical potential generated when a muscle cell is electrically or neurologically stimulated. To analyse the muscular activity, determining the degree of recruitment or activation, the EMG signals can be examined. EMG and activity of voluntary muscular constructions are related [3].

An EMG test may be used to assess the neuromuscular disorders. An EMG test aids in the diagnosis of degenerative ailments, motor tissues, nerve damage, and neuromuscular diseases. Neuromuscular illnesses such as amyotrophic lateral sclerosis, peripheral neuropathies, muscular dystrophy, and myasthenia gravis can be evaluated and managed using electromyography [4]. For the analysis of muscular paralysis the evaluation and assessment of ALS and Myopathy disorders can be used. Most of neuromuscular disorder results in paralysis, including ALS and Myopathy conditions.

Lou Gehrig's illness or Amyotrophic Lateral Sclerosis is a degenerative neuromuscular condition. The loss

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of motor nerve cells in the brain and spinal cord is the condition of ALS. Muscular weakness occurs due to the muscles function loss. The muscle function loss results when the motor neurons are unable to deliver signals to the muscles. ALS has no negative effects on a person's intelligence, capacity to see or hear, or even their sense of taste, smell, or touch [5].

ALS is also referred to as a distinctive condition. ALS strikes suddenly and seldom. The illness can affect persons most frequently between the ages of 40 and 70. Many patients with ALS can even live longer because of intensive research and development into the main cause of ALS, prevention, and sophisticated treatment for the disease. The timely and proper diagnosis increases the normal life time of the ALS subjects.

The term "Myopathy" is used to describe diseases related to muscle. The person with Myopathy disease, the muscles work less effectively than normal, it may be due to abnormal development of muscle, damaged muscle, or lacking important components in the muscle system [6]. Proteins and other structural elements work in unison to contract a muscle. Myopathy may result from a deficiency in one of these parts.

A significant portion of the examination of patients with neuromuscular diseases involves electro diagnostic tests. The main purpose of electromyography (EMG) is to supplement clinical examinations. Peripheral nerve system problems are diagnosed using EMG [7].

The EMG is acquired using surface electrodes or needle electrodes, placed or inserted for specific muscles under investigation. EMG of ALS and Myopathy conditions provide the performance analysis of muscular activity in subjects with paralysis.

EMG Features are the distinctive pattern representations of reduced dimensional signals. Finding a few traits that are exceptionally distinctive and instructive is the aim of feature extraction. Time Domain (TD), Frequency Domain (FD), and Time-Frequency domain (TFD) features are used to study the EMG characteristics. TD represents signal characteristics versus time. FD represents the signal characteristics versus frequency. Frequency spectrum of signal indicates the frequencies contained in the signal. TFD features provide the information about both temporal and spectral characteristics of the signal. Several aspects are considered for the EMG signal categorization, which includes features taken independently and number of features in groups taken for analysis in TD, FD, and TFD [8]. Machine learning allows software applications and algorithms for systems to identify patterns, make decisions. Machine learning algorithms works on input data and predict new output values. EMG classification is performed with the aid of machine learning techniques.LITERATURE SURVEY

Muscle fibers constitute the muscular system. Skeletal muscles contribute majority to the total body mass. Skeletal muscles attached to the bones and other organs are responsible for performing a wide range of movements and function. Muscle contractions result in movements of the body. The loss of muscular activity results in Paralysis.

Natalie Slivinski [9], describes the condition of paralysis. Paralysis refers to inability to move certain parts of the body due to disturbance in signal transmission between brain and body parts. Paralysis can occur either temporarily or permanent. Dennis L. Kasper et.al [10], discussed about Muscle weakness and Paralysis. Muscle Weakness refers to reduction of power in one or more muscles. Complete Paralysis indicates severe muscle weakness in which the muscle cannot able to contract. Paresis refers to partial paralysis indicates less severe muscle weakness.

EMG describes the electrical activity of the muscles. The ability of EMG signals to differentiate neuromuscular diseases aid in early diagnosis of Paralysis. In the study by Eric Verin et.al [11], the EMG of diaphragm is evaluated for diaphragmatic strength in patients with unilateral diaphragmatic paralysis. The study revealed that the diaphragmatic strength after diaphragmatic paralysis recover with time by re-innervations of the diaphragm or muscular modification of the diaphragm. The algorithm developed by Dow D.E. et.al [12], uses EMG signals to detect the inspiratory events from diaphragmatic paralysis which in turn helps to control the assisted inspirations.

The work by Melo M.C et.al [13], presents a proposal for the creation of a EMG based computational system in real time. This system can be used for treatment of patients with stroke.

Use of several EMG methods for examination will be beneficial for Myopathy diagnosis. The turns amplitude studies and manual study of the individual MUAPs are most helpful. Power spectrum analysis, multi-channel surface EMG, and measurement of the firing rate of motor units may also be utilized in the diagnostics but are less frequently [14]. Low-amplitude, short-duration, and polyphasic shapes of individual MUAPs are indicative of both muscle fibre degradation and regeneration in patients with myopathy [15].

The motor unit firing rate is a further parameter that needs to be examined. Early recruitment may occur in Myopathy that is more MUAPs may be present for the level of muscle contraction in comparison to normal subjects, as a result of the muscle's weakness. Although it has been demonstrated that the study of individual MUAPs is more sensitive for detecting Myopathy than the examination of the EMG signal frequency spectrum [16], the frequency spectrum of the EMG can still be used.

A biological signal called an electromyography signal is used to quantify the electrical current produced in muscles during neuromuscular activities. The study by N. Sengar et.al [17] describes a method for identifying Amyotrophic Lateral Sclerosis disease using machine learning and EMG data obtained from the biceps brachii muscles. Using signal processing, the work proposes a basic analysis and classification of EMG signals obtained from healthy and ALS participants for automated ALS disease screening. To automate the diagnosis of ALS disease, some EMG signal parameters, including maximum amplitude and mean of amplitude, are selectively analyzed and categorized.

Feature extraction is a crucial step in the analysis of signals in order to obtain the precise or required parameters from the obtained EMG signals. Typically, time domain, frequency domain, and time-frequency domain analyses are used to identify characteristics in the study of EMG data, Tsai, A.C et al, Hogan, N et al, Englehart, K et al, [18] [19][20]. In time domain analysis, signal amplitude, which

varies over time, is used to evaluate the features. During the monitoring process, the fluctuations in signal amplitude are related to the type and state of the muscle [21]. Frequency domain representations of the signal can be used to estimate the majority of distinguishable information. The Fourier transform should be applied to the signal being studied in the frequency domain. Parameters including the mean frequency, and power spectral density (PSD) are used to evaluate the signal.

The study by Archana B. Kanwade, and V.K. Bairagi [22], described the EMG signal feature extraction in the time and frequency domain for various muscle states in myopathy, neuropathy, and healthy subjects. Peak amplitude, the Root Mean Square (RMS), the mean, median, variance, and the total number of peaks are only a few examples of time domain and frequency domain features that are extracted.. RMS value, integration, mean amplitude, and the total peaks in both domains are used to compare the results.

The study by Artameeyanant, P et.al [23] discussed the detection of myopathy and ALS, from EMG based feature extraction method. Six useful features are statistically chosen in the study. The features are average cluster coefficient, average degree, density, average weight, kurtosis, and skewness.

EMG features describe the characteristics of the EMG signal and gives information about the muscular activity. The article by Angkoon Phinyomark et.al. [24], described the some of the EMG features, which can be used to analyze the muscular activity.

A Bakiya et.al [25] discussed the accurate differentiation of aberrant EMG signals, Myopathy, and Amyotrophic Lateral Sclerosis, which plays a significant role in automatic diagnostic aid tools. Since an effective classifier are essential for computer assisted identification of anomalies, Bat algorithm is used to model a deep neural network classifier for a certain feature subset using features that are taken from time and time-frequency characteristics. The research demonstrates the value of both conventional and deep neural networks when diagnosing aberrant signals in the neuromuscular system utilizing effective categorization.

The study by Elamvazuthia et.al [26], describe the classification of the neuromuscular illness based on EMG signal. Five Features were extracted using feature extraction techniques, and features are Autoregressive (AR), Zero Crossing, Root Mean Square, Waveform length, and Mean Absolute Value. The classification was performed using the Multilayer Perceptron.

The study by Abdulhamit Subasi [27], suggested to use an evolutionary design method to optimize automatic parameter adjustment when creating an SVM-based classifier (ESVM). Using normal, myopathic, and neurogenic datasets, a typical application to classify EMG signals is used to demonstrate and assess the effectiveness of ESVM. The discrete wavelet transform was used in the proposed method to decompose the EMG signals into frequency sub-bands, and a set of statistical features were then recovered from the sub-bands to reflect the distribution of wavelet coefficients. It is demonstrated that ESVM can get a high accuracy of 97% for EMG datasets by utilizing tenfold cross-validation. The heart of ESVM, which is a variety of SVMs, is designed to be an effective tool for the quick diagnosis of neuromuscular problems.

The study by Richa Singh and Ram Bilas Pachori et.al [28], proposed a new approach to classify normal and abnormal EMG signals in order to diagnose ALS (amyotrophic lateral sclerosis). Each level of intrinsic model functions (IMFs) has its own computation of features such cross information potential (CIP), Correntropy (COR), Cauchy-Schwartz quadratic mutual information (QMIED), and Euclidean distance quadratic mutual information (QMIED). For the classification of normal and ALS EMG data, the derived features are fed into three different classifiers, the: JRip rules classifier reduces error pruning (REP) tree classifier, and random forest classifier. The classification process's outcomes demonstrate that the suggested classification approach performs far better than the pre-existing methods in classifying normal and ALS EMG data.

The study by Shashank Kumar Singh et.al [29], focusses on the development of a reliable sign language recognition system using surface electromyography signal. To create a classifier that can accurately and consistently identify American Sign Language (ASL) from surface electromyography data, the boosting-based approach is used. Ten adult volunteers' surface Electromyography signals were collected to create data set. The accuracy of 99.09% achieved for the classification model after training it with the Extreme gradient boosting technique.

The study by S. Samui et.al [30], discussed on the Extreme Gradient Boosting (EGB) method, one of the most widely used pattern recognition techniques for analyzing surface electromyography signals and determining the underlying muscle motions. The experiment is conducted on the dataset of sEMG signals that were gathered from eleven subjects in five different upper limb positions. The suggested technique is based on the feature extraction, which transforms the sEMG signal into correlated time-domain descriptors (cTDD), a collection of descriptive values in Euclidean space that aid in learning the gradient boosting classifier. The Baysian optimization method has been used to adopt and fine-tune the classifier for each subject to achieve the best results for the categorization of EMG signals.

The study by Mohammad Tafhim Khan et.al [31], demonstrate method for classifying EMG signals as a tool for diagnosing neuromuscular disorders. Three groups of EMG signals with wavelet features are used as input to classifiers. The classifiers KNN and SVM are employed. While the SVM classifier can classify this data with an accuracy of 92.33%, the KNN approach can do it with up to 82% accuracy.

In the study by H. Kucuk et.al [32], a total of 10 feature vectors are used to represent MUAPs in an EMG data collection that includes both healthy and Amyotrophic Lateral Sclerosis illness subjects. The K-Nearest Neighbor and Support vector machine classifiers are two pattern recognition techniques that are used and contrasted. For the data set and feature vectors, the K-NN classifier has a little greater success rate than the SVM classifier in terms of classification accuracy.

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## III METHODOLOGY

The approach used in this research work is described in the block diagram displayed in figure 1. For feature extraction in the time, and frequency domain, EMG data from amyotrophic lateral sclerosis, myopathy, and normal conditions are used.

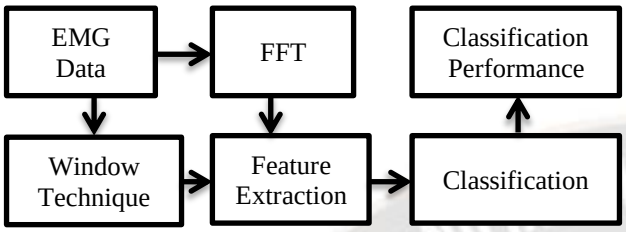


Figure 1: Block Diagram of the Proposed Method

To extract features in frequency domain FFT has been applied to EMG data. For classifier models, the features that were retrieved from the EMG served as input. It is done to categorize paralysis and normal conditions. To assess the effectiveness of the classifier models, the classification accuracy, precision and recall values are calculated.

In the present work the dataset [33], used consists of EMG signals recorded from needle electrodes. The electrode insertion levels are low, medium, and deep. The recordings were performed for steady isometric contractions. The EMG signals sampling frequency is selected to 23.435 kHz. The table 1 give the details of the EMG data set. All EMG data samples are recorded for the duration 11.2 seconds.

Table 1: Details of EMG Data

| Group | Age | Number of EMG recordings |
|---|---|---|
| Normal | 21-37 | 300 |
| ALS | 35-67 | 332 |
| Myopathy | 19-63 | 315 |

The EMG has a sampling rate of 23.435 kHz. Rectangular windows of 300.37 msec with a 99.84 msec overlap are utilised for feature extraction. 110 segments were produced from 11.20 seconds of data using the window approach.

For time domain analysis the Features considered in the work are Mean Value, Variance, Mean Absolute Value (MAV), Root Mean Square (RMS), Waveform Length (WL), Zero crossing (ZC), Log Detector (LD), Difference Absolute Standard Deviation Value (DASDV), Average Amplitude Change (AAC), Variance Absolute Value (VAV), Kurtosis of signal, and Skewness of signal.

The EMG Data from Normal, ALS, and Myopathy Conditions are used. By application FFT, the Data is represented in frequency domain. For frequency domain analysis the features considered are Mean Frequency (MNF), Median Frequency (MDF), Power Spectral Density (PSD), and Power Spectrum Deformation.

The classifier models employed are Multilayer Perceptron, Support Vector Machine, Random Forest, Gradient Boosting, and K-Nearest Neighbour Classifiers. The MLP classifier consists of twelve inputs, forty eight hidden processing elements, and three outputs (MLP(12-48-3)). The twelve statistical feature values are inputs, forty eight hidden layers are in the model, and three outputs are in the model for classification of ALS, Myopathy, and Normal condition.

The SVM classifier is used with kernel = 'rbf'. In RF classifier fifteen estimators used with maximum depth of the tree equal to fifteen. The XGBOOST classifier is employed with learning rate 1.0, with fifteen estimators, and maximum depth of the estimator equal to fifteen. The KNN classifier is used with K value chosen to nine. For time domain analysis all five classifier models are employed. For frequency domain and time-frequency domain analysis MLP, RF, XGBOOST, and KNN classifier models are employed.

## IV RESULTS AND DISCUSSION

### TIME DOMAIN FEATURE EXTRACTION

The samples of normal, Amyotrophic Lateral Sclerosis, and Myopathy are taken from the dataset for analysis. In this work twelve time domain features Mean, 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, are considered.

The time domain features are extracted from Normal data, ALS Data and Myopathy Data. The Normal data consist of 300 data samples, ALS data consist of 332 samples and Myopathy data consist of 315 samples. Each sample recorded for 11.2 seconds duration. From the application of rectangular window of size 300.37 msec, with overlap size of 99.84 msec, each sample in the data set yield 110 segments. The feature values are computed for each segment of the samples.

Statistical F-Test has been carried to analyse the Data. From the statistical F-test analysis all twelve features are found significant to differentiate Normal data with ALS and Myopathy Data with $p<0.05$, and hence the Paralysis condition from Normal condition. The figures 2 to 13 show the time domain features extracted from ALS, Myopathy and Normal Data. The features are represented using Box Plots.

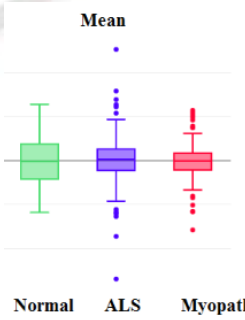


Figure 2: Mean of EMG Data

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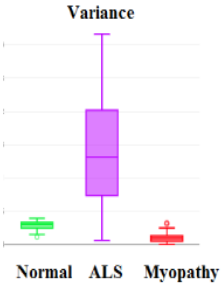

Figure 3: Variance of EMG Data

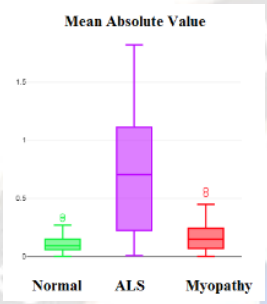

Figure 4: Mean Absolute of EMG Data

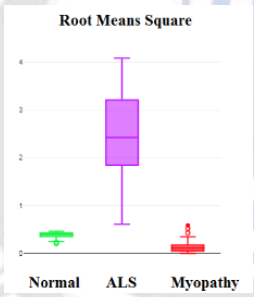

Figure 5: Root Means Square of EMG Data

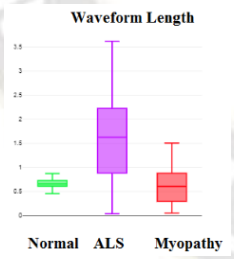

Figure 6: Waveform Length of EMG Data

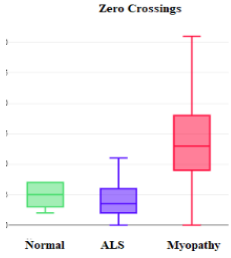

Figure 7: Zero Crossings of EMG Data

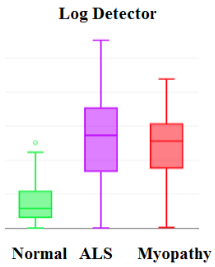

Figure 8: Log Detector of EMG Data

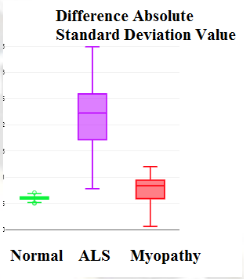

Figure 9: DASDV of EMG Data

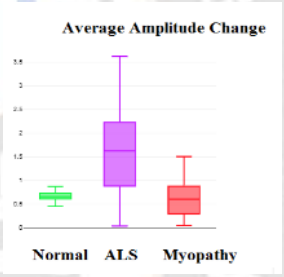

Figure 10: Average Amplitude Change of EMG Data

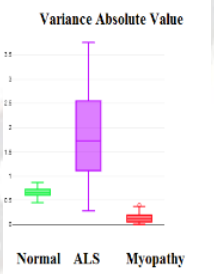

Figure 11: Variance Absolute Value of EMG Data

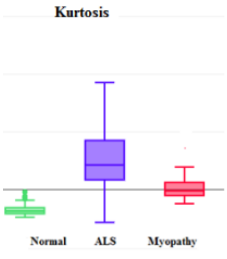

Figure 12: Kurtosis of EMG Data

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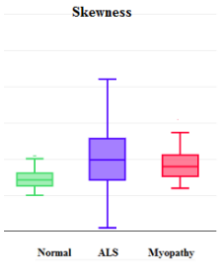

Figure 13: Skewness of EMG Data

Figure 2: Time Domain EMG Features extracted from ALS, Myopathy and Normal Data.

The ALS data and Myopathy data have greater Mean peak values than the Normal data. The range of Mean values is greater in ALS and Myopathy data when compared to Normal data. The muscle fatigue is more in ALS and Myopathy subjects. Because of fatigued muscle fibers less force is produced. In order to maintain the constant muscle force additional motor units are recruited and flexor joint torque for maintaining the isometric position. Hence the EMG magnitude increases with increase in muscle fatigue.

The range of Variance values is greater in ALS and Myopathy data when compared to Normal data. Because of increased EMG magnitude due to muscle fatigue in ALS and Myopathy subjects, the signal power also increases, which is indicated by increased range of variance values.

The ALS data and Myopathy data have higher MAV peak values than the Normal data. The range of MAV values is greater in ALS and Myopathy data when compared to Normal data. The MAV values in ALS and Myopathy subjects are greater due to increased motor recruitment to produce the constant muscle force during isometric contractions.

The ALS data and Myopathy data have higher RMS peak values than the Normal data. The range of RMS values is greater in ALS and Myopathy data when compared to Normal data. The root mean square values describe the force or torque produced by the muscles. To maintain the isometric position the torque produced in ALS and Myopathy subjects are greater compared to Normal subjects.

The ALS data and Myopathy data have higher WL peak values than the Normal data. The range of WL values is greater in ALS and Myopathy data when compared to Normal data. The higher cumulative values describe the increased complexity.

The ALS data and Myopathy data have higher ZC rates than the Normal data. The range of ZC is greater in ALS and Myopathy data when compared to Normal data.

The ALS data and Myopathy data have higher LD peak values than the Normal data. The range of LD values is greater in ALS and Myopathy data when compared to Normal data. The LD values describe the exerted muscle force. The ALS data and Myopathy data have higher DASDV peak values than the Normal data. The range of DASDV values is greater in ALS and Myopathy data when compared to Normal data.

The ALS data and Myopathy data have higher AAC peak values than the Normal data. The range of AAC values is greater in ALS and Myopathy data when compared to Normal data.

The ALS data has higher VAV peak than the Normal data. Myopathy data

has lower VAV peak than the Normal data.

The ALS data and Myopathy data have higher Kurtosis peak values than the Normal data. The range of Kurtosis values is greater in ALS and Myopathy data when compared to Normal data. The decrease in muscle contractions yield increase in Kurtosis values. The ALS and Myopathy subjects possess muscle weakness results in decreased muscle contraction.

The ALS data and Myopathy data have higher Skewness peak values than the Normal data. The range of Skewness values is greater in ALS and Myopathy data when compared to Normal data.

## FREQUENCY DOMAIN FEATURE EXTRACTION

The frequency domain features are extracted from Normal, ALS, and Myopathy Data. The feature values are further used for analysis and classification of Paralysis. Features Mean Frequency, Median Frequency, Power Spectral Density, and Power Spectrum Deformation are extracted.
The values of features obtained from frequency domain are considered for the statistical analysis. The features are found statistically significant to differentiate paralysis condition with normal condition with $p<0.05$. The figures 14 to 17 show the frequency domain features extracted from ALS, Myopathy and Normal Data. The features are represented using Box Plots.

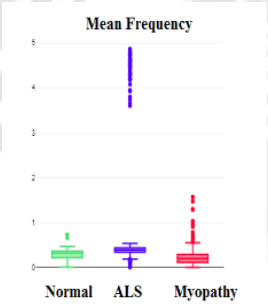

Figure 14: Mean Frequency of EMG Data

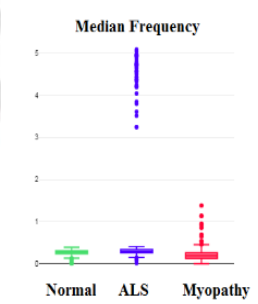

Figure 15: Median Frequency of EMG Data

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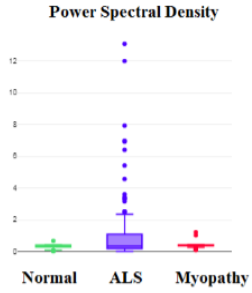


Figure16: Power Spectral Density of EMG Data

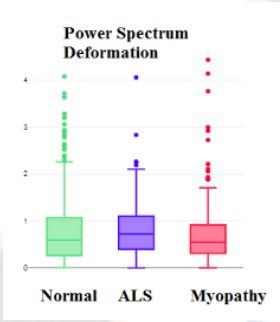


Figure 17: Power Spectrum Deformation of EMG Data

Figure 3: Frequency Domain EMG Features extracted from ALS, Myopathy and Normal Data.

The Mean Frequency peak values are found in ALS data and Myopathy data compared to Normal data. The range of Mean Frequency values are greater in ALS data and Myopathy data compared to Normal data. The muscle fatigue is more in ALS and Myopathy subjects. The muscle fatigue is described as decrease in the muscle force. The decrease in the muscle force causes increase in the Mean Frequency.
The Median Frequency peak values are found in ALS data and Myopathy data compared to Normal data. The range of MDF values are greater in ALS data and Myopathy data compared to Normal data. The Median Frequency values increases with decrease in muscle force resulted from muscle fatigue in ALS and Myopathy subjects.
The Power Spectral Density peak values are found in ALS data and Myopathy data compared to Normal data. The range of Power Spectral Density values are greater in ALS data and Myopathy data compared to Normal data.

Classification of Paralysis and Normal condition
The accurate characterisation of electromyographic signals is essential for the diagnosis of neuromuscular disorders. These characterizations are frequently generated using machine learning based pattern categorization algorithms. In order to develop precise and computationally effective methods for EMG signal characterisation, a number of classifiers have been used. This work focuses on neuromuscular pathology, and presents machine learning algorithms used for classification of EMG signals based on normal and paralysis conditions. The performance analysis of classifier models are evaluated by computing Accuracy, Precision, Recall or Sensitivity, Specificity, Misclassification Rate, F1-Score, and plotting Receiver Operating Characteristic(ROC) Curves.
Accuracy is obtained by computing fraction of the total samples correctly classified. Equation (1) shows the formula used for calculation of Accuracy.

$$\text{Accuracy} = (TP+TN) / (TP+TN+FP+FN)$$

Where TP is true positives, TN is true negatives, FP is false positives, and FN is false negatives.
Precision is obtained by computing the ratio of true positives to total predicted positives. Equation (2) shows the formula used for calculation of Precision.

$$\text{Precision} = TP / (TP+FP)$$

Recall or Sensitivity is obtained by computing the ratio of true positives to total positives.
Equation (3) shows the formula used for calculation of Recall or Sensitivity.

$$\text{Recall or Sensitivity} = TP / (TP+FN)$$

Specificity is obtained by computing the fraction of all negatives samples are correctly predicted as negatives. Equation (4) shows the formula used for calculation of Specificity.

$$\text{Specificity} = TN / (TN+FP)$$

Misclassification Rate is obtained by computing the fraction of predictions which are incorrect. Equation (5) shows the formula used for calculation of Misclassification Rate.

$$\text{Misclassification Rate} = (FP+FN) / (TP+TN+FP+FN)$$

F1-Score is obtained by computing harmonic mean of Precision and Recall. Equation (6) shows the formula used for calculation of F1-Score.

$$\text{F1-Score} = (2*(\text{Precision}*\text{Recall}) / (\text{Precision}+\text{Recall})) = 2TP / (2TP+FP+FN)$$

Receiver Operating Characteristic Curves show the performance of a classification model at all classification thresholds. This curve plots True Positive Rate versus False Positive Rate.

In this work the training data set sizes taken are 90%, 80%, 70%, and 60%, for corresponding test data set sizes of 10%, 20%, 30% and 40% respectively. The obtained Accuracy, Precision, Recall or Sensitivity, Specificity, Misclassification Rate, F1-Score, are tabulated and ROC curves are plotted.

The table 2 shows the Performance Analysis of MLP Classifier Model using time domain EMG features.

Table 2: Performance Analysis of MLP Classifier with Time Domain EMG Features

| **MLP Classifier** | Test Sample Size = 40% | Test Sample Size = 30% | Test Sample Size = 20% | Test Sample Size = 10% |
|---|---|---|---|---|
| Accuracy | 0.72 | 0.76 | 0.77 | 0.68 |
| Precision | 0.73 | 0.77 | 0.77 | 0.72 |

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| | | | | |
|---|---|---|---|---|
| Sensitivity | 0.72 | 0.76 | 0.77 | 0.69 |
| Specificity | 0.84 | 0.87 | 0.87 | 0.83 |
| Misclassification Rate | 0.28 | 0.24 | 0.23 | 0.32 |
| F1-Score | 0.72 | 0.76 | 0.77 | 0.70 |

The figures 18(a), 18(b), 18(c), and 18(d) show the ROC curves plotted for MLP Classifier with test sample sizes of 40%, 30%, 20%, and 10% respectively, for time domain EMG features

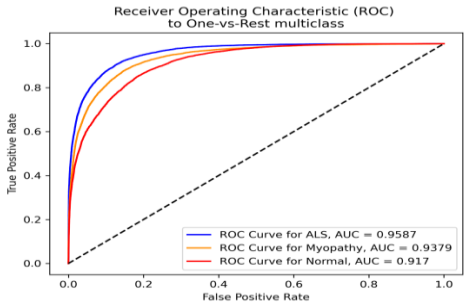


Figure 18(a): ROC curve for MLP Classifier with test sample size of 40%, for time domain EMG features.

| **SVM Classifier** | Test Sample Size = 40% | Test Sample Size = 30% | Test Sample Size = 20% | Test Sample Size = 10% |
|---|---|---|---|---|
| Accuracy | 0.75 | 0.76 | 0.77 | 0.77 |
| Precision | 0.76 | 0.78 | 0.78 | 0.81 |
| Sensitivity | 0.75 | 0.76 | 0.77 | 0.78 |
| Specificity | 0.86 | 0.87 | 0.88 | 0.84 |
| Misclassification Rate | 0.25 | 0.24 | 0.23 | 0.23 |
| F1-Score | 0.75 | 0.77 | 0.77 | 9.79 |

AUC FOR ALS V/S REST: 95.87%

AUC for Myopathy v/s rest: 93.79%
AUC for Normal v/s rest: 91.7%

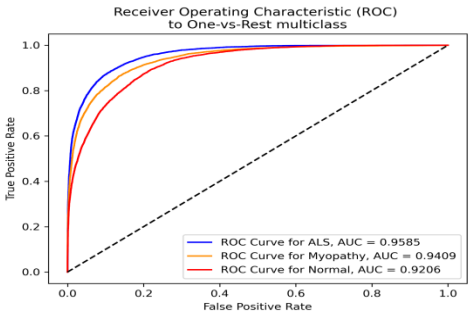


Figure 18(b): ROC curve for MLP Classifier with test sample size of 30%, for time domain EMG features.
AUC for ALS v/s rest: 95.85%
AUC for Myopathy v/s rest: 94.09%
AUC for Normal v/s rest: 92.06%

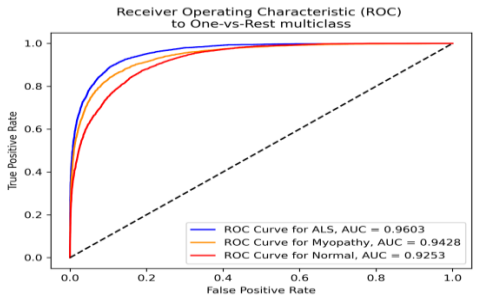


Figure 18(c): ROC curve for MLP Classifier with test sample size of 20%, for time domain EMG features.
AUC for ALS v/s rest: 96.03%
AUC for Myopathy v/s rest: 94.28%
AUC for Normal v/s rest: 92.53%

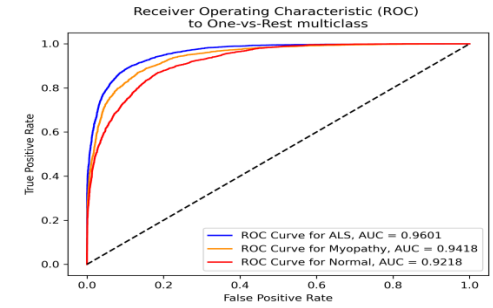


Figure 18(d): ROC curve for MLP Classifier with test sample size of 10%, for time domain EMG features.
AUC for ALS v/s rest: 96.01%
AUC for Myopathy v/s rest: 94.18%
AUC for Normal v/s rest: 92.18%
Since AUC values are higher, it shows the better performance of the MLP Classifier.

The table 3 shows the Performance Analysis of SVM Classifier Model using time domain EMG features.

Table 3: Performance Analysis of SVM Classifier with Time Domain EMG Features

The figures 19(a), 19(b), 19(c), and 19(d) show the ROC curves plotted for SVM Classifier with test sample sizes of 40%, 30%, 20%, and 10% respectively, for time domain EMG features.

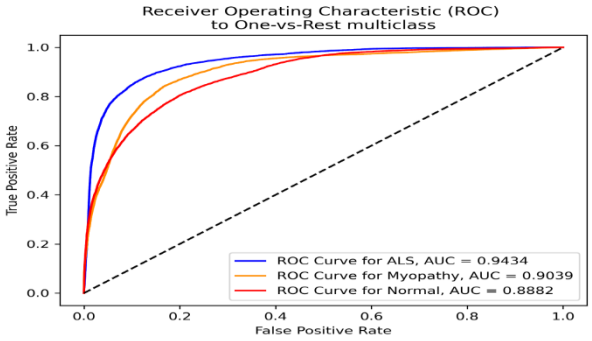


Figure 19(a): ROC curve for SVM Classifier with test sample size of 40%, for time domain EMG features.

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AUC for ALS v/s rest: 94.34%
AUC for Myopathy v/s rest: 90.39%
AUC for Normal v/s rest: 88.62%

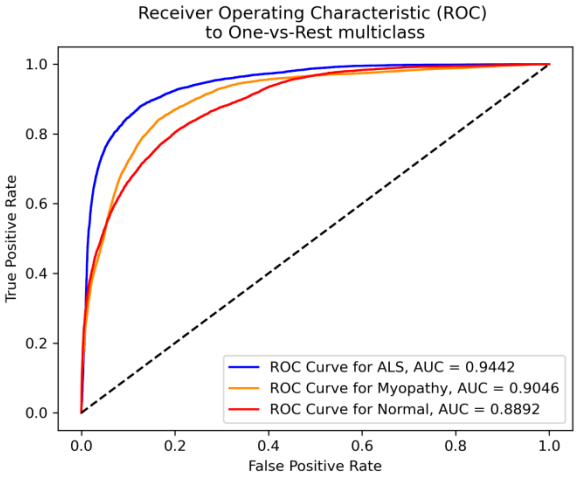


Figure 19(b): ROC curve for SVM Classifier with test sample size of 30%, for time domain EMG features.
AUC for ALS v/s rest: 94.42%
AUC for Myopathy v/s rest: 90.46%
AUC for Normal v/s rest: 88.92%

| **RF Classifier** | Test Sample Size = 40% | Test Sample Size = 30% | Test Sample Size = 20% | Test Sample Size = 10% |
|---|---|---|---|---|
| Accuracy | 0.75 | 0.74 | 0.74 | 0.76 |
| Precision | 0.75 | 0.74 | 0.74 | 0.77 |
| Sensitivity | 0.75 | 0.74 | 0.74 | 0.76 |
| Specificity | 0.86 | 0.86 | 0.86 | 0,87 |
| Misclassification Rate | 0.25 | 0.26 | 0.26 | 0.24 |
| F1-Score | 0.75 | 0.74 | 0.74 | 0.76 |

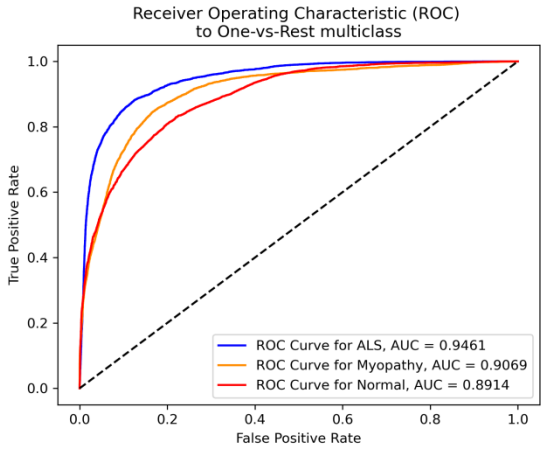


Figure 19(c): ROC curve for SVM Classifier with test sample size of 20%, for time domain EMG features.
AUC for ALS v/s rest: 94.61%
AUC for Myopathy v/s rest: 90.69%
AUC for Normal v/s rest: 89.16%

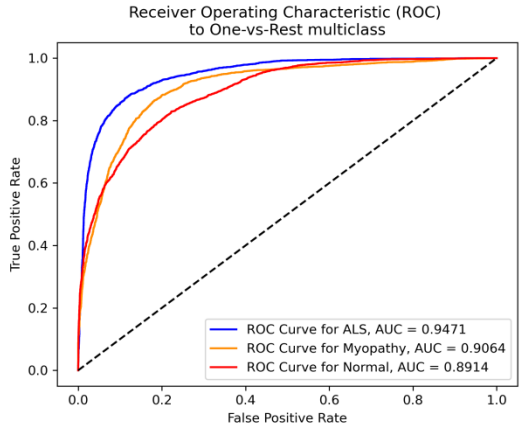


Figure 19(d): ROC curve for SVM Classifier with test sample size of 10%, for time domain EMG features.
AUC for ALS v/s rest: 94.71%
AUC for Myopathy v/s rest: 90.64%
AUC for Normal v/s rest: 89.14%

The table 4 shows the Performance Analysis of RF Classifier Model using time domain EMG features.

Table 4: Performance Analysis of RF Classifier with Time Domain EMG Features

The figures 20(a), 20(b), 20(c), and 20(d) show the ROC curves plotted for RF Classifier with test sample sizes of 40%, 30%, 20%, and 10% respectively, for time domain EMG features

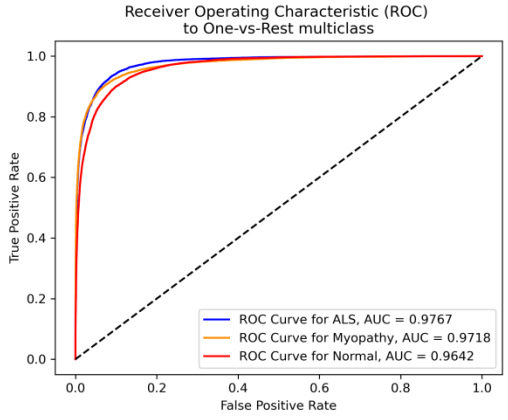


Figure 20(a): ROC curve for RF Classifier with test sample size of 40%, for time domain EMG features.
AUC for ALS v/s rest: 97.67%
AUC for Myopathy v/s rest: 97.18%
AUC for Normal v/s rest: 96.42%

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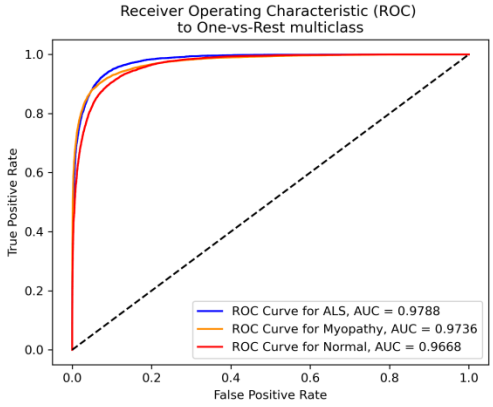


Figure 20(b): ROC curve for RF Classifier with test sample size of 30%, for time domain EMG features.
AUC for ALS v/s rest: 97.88%
AUC for Myopathy v/s rest: 97.36%
AUC for Normal v/s rest: 96.68%

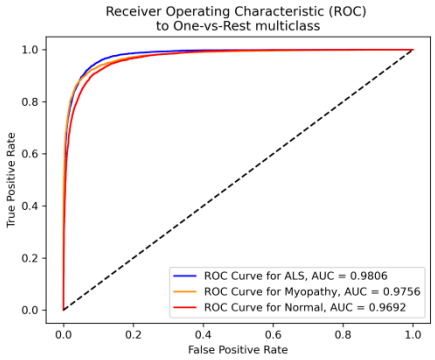


Figure 20(c): ROC curve for RF Classifier with test sample size of 20%, for time domain EMG features.
AUC for ALS v/s rest: 98.06%
AUC for Myopathy v/s rest: 97.56%
AUC for Normal v/s rest: 96.92%

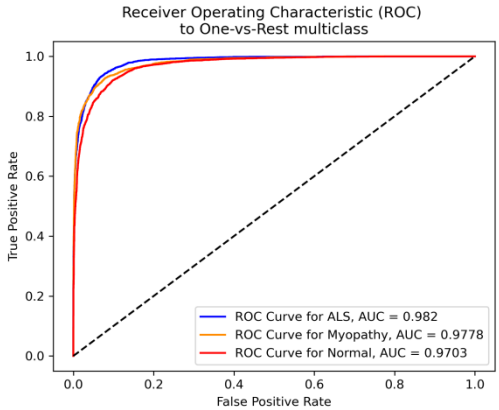


Figure 20(d): ROC curve for RF Classifier with test sample size of 10%, for time domain EMG features.
AUC for ALS v/s rest: 98.2%
AUC for Myopathy v/s rest: 97.78%
AUC for Normal v/s rest: 97.03%

The table 5 shows the Performance Analysis of XGBOOST Classifier Model using time domain EMG features

Table 5: Performance Analysis of XGBOOST Classifier with Time Domain EMG Features

| **XGBOOST Classifier** | Test Sample Size = 40% | Test Sample Size = 30% | Test Sample Size = 20% | Test Sample Size = 10% |
|---|---|---|---|---|
| Accuracy | 0.77 | 0.73 | 0.74 | 0.73 |
| Precision | 0.77 | 0.72 | 0.74 | 0.75 |
| Sensitivity | 0.77 | 0.72 | 0.74 | 0.72 |
| Specificity | 0.88 | 0.84 | 0.86 | 0.85 |
| Misclassification Rate | 0.23 | 0.27 | 0.26 | 0.27 |
| F1-Score | 0.77 | 0.72 | 0.74 | 0.73 |

. The figures 21(a), 21(b), 21(c), and 21(d) show the ROC curves plotted for XGBOOST Classifier with test sample sizes of 40%, 30%, 20%, and 10% respectively, for time domain EMG features.

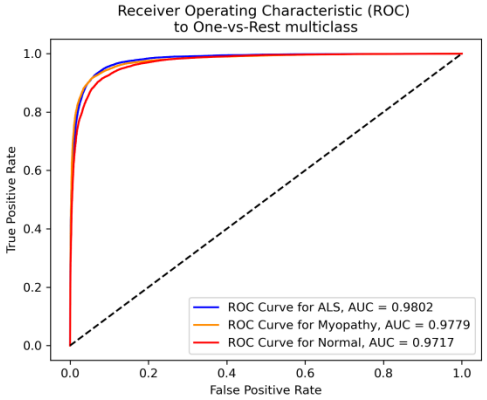


Figure 21(a): ROC curve for XGBOOST Classifier with test sample size of 40%, for time domain EMG features. AUC for ALS v/s rest: 98.02%
AUC for Myopathy v/s rest: 97.79%
AUC for Normal v/s rest: 97.17%

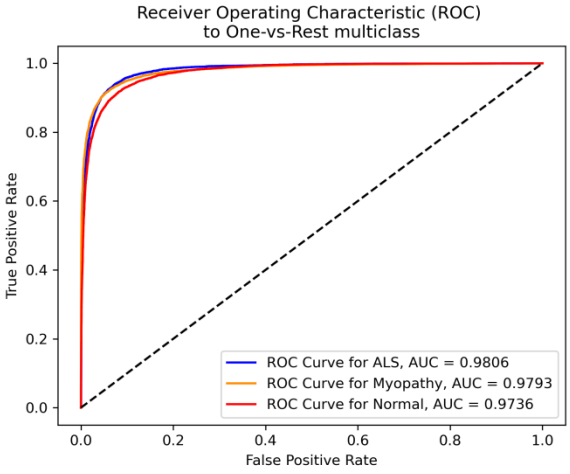


Figure 21(b): ROC curve for XGBOOST Classifier with test sample size of 30%, for time domain EMG features. AUC for ALS v/s rest: 98.06%
AUC for Myopathy v/s rest: 97.93%
AUC for Normal v/s rest: 97.36%

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| **KNN Classifier** | Test Sample Size = 40% | Test Sample Size = 30% | Test Sample Size = 20% | Test Sample Size = 10% |
|---|---|---|---|---|
| Accuracy | 0.76 | 0.73 | 0.73 | 0.73 |
| Precision | 0.76 | 0.74 | 0.74 | 0.76 |
| Sensitivity | 0.76 | 0.73 | 0.73 | 0.73 |
| Specificity | 0.87 | 0.85 | 0.85 | 0.86 |
| Misclassification Rate | 0.24 | 0.27 | 0.27 | 0.27 |
| F1-Score | 0.76 | 0.73 | 0.73 | 0.74 |

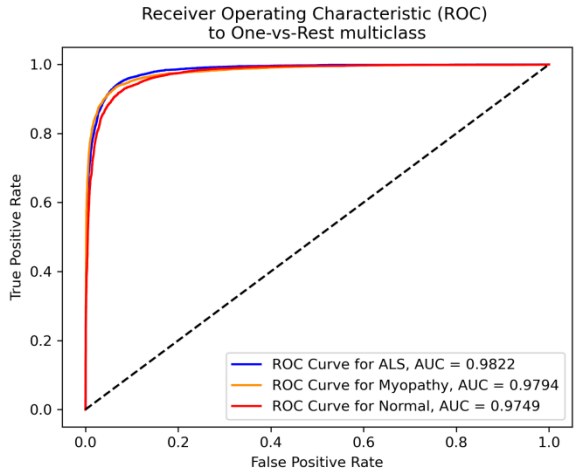


Figure 21(c): ROC curve for XGBOOST Classifier with test sample size of 20%, for time domain EMG features. AUC for ALS v/s rest: 98.22%
AUC for Myopathy v/s rest: 97.94%
AUC for Normal v/s rest: 97.49%

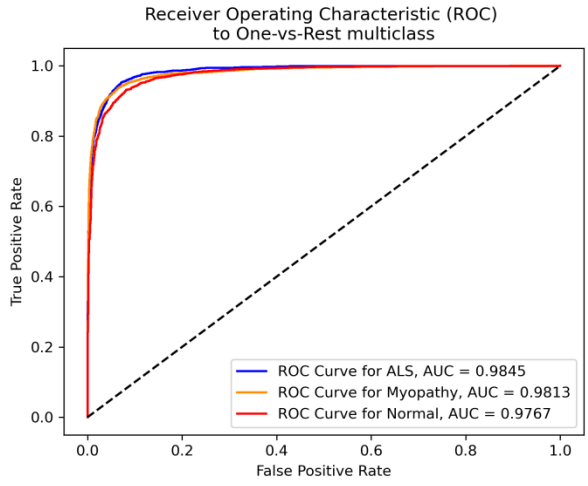


Figure 21(d): ROC curve for XGBOOST Classifier with test sample size of 10%, for time domain EMG features. AUC for ALS v/s rest: 98.45%
AUC for Myopathy v/s rest: 98.13%
AUC for Normal v/s rest: 97.67%

The table 6 shows the Performance Analysis of KNN Classifier Model using time domain EMG features.

Table 6: Performance Analysis of KNN Classifier with Time Domain EMG Features

The figures 22(a), 22(b), 22(c), and 22(d) show the ROC curves plotted for KNN Classifier with test sample sizes of 40%, 30%, 20%, and 10% respectively, for time domain EMG features.

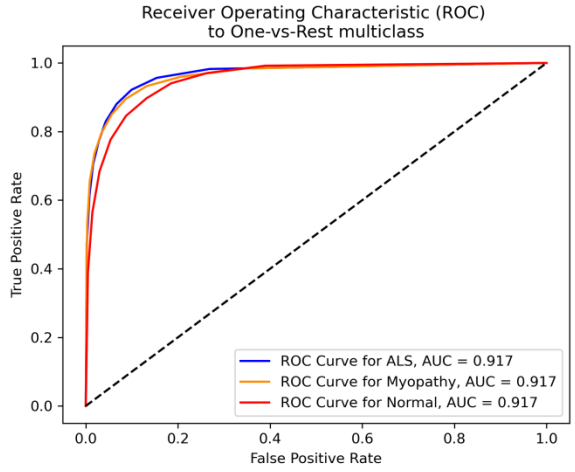


Figure 22(a): ROC curve for KNN Classifier with test sample size of 40%, for time domain EMG features.
AUC for ALS v/s rest: 91.7%
AUC for Myopathy v/s rest: 91.7%
AUC for Normal v/s rest: 91.7%

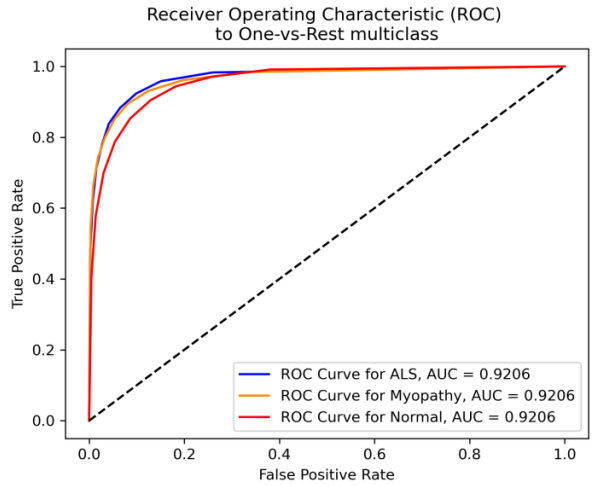


Figure 22(b): ROC curve for KNN Classifier with test sample size of 30%, for time domain EMG features
AUC for ALS v/s rest: 92.06%
AUC for Myopathy v/s rest: 92.06%
AUC for Normal v/s rest: 92.06%

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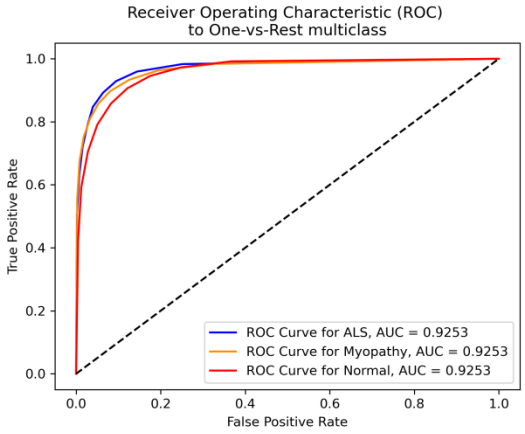


Figure 22(c): ROC curve for KNN Classifier with test sample size of 20%, for time domain EMG features.
AUC for ALS v/s rest: 92.53%
AUC for Myopathy v/s rest: 92.53%
AUC for Normal v/s rest: 92.53%

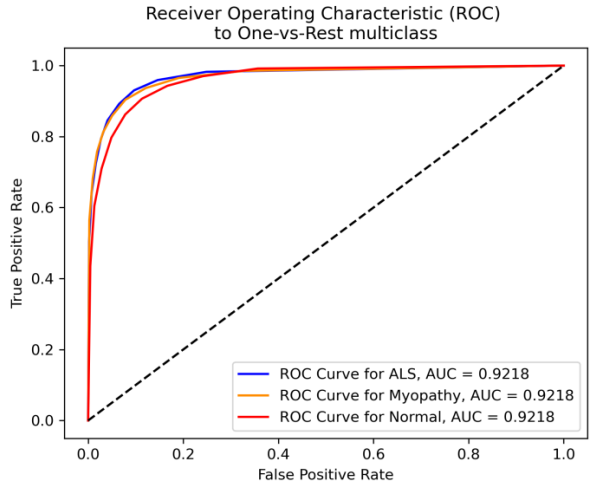


Figure 22(d): ROC curve for KNN Classifier with test sample size of 10%, for time domain EMG features.
AUC for ALS v/s rest: 92.18%
AUC for Myopathy v/s rest: 92.18%
AUC for Normal v/s rest: 92.18%
The better classification accuracy is achieved with SVM classifier model compared to MLP, RF, XGBOOST, and KNN classifier models.

For the analysis and classification of muscular paralysis, the features extracted in frequency domain are used. The 4 features are extracted from the EMG Dataset. The features considered are Mean Frequency, Median Frequency, Power Spectral Density, and Frequency Deformation. These features are used as input to the classifier models employed. The classifier models employed are MLP, RF, XGBOOST, and KNN classifier models.
The training data set sizes taken are 90%, 80%, 70%, and 60%, for corresponding test data set sizes of 10%, 20%, 30% and 40%. The obtained Accuracy, Precision, Recall or Sensitivity, Specificity, Misclassification Rate, F1-Score, are tabulated and ROC curves are plotted.

The table 7 shows the Performance Analysis of MLP Classifier Model using frequency domain EMG features.

Table 7: Performance Analysis of MLP Classifier with Frequency Domain EMG Features

| **MLP Classifier** | Test Sample Size = 40% | Test Sample Size = 30% | Test Sample Size = 20% | Test Sample Size = 10% |
|---|---|---|---|---|
| Accuracy | 0.73 | 0.74 | 0.78 | 0.71 |
| Precision | 0.74 | 0.75 | 0.78 | 0.73 |
| Sensitivity | 0.73 | 0.74 | 0.78 | 0.71 |
| Specificity | 0.86 | 0.86 | 0.88 | 0.84 |
| Misclassification Rate | 0.27 | 0.26 | 0.22 | 0.29 |
| F1-Score | 0.73 | 0.74 | 0.78 | 0.72 |

The figures 23(a), 23(b), 23(c), and 23(d) show the ROC curves plotted for MLP Classifier with test sample sizes of 40%, 30%, 20%, and 10% respectively, for frequency domain EMG features.

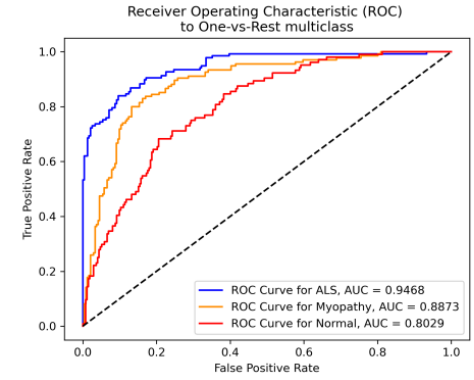


Figure 23(a): ROC curve for MLP Classifier with test sample size of 40%, for frequency domain EMG features.
AUC for ALS v/s rest: 94.68%
AUC for Myopathy v/s rest: 88.73%
AUC for Normal v/s rest: 80.29%

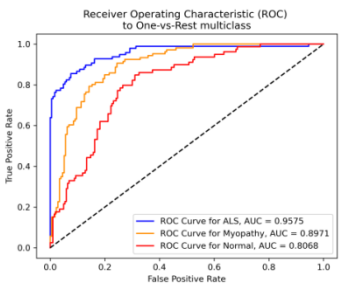


Figure 23(b): ROC curve for MLP Classifier with test sample size of 30%, for frequency domain EMG features.

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AUC for ALS v/s rest: 95.75%
AUC for Myopathy v/s rest: 89.71%
AUC for Normal v/s rest: 80.68%

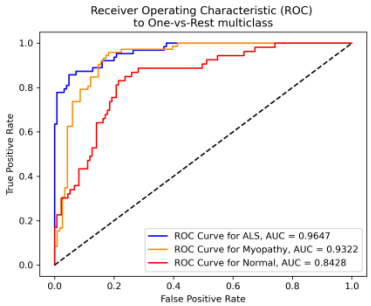


Figure 23(c): ROC curve for MLP Classifier with test sample size of 20%, for frequency domain EMG features.

AUC for ALS v/s rest: 96.47%
AUC for Myopathy v/s rest: 93.22%
AUC for Normal v/s rest: 84.28%

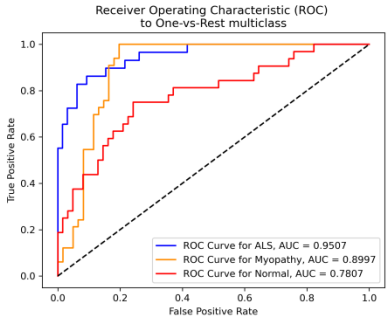


Figure 23(d): ROC curve for MLP Classifier with test sample size of 10%, for frequency domain EMG features.

AUC for ALS v/s rest: 95.07%
AUC for Myopathy v/s rest: 89,97%
AUC for Normal v/s rest: 92.18%

The table 8 shows the Performance Analysis of RF Classifier Model using frequency domain EMG features.

Table 8: Performance Analysis of RF Classifier with Frequency Domain EMG Features

| **RF Classifier** | Test Sample Size = 40% | Test Sample Size = 30% | Test Sample Size = 20% | Test Sample Size = 10% |
|---|---|---|---|---|
| Accuracy | 0.72 | 0.76 | 0.78 | 0.74 |
| Precision | 0.71 | 0.75 | 0.77 | 0.75 |
| Sensitivity | 0.71 | 0.75 | 0.77 | 0.75 |
| Specificity | 0.84 | 0.87 | 0.88 | 0.86 |
| Misclassification Rate | 0.28 | 0.24 | 0.22 | 0.26 |
| F1-Score | 0.71 | 0.75 | 0.77 | 0.75 |

The figures 24(a), 24(b), 24(c), and 24(d) show the ROC curves plotted for RF Classifier with test sample sizes of 40%, 30%, 20%, and 10% respectively, for frequency domain EMG features.

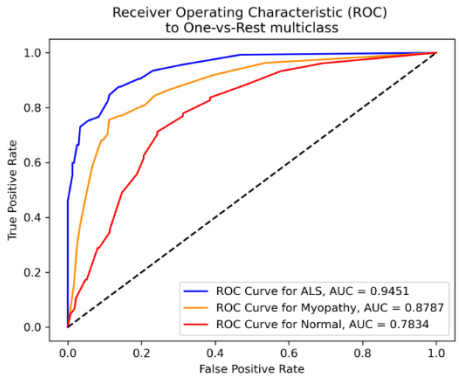


Figure 24(a): ROC curve for RF Classifier with test sample size of 40%, for frequency domain EMG features. AUC for ALS v/s rest: 94.51%
AUC for Myopathy v/s rest: 87.87%
AUC for Normal v/s rest: 78.34%

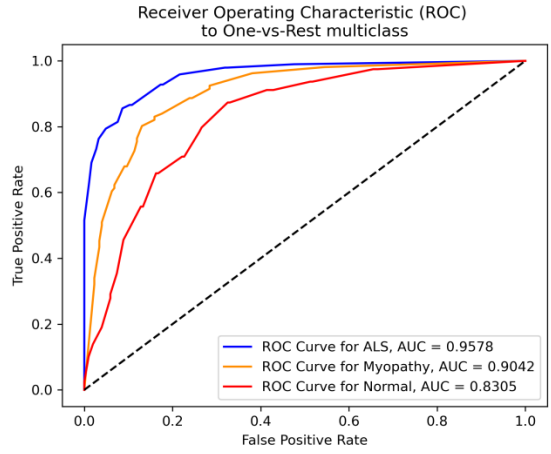


Figure 24(b): ROC curve for RF Classifier with test sample size of 30%, for frequency domain EMG features.
AUC for ALS v/s rest: 95.78%
AUC for Myopathy v/s rest: 90.42%
AUC for Normal v/s rest: 83.05%

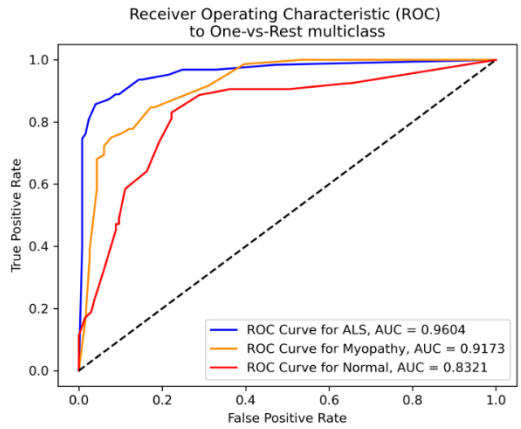


Figure 24(c): ROC curve for RF Classifier with test sample size of 20%, for frequency domain EMG features.
AUC for ALS v/s rest: 96.04%
AUC for Myopathy v/s rest: 91.73%
AUC for Normal v/s rest: 83.21%

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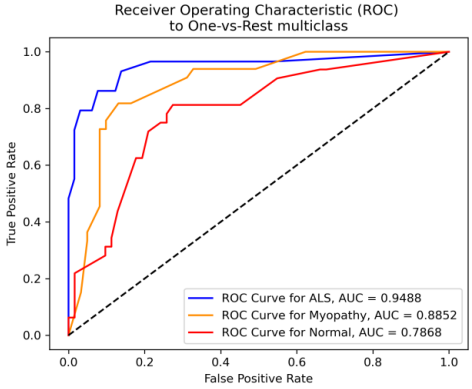


Figure 24(d): ROC curve for RF Classifier with test sample size of 10%, for frequency domain EMG features.
AUC for ALS v/s rest: 94.88%
AUC for Myopathy v/s rest: 88.52%
AUC for Normal v/s rest: 78.68%

The table 9 shows the Performance Analysis of XGBOOST Classifier Model using frequency domain EMG features.

Table 9: Performance Analysis of XGBOOST Classifier with Frequency Domain EMG Features

| **XGBOOST Classifier** | Test Sample Size = 40% | Test Sample Size = 30% | Test Sample Size = 20% | Test Sample Size = 10% |
|---|---|---|---|---|
| Accuracy | 0.69 | 0.70 | 0.77 | 0.76 |
| Precision | 0.67 | 0.68 | 0.76 | 0.76 |
| Sensitivity | 0.67 | 0.68 | 0.76 | 0.76 |
| Specificity | 0.82 | 0.82 | 0.87 | 0.86 |
| Misclassification Rate | 0.31 | 0,30 | 0.23 | 0.24 |
| F1-Score | 0.67 | 0.68 | 0.76 | 0.76 |

The figures 25(a), 25(b), 25(c), and 25(d) show the ROC curves plotted for XGBOOST Classifier with test sample sizes of 40%, 30%, 20%, and 10% respectively, for frequency domain EMG features.

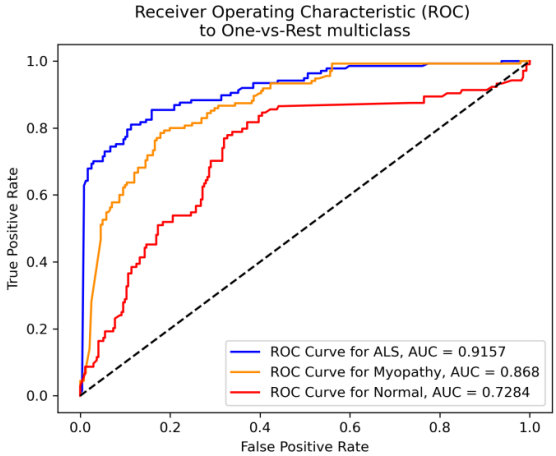


Figure 25(a): ROC curve for XGBOOST Classifier with test sample size of 40%, for frequency domain EMG features.

AUC for ALS v/s rest: 91.57%
AUC for Myopathy v/s rest: 86.80%
AUC for Normal v/s rest: 72.84%

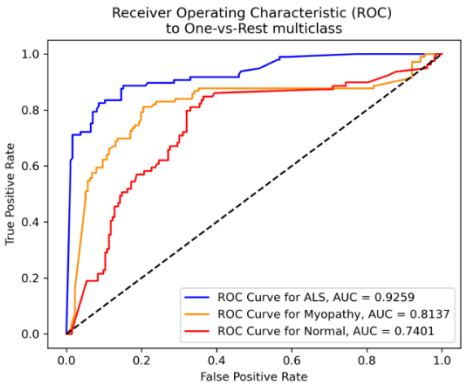


Figure 25(b): ROC curve for XGBOOST Classifier with test sample size of 30%, for frequency domain EMG features.
AUC for ALS v/s rest: 92.59%
AUC for Myopathy v/s rest: 81.37%
AUC for Normal v/s rest: 74.01%

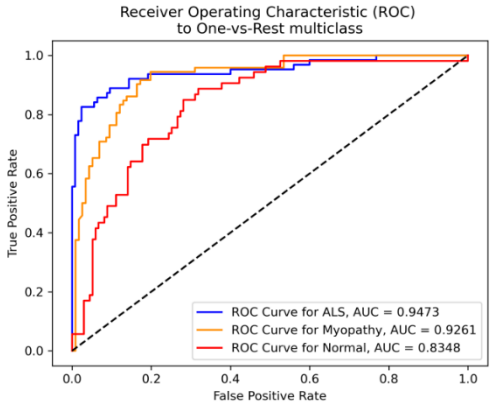


Figure 25(c): ROC curve for XGBOOST Classifier with test sample size of 20%, for frequency domain EMG features.
AUC for ALS v/s rest: 94.73%
AUC for Myopathy v/s rest: 92.61%
AUC for Normal v/s rest: 83.48%

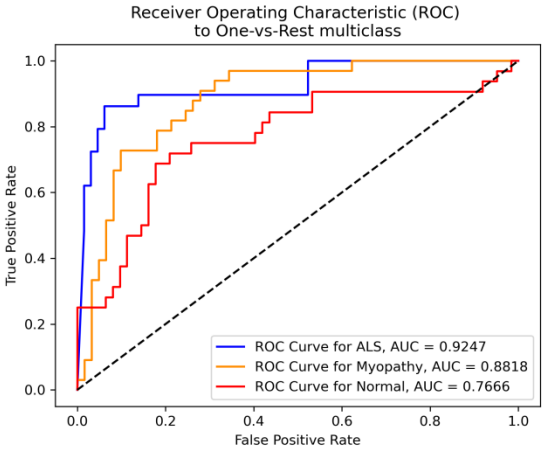


Figure 25(d): ROC curve for XGBOOST Classifier with test sample size of 10%, for frequency domain EMG features.
AUC for ALS v/s rest: 92.47%
AUC for Myopathy v/s rest: 88.18%

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AUC for Normal v/s rest: 76.66%

The table 10 shows the Performance Analysis of KNN Classifier Model using frequency domain EMG features.

Table 10: Performance Analysis of KNN Classifier with Frequency Domain EMG Features

| **KNN Classifier** | Test Sample Size = 40% | Test Sample Size = 30% | Test Sample Size = 20% | Test Sample Size = 10% |
|---|---|---|---|---|
| Accuracy | 0.71 | 0.73 | 0.75 | 0.69 |
| Precision | 0.71 | 0.73 | 0.74 | 0.69 |
| Sensitivity | 0.70 | 0.72 | 0.74 | 0.69 |
| Specificity | 0.84 | 0.85 | 0.86 | 0.82 |
| Misclassification Rate | 0.29 | 0.27 | 0.25 | 0.31 |
| F1-Score | 0.70 | 0.72 | 0.74 | 0.69 |

The figures 26(a), 26(b), 26(c), and 26(d) show the ROC curves plotted for KNN Classifier with test sample sizes of 40%, 30%, 20%, and 10% respectively, for frequency domain EMG features.

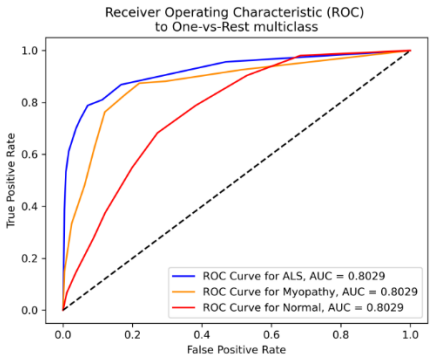


Figure 26(a): ROC curve for KNN Classifier with test sample size of 40%, for frequency domain EMG features.

AUC for ALS v/s rest: 80.29%
AUC for Myopathy v/s rest: 80.29%
AUC for Normal v/s rest: 80.29%

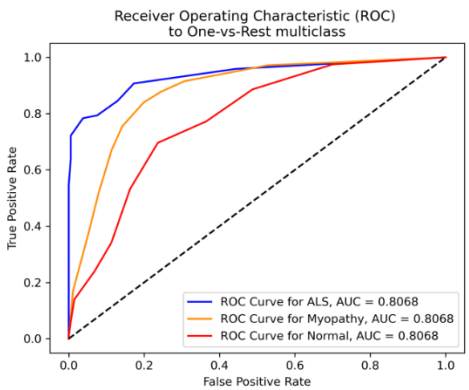


Figure 26(b): ROC curve for KNN Classifier with test sample size of 30%, for frequency domain EMG features.

AUC for ALS v/s rest: 80.68%
AUC for Myopathy v/s rest: 80.68%
AUC for Normal v/s rest: 80.68%

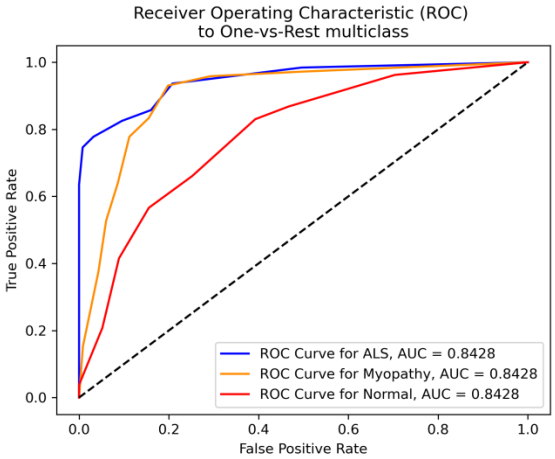


Figure 12(c): ROC curve for KNN Classifier with test sample size of 20%, for frequency domain EMG features.

AUC for ALS v/s rest: 84.28%
AUC for Myopathy v/s rest: 84.28%
AUC for Normal v/s rest: 84.28%

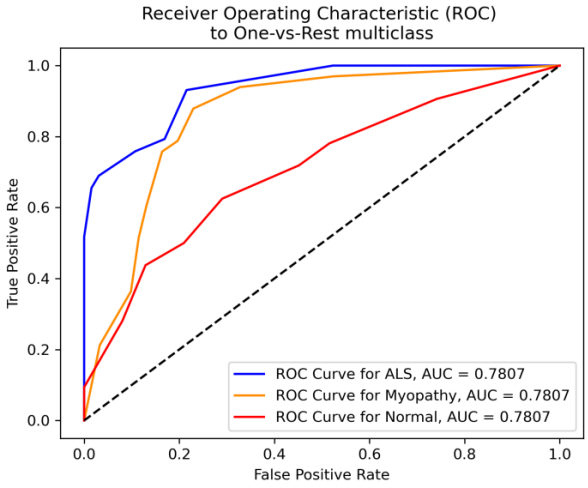


Figure 12(d): ROC curve for KNN Classifier with test sample size of 10%, for frequency domain EMG features.

AUC for ALS v/s rest: 78.07%
AUC for Myopathy v/s rest: 78.07%
AUC for Normal v/s rest: 78.07%

## V CONCLUSION AND FUTURE SCOPE

The EMG features in the time domain, and frequency domain, are considered for analysis of paralysis disease. Here, the features are extracted from EMG are used for analysis and classification purpose. The normal, ALS and Myopathy data samples are used for training and testing the samples with different sizes, for analysing the paralysis disease. The MLP, SVM, RF, XGBOOST and KNN are used as classification models. In time domain analysis SVM classifier found to be better with classification accuracy 77%. In frequency domain analysis, the MLP, and RF classifiers found to be better with classification accuracy

77.7%. The present work can be extended for development of portable system for acquisition and analysis of EMG, for the assessment of muscular activity.

## REFERENCES

[1] S. Chopra, A. K. Tripathy, A. Alphonso, M. Carvalho and C. Sancia, "Brain computer interface and electro stimulation of muscles to assist paralyzed patients in limited movement of hands," 2017 International Conference on Nascent Technologies in Engineering (ICNTE), 2017, pp. 1-6, doi: 10.1109/ICNTE.2017.7947950.

[2] Heaven Stubblefield, "Paralysis", Healthline, 2018 https://www.healthline.com/health/paralysis#diagnosis

[3] David H. Sutherland, "The Evolution of Clinical Gait Analysis Part L: Kinesiological EMG", Elsevier, Gait and Posture 14, 2001, pp: 61–70 https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.501.2507&rep=rep1&type=pdf

[4] https://www.brighamandwomens.org/medical-resources/emg-test

[5] https://www.medicalnewstoday.com/articles/281472#who-gets-it

[6]Conforto, S., D'Alessio T. D., Pignatelli S., Optimal Rejection of Movement Artefacts from Myoelectric Signals by Means of a Wavelet Filtering Procedure, J. Electromyogr. Kinesiol., 1999, Vol.9, pp. 47–57

[7]David C. Preston, and Barbara E. Shapiro, "Electromyography and Neuromuscular Disorders Clinical-Electrophysiologic Correlations" Third Edition, Elsevier Inc. 2013

[8]Christopher S, MdRasedul I, M Assad-Uz Z, Mohammad H R, "A Comprehensive Study on EMG Feature Extraction and Classifiers", Op Acc J Bio Eng& Bio Sci 1(1)- 2018, Pp. 17-26. OAJBEB.MS.ID.000104. DOI: 10.32474/OAJBEB.2018.01.000104. https://lupinepublishers.com/biomedical-sciences-journal/fulltext/a-comprehensive-study-on-eMG-feature- extraction-and-classifiers.ID.000104.php

[9]https://www.webmd.com/brain/paralysis-types

[10]Dennis L. Kasper, Anthony S. Fauci, Stephen L. Hauser, Dan L. Longo, J. Larry Jameson, and Joseph Loscalzo, "Harrison's Manual of Medicine", 19th Edition, McGraw-Hill Education, 2016. ISBN 978-0-07-182852-9, MHID0-07-182852-4. https://accessmedicine.mhmedical.com/content.aspx?bookid=1820&sectionid=127554873

[11]EricVerin, Jean-PaulMarie, CatherineTardif and PhilippeDenis, "Spontaneous recovery of diaphragmatic strength in unilateral diaphragmatic paralysis", Respiratory Medicine (2006) 100, pp 1944-1951

[12]Dow D.E., Petrilli A.M., Mantilla C.B.andWen-Zhi Zhan., "Electromyogram Triggered Inspiratory Event Detection Algorithm", Soft Computing and Intelligent Systems (SCIS) and 13th International Symposium on Advanced Intelligent Systems (ISIS) 2012, pp 789 – 794

[13]Melo, M.C. , de Sa, A.A.R.,Silva, A.N. and Soares, A.B., "Proposal of a computational interface of biofeedback for rehabilitation of victims of stroke", Biosignals and BioroboticsConference (BRC), 2013 ISSNIP, pp 1-6

[14]Sun T.Y., Lin T.S., Chen J.J., Multi electrode surface EMG for noninvasive estimation of motor unit size, Muscle & Nerve, Vol. 22, No. 8, 1999, pp. 1063– 1070

[15]Fuglsang-Frederiksen A., The Role of Different EMG Methods in Evaluating Myopathy, Clinical Neurophysiology, Vol. 117, No. 6, 2006, pp. 1173– 1189

[16]Hilfiker P., and Meyer M.., Normal and Myopathic Propagation of Surface Motor Unit Action Potentials, Electroencephalogram Clinical Neurophysiology, Vol. 57, No. 1, 1984, pp. 21–31

[17]N. Sengar, M. K. Dutta and C. M. Travieso, "Identification of Amyotrophic Lateral Sclerosis using EMG Signals," 2017 4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON), 2017, pp. 468-471, doi: 10.1109/UPCON.2017.8251093.

[18]Tsai, A. C., Hsieh, T.H.,Luh J.J., Lin, T. T., A Comparison of Upper-Limb Motion Pattern Recognition using EMG Signals during Dynamic and Isometric Muscle Contractions. Biomed. Signal Process Control, 2014, Vol.11, pp.17–26

[19]Hogan N., Mann R.W., Myoelectric Signal Processing Optimal Estimation Applied to Electromyography-Part I: Derivation of the Optimal Myoprocessor, IEEE Trans. Biomed. Eng., BME-27, 1980, pp.382–395

[20]Englehart K., Hudgins B., Parker P.A., Stevenson M., Classification of the Myoelectric Signal using Time-Frequency based Representations. Med. Eng. Phys. Vol.21, 1999, pp. 431–438

[21]Khezri M., Jahed M., Real-time intelligent pattern recognition algorithm for surface EMG signals. Biomed Eng., Vol. 6,2007,pp.45

[22]Archana B. Kanwade, and V. K. Bairagi, "Feature Extraction of EMG Signals in Time and Frequency Domain for Myopathy, Neuropathy and Healthy Muscle**",** 3rd International Conference on Electrical, Electronics, Engineering Trends, Communication, Optimization and Sciences (EEECOS), pp. 971-921, 2016

[23]Artameeyanant, P., Sultornsanee, S. & Chamnongthai, K. "An EMG-Based Feature Extraction Method Using A Normalized Weight Vertical Visibility Algorithm for Myopathy and Neuropathy Detection". Springer Plus 5, 2101 (2016). https://doi.org/10.1186/s40064-016-3772-2

[24]Angkoon Phinyomark, Rami N. Khushaba, Esther Ibáñez-Marcelo, Alice Patania, Erik Scheme, and Giovanni Petri. (2017). "Navigating Features A Topologically Informed Chart of Electromyographic Features Space". Journal of The Royal Society Interface. 14. DOI: https://doi.org/10.1098/rsif.2017.0734.

[25]A.Bakiya, A. Anitha, T. Sridevi, and K. Kamalanand, "Classification of Myopathy and Amyotrophic Lateral Sclerosis Electromyograms Using Bat Algorithm and Deep Neural Networks",Hindawi Behavioural Neurology, Volume 2022, Article ID 3517872, pages.1-9, https://doi.org/10.1155/2022/3517872

[26]Elamvazuthia, N.H.X. Duya , Zulfiqar Alia , S.W. Sub , M.K.A. AhamedKhanc and S. Parasuramand, "Electromyography (EMG) based Classification of Neuromuscular Disorders using Multi-Layer Perceptron", 2015, IEEE International Symposium on Robotics and Intelligent Sensors (IRIS 2015)

[27]Abdulhamit Subasi, "A Decision Support System for Diagnosis of Neuromuscular Disorders using DWT and Evolutionary Support Vector Machines", Springer-Verlag London 2013. DOI 10.1007/s11760-013-0480-z

[28]Richa Singh and Ram Bilas Pachori, "Iterative Filtering-Based Automated Method for Detection of Normal and ALS EMG Signals", pp.33-53, 2020, https://www.researchgate.net/publication/338384117

[29]Shashank Kumar Singh, Amrita Chaturvedi, and Alok Prakash, "Applying Extreme Gradient Boosting for Surface EMG Based Sign Language Recognition", Proceedings of International Conference on Machine Learning and Big Data Analytics (ICMLBDA), 2021.

[30]S. Samui, A. K. Mukhopadhyay, P. K. Ghadge and G. Kumar, "Extreme Gradient Boosting for Limb Position Invariant Myoelectric Pattern Recognition," 2020 IEEE International Symposium on Smart Electronic Systems (iSES) (Formerly iNiS), 2020, pp. 81-85, doi: 10.1109/iSES50453.2020.00029

[31]Mohammad Tafhim Khan, and M. Tahseenul Hasan, "Comparison between KNN and SVM for EMG Signal Classification", International Journal on Recent and Innovation Trends in Computing and Communication, Volume: 3, Issue 12, December 2015, ISSN: 2321-8169

[32]H. Kucuk, CengizTepe, and I. Eminoglu, "Classification of EMG Signals by k-Nearest Neighbor Algorithm and Support Vector Machine Methods", Conference: Signal Processing and Communications Applications Conference (SIU), 2013. DOI: 10.1109/SIU.2013.6531240

[33]Database of Clinical Signals. Nikolic M, Rigshospitalet, Copenhagen, DK, dataset N2001 at http://www.emglab.net of a figure.