

# Classification of Muscular Paralysis Based on EMG Decomposition using Daubecheis Wavelets

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## ABSTRACT

Muscle function is lost as a result of paralysis, which limits muscle action on the side of the body that is affected. The Electromyography (EMG) signal is directly impacted by this. Analysing the signal alterations is necessary to determine the paralysis condition. In order to create a classification system for paralysis and normal conditions, this work intends to assess EMG data in time-frequency domain. The daubecheis wavelets are used for decomposition of EMG data. The EMG dataset N2001 available at [emglab.net](http://emglab.net) is used in this work. The dataset consists of EMG of ALS, myopathy and normal conditions ALS and myopathy are considered for paralysis condition. Four Classifier models MLP, RF, XGBOOST and KNN are employed. The statistical features are extracted and used for classification. The performance of classifier models are evaluated by computing accuracy, precision sensitivity, specificity, misclassification rate, F1-score, and plotting ROC curves. The XGBOOST classifier accuracy is greater over other classifier models with average value of accuracy is 97%, precision is 97%, sensitivity is 97%, specificity is 99%, misclassification rate is 3%, and F1-score is 97%. The ROC plots are obtained with AUC values ranging from 98% - 100%.

**Keywords:** Paralysis, Electromyography (EMG), Amyotrophic Lateral Sclerosis (ALS), Myopathy, Multilayer Perceptron (MLP), Random Forest (RF), Gradient Boosting (XGBOOST), K-Nearest Neighbor (KNN).

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## 1 INTRODUCTION

The muscular system is made up of muscle fibres. The bulk of bodily mass is made up of skeletal muscles. Numerous actions and functions are carried out by skeletal muscles that are connected to the bones and other organs. The body moves as a result of muscle contractions. Paralysis is the outcome of losing muscle contraction. EMG describes the electrical activity of the muscles. The ability of EMG signals to differentiate neuromuscular diseases aid in early diagnosis of paralysis. The needle EMG techniques are predominant in the diagnosis of neuromuscular diseases, although initiatives to employ sEMG for diagnostic reasons are also emerging [1][2][3]. Evaluation of the clinical value of sEMG was published by the American Association of Electrodiagnostic Medicine [4] due to the significant discrepancies between sEMG and traditional electro diagnostic procedures. They analyzed the standard methods used in needle EMG assessment and looked for sEMG analogues.

Use of several EMG methods for examination will be beneficial for myopathy diagnosis. The amplitude studies 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 [3]. Low-amplitude, short-duration, and polyphasic shapes of individual MUAPs are indicative of both muscle fibre degradation and regeneration in patients with myopathy [5]. 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. The EMG signal was subjected to time-frequency analysis, is a novel method. This method creates a continuous depiction of the signal's changing spectrum throughout time.

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 [6] 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.

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 (TD), frequency domain (FD), and time-frequency domain (TFD), analyses are used to identify characteristics in the study of EMG data, TFD features can display variable frequency information at various time intervals, offering efficient non stationary information about the examined signals.

Several classification methods are used for classification of neuromuscular diseases. The classifier models for neuromuscular illnesses that can be employed include bayesian techniques, neural networks, multilayer perceptrons, fuzzy approaches, support vector machines, and neuro-fuzzy systems [7].

## II LITERATURE SURVEY

Natalie Slivinski [8], 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 [9], 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. The types of paralysis are monoplegia, hemiplegia, paraplegia, and quadriplegia. Monoplegia affects single arm/leg, hemiplegia affects half of the body, paraplegia affects both legs, and quadriplegia affects all four limbs. Heaven Stubble Field [10], describes flaccid paralysis and spastic paralysis. The flaccid paralysis causes muscles to shrink. Spastic paralysis causes muscle tightness and hardness. Heidi Moawad M D[11], discussed the symptoms and causes of the paralysis. The symptoms include numbness or tingling, loss of sensation, and floppiness in the weak area of the body. Paralysis is caused by damage in the nervous system. Kaushik Bharati [12], discussed the methods used for diagnosis of paralysis. X-ray, CT scan, MRI, myelography, and electromyography are the methods used. EMG is used to evaluate muscle function efficiently by analyzing the electrical activity associated with muscles.

Electromyography is the test used to assess the health of the muscles and nerve cells. Acquired EMG is used to examine the muscle function, nerve function, or disturbance in nerve-to-muscle signal transmission. EMG results aid in proper diagnose of neuromuscular disorders which include amyotrophic lateral sclerosis, peripheral neuropathies, muscular dystrophy, myasthenia

gravis, and myopathy. EMG is performed with low risk factors. There is a chance of occurrence of risk factors during EMG procedure are bleeding, nerve injury, infection, and pneumothorax [13].

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, myopathies, muscular dystrophy, and myasthenia gravis can be evaluated and managed using electromyography [14].

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 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 [15]. 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 [16].

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 [17].

Wavelets are mathematical operations that break data down into several frequency components. Each frequency component is then examined with a resolution appropriate to its scale. For the study of the electromyography signal, wavelet transform has emerged as the most potent signal processing tool. It is extensively used in EMG recognition systems. The important EMG features can be extracted from the EMG signal with the help of multiple-level wavelet decomposition. The EMG signal's usable resolution components

were extracted using various mother wavelet levels. [18].

Time domain features provides the temporal and frequency information of the signal. Since EMG is non-stationary signal, using TFD features, the signal characteristics in time-frequency plane are obtained. EMG signal information from TFD features aid to analyze and classify the muscular paralysis in an efficient manner [17] [19].

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. The MLP processes the input dimension and transforms it into the desired dimension. A neural network with numerous layers is referred to as a multi-layer perception. Neurons are combined to form neural networks. Some neurons' outputs serve as the inputs for other neurons [20]. Random Forest (RF): The random forest consisting of many decisions trees, RF generates uncorrelated forest of trees which provide accurate prediction [21].

Gradient Boosting (XGHOOST): A class of machine learning techniques known as gradient boosting classifiers combines a number of weak learning models to produce a powerful predicting model [22]. K-Nearest Neighbour (KNN): The neural network algorithm examines the degree of similarity between the new data and the existing data and categories the new data accordingly [23].

The analysis, classification and diagnosis of paralysis are most preferred in order to aid better treatment options. Assessment of muscular activity by EMG has becomes a popular method. With the rapid advancements in signal processing technology, electro physiological parameters can be assessed and recorded, which provides necessary information for diagnosis and treatment. Electromyography is a technique developed to detect the electrical activities of the muscles.

Healthcare is becoming a major issue in developing countries. This concern is increasing across the section of people living with paralysis. They are looking for a better treatment options to improve the quality of the life. Several studies have been carried with few EMG features for analysis of neuromuscular disorders. The effective EMG analysis can be performed with considering several EMG features for analysis of neuromuscular disorders. In health care sectors with EMG based approach for analysis and assessment of muscular activity in paralysed subjects, will help in early diagnosis and clinical treatment.

### III MATERIALS AND METHODOLOGY

In the present work the dataset [24], 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 ALS data have the disease onset duration of 0.5 years to 5 years. The myopathy data have the disease onset duration of less than one month to 26 years. The data include early stage as well as many years of disease affected subjects EMG signal filtering is performed using filters with 2 Hz and 10 kHz cut off frequencies. All EMG data samples are recorded for the duration 11.2 seconds. Rectangular windows of 300.37 msec with a 99.84 msec overlap are utilised for feature extraction.

The figures 1, 2 and 3 show the EMG of normal data sample, ALS data sample, and myopathy data sample.

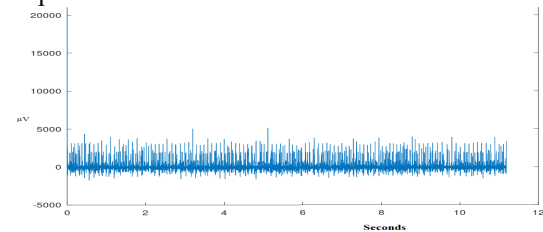


Figure 1: EMG of Normal Data Sample

The figure 1 shows the EMG of normal data sample recorded for 11.2 seconds. The normal data consist of 300 data samples. The 300 data samples are considered for feature extraction.

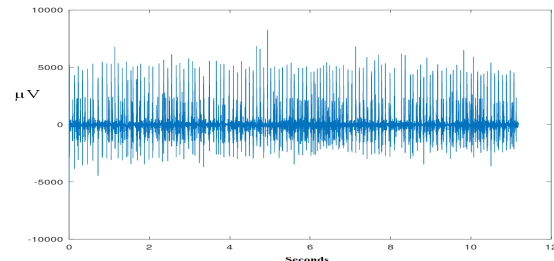


Figure 2: EMG of ALS Data Sample

The figure 2 shows the EMG of ALS data sample recorded for 11.2 seconds. The ALS data consist of 323 data samples. The 323 data samples are considered for feature extraction.

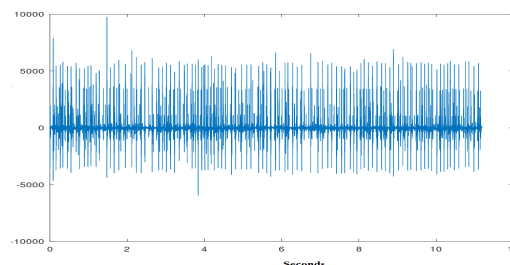


Figure 3: EMG of Myopathy Data Sample

The figure 3 shows the EMG of myopathy data sample recorded for 11.2 seconds. The myopathy data consist of 315 data samples. The 315 data samples are considered for feature extraction.

Wavelet decomposition is achieved using daubecheis wavelets of order 2 to 10. The block diagram for the method used is shown in Figure4.

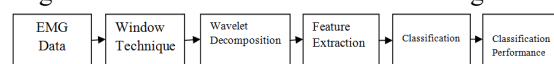


Figure 4: Time-Frequency Domain Feature Extraction and Classification of EMG Data

In the present work, the decomposition of EMG is performed in five levels. The approximate bands are A1, A2, A3, A4, and A5 bands. The detail bands are D1, D2, D3, D4, and D5 bands.

The A1 band consists of frequencies ranging from 0-5.75KHz, A2 band ranging from 0 - 2.875 KHz, A3 band ranging from 0 - 1.44 KHz, A4 band ranging from 0 - 0.72 KHz, and A5 band ranging from 0 - 0.36 KHz.

The D1 band ranging from 5.75 - 11.5 KHz, D2 band ranging from 2.875 - 5.75 KHz. D3 band ranging from 1.44 - 2.875 KHz, D4 band ranging from 0.72 - 1.44 KHz, and D5 band ranging from 0.36 - 0.72 KHz.

The lower approximation bands represent the lower frequencies in the decomposition and detail bands represent the higher frequencies in the decomposition. The features mean, variance, mean absolute value, root means square, waveform length, zero crossings, log detector, difference absolute standard deviation value, average amplitude change, variance absolute value, kurtosis, and skewness are extracted from the EMG data. The features are extracted in approximate band A5, detail bands D5, D4, D3, D2, and D1 bands.

The figure 5 show the average values of features obtained from wavelet decomposition using daubecheis wavelets for normal data.

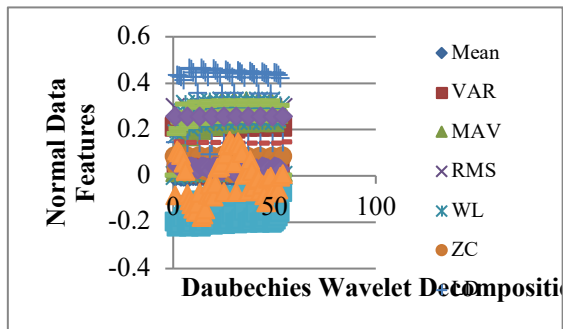


Figure 5: Scatter Plot of Average Values of Features with Daubechies Wavelet Decomposition for normal Data

These feature values are used further for analysis and classification.

The figure 6 show the average values of features obtained from wavelet decomposition using daubecheis wavelets for ALS data.

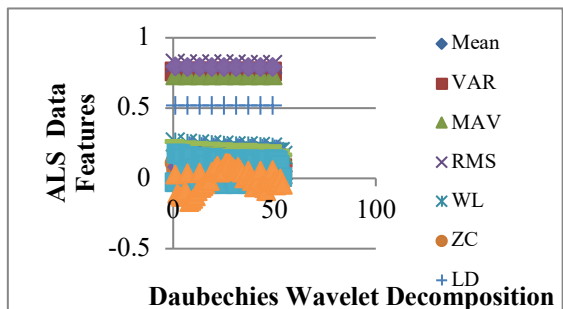


Figure 6: Scatter Plot of Average Values of Features with Daubechies Wavelet Decomposition for ALS Data

These feature values are used further for analysis and classification.

The figure 7 show the average values of features obtained from wavelet decomposition using daubecheis wavelets for the myopathy data.

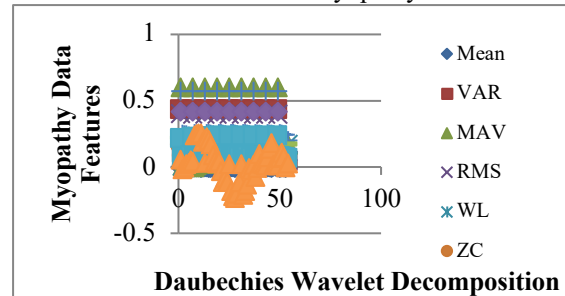


Figure 7: Scatter Plot of Average Values of Features with Daubechies Wavelet Decomposition for Myopathy Data

These feature values are used further for analysis and classification.

In the present work the MLP, RF, XGBOOST and KNN classifiers are employed for classification of normal and paralysis condition. Twelve statistical feature values extracted in D5, D4, D3, D2, D1, and A5 bands are used for classification. The data is divided in to training set and test set. The training data set sizes choosen are 60%, 70%, 80%, and 90%, with corresponding test data set sizes 40%, 30%, 29%, and 10%, respectively. The classification performance values are computed and ROC curves are plotted.

#### IV RESULTS AND DISCUSSION

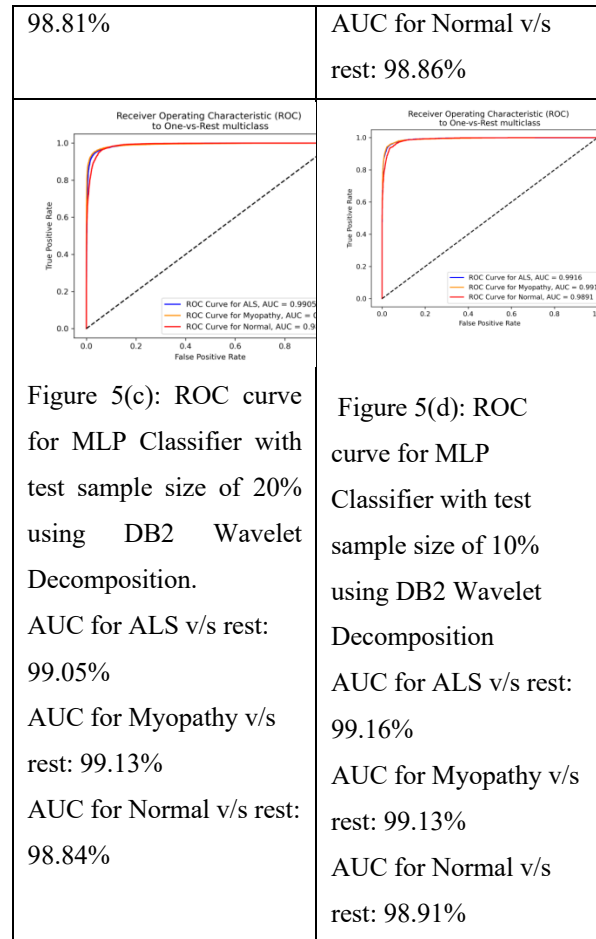
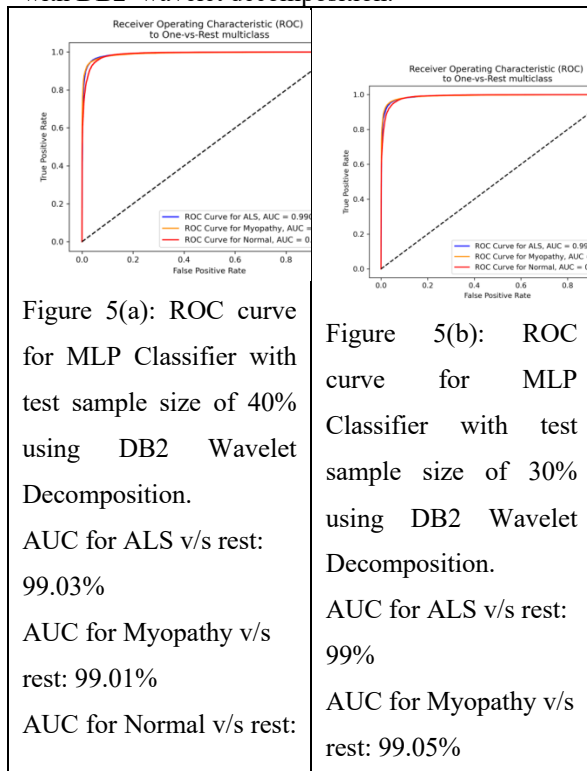
The classification performance of MLP classifier model with wavelet decomposition using DB2 to DB10 wavelets is shown in table 1.

Table 1: Performance of MLP Classifier Model

| M<br>L<br>P | Average of Performance Values |                                   |                                             |                                             |                                   |                              | A<br>U<br>C<br>R<br>a<br>n<br>g<br>e<br>(<br>%<br>) |
|-------------|-------------------------------|-----------------------------------|---------------------------------------------|---------------------------------------------|-----------------------------------|------------------------------|-----------------------------------------------------|
|             | Acc<br>u<br>r<br>a<br>c<br>y  | Pre<br>c<br>i<br>s<br>i<br>o<br>n | Sen<br>s<br>i<br>t<br>i<br>v<br>i<br>t<br>y | Spe<br>c<br>i<br>f<br>i<br>c<br>i<br>t<br>y | Miscla<br>ssificat<br>ion<br>Rate | F<br>1-<br>Sc<br>o<br>r<br>e |                                                     |
| D<br>B<br>2 | 0.94                          | 0.95                              | 0.94                                        | 0.96                                        | 0.06                              | 0.95                         | 98 - 99                                             |
| D<br>B<br>3 | 0.93                          | 0.93                              | 0.93                                        | 0.97                                        | 0.07                              | 0.93                         | 98 -                                                |

|    |     |     |      |      |      |    |    |
|----|-----|-----|------|------|------|----|----|
| 3  |     |     |      |      |      |    | 99 |
| D  |     |     |      |      |      |    | 98 |
| B  | 0.9 | 0.9 |      |      |      | 0. | -  |
| 4  | 3   | 3   | 0.93 | 0.97 | 0.07 | 93 | 99 |
| D  |     |     |      |      |      |    | 98 |
| B  | 0.9 | 0.9 |      |      |      | 0. | -  |
| 5  | 2   | 3   | 0.92 | 0.97 | 0.08 | 92 | 99 |
| D  |     |     |      |      |      |    | 98 |
| B  | 0.9 | 0.9 |      |      |      | 0. | 98 |
| 6  | 2   | 2   | 0.92 | 0.97 | 0.08 | 92 |    |
| D  |     |     |      |      |      |    | 98 |
| B  | 0.9 | 0.9 |      |      |      | 0. | 98 |
| 7  | 2   | 2   | 0.92 | 0.97 | 0.08 | 92 |    |
| D  |     |     |      |      |      |    | 98 |
| B  | 0.9 | 0.9 |      |      |      | 0. | -  |
| 8  | 2   | 2   | 0.91 | 0.97 | 0.08 | 91 | 99 |
| D  |     |     |      |      |      |    | 97 |
| B  | 0.9 | 0.9 |      |      |      | 0. | -  |
| 9  | 2   | 1   | 0.92 | 0.96 | 0.08 | 91 | 98 |
| D  |     |     |      |      |      |    | 97 |
| B  | 0.9 | 0.9 |      |      |      | 0. | -  |
| 10 | 1   | 1   | 0.91 | 0.96 | 0.09 | 91 | 98 |

The figure 5 show the ROC plots of MLP classifier with DB2 wavelet decomposition.



The AUC values obtained are ranging from 98% to 99% and show the better performance of the MLP classifier

Similarly the range of AUC values obtained from ROC plots of MLP classifier with DB3 to DB10 wavelets decomposition is shown in table 1.

For MLP the overall accuracy is 92%, precision is 92%, sensitivity is 92%, specificity is 97%, misclassification rate is 8%, F1-score is 92%. The AUC values are ranging from 97% - 99%.

The classification performance of RF classifier model with wavelet decomposition using DB2 to DB10 wavelets is shown in table 2.

Table 2: Performance of RF Classifier Model

| R | Average of Performance Values |      |       |      |          |      | A  |
|---|-------------------------------|------|-------|------|----------|------|----|
|   | Acc                           | Pre  | Sen   | Spe  | Miscla   | F    |    |
| F | ura                           | cisi | sitiv | ific | ssificat | 1-Sc | UC |
|   | cy                            | on   | ity   | ity  | ion      | or   | R  |
|   |                               |      |       |      | Rate     | e    | an |
|   |                               |      |       |      |          |      | ge |
|   |                               |      |       |      |          |      | (  |
|   |                               |      |       |      |          |      | %) |

|           |     |     |      |      |      |    |    |
|-----------|-----|-----|------|------|------|----|----|
| <b>D</b>  | 0.9 | 0.9 | 0.96 | 0.98 | 0.04 | 0. | 98 |
| <b>B</b>  | 6   | 6   |      |      |      | 96 | -  |
| <b>2</b>  |     |     |      |      |      |    | 99 |
| <b>D</b>  | 0.9 | 0.9 | 0.96 | 0.98 | 0.04 | 0. | 98 |
| <b>B</b>  | 6   | 6   |      |      |      | 96 | -  |
| <b>3</b>  |     |     |      |      |      |    | 99 |
| <b>D</b>  | 0.9 | 0.9 | 0.95 | 0.98 | 0.05 | 0. | 98 |
| <b>B</b>  | 5   | 5   |      |      |      | 95 | -  |
| <b>4</b>  |     |     |      |      |      |    | 99 |
| <b>D</b>  | 0.9 | 0.9 | 0.95 | 0.98 | 0.05 | 0. | 98 |
| <b>B</b>  | 5   | 5   |      |      |      | 95 | -  |
| <b>5</b>  |     |     |      |      |      |    | 99 |
| <b>D</b>  | 0.9 | 0.9 | 0.95 | 0.98 | 0.05 | 0. | 98 |
| <b>B</b>  | 5   | 5   |      |      |      | 95 | -  |
| <b>6</b>  |     |     |      |      |      |    | 99 |
| <b>D</b>  | 0.9 | 0.9 | 0.94 | 0.98 | 0.06 | 0. |    |
| <b>B</b>  | 4   | 4   |      |      |      | 94 | 99 |
| <b>7</b>  |     |     |      |      |      |    |    |
| <b>D</b>  | 0.9 | 0.9 | 0.94 | 0.97 | 0.06 | 0. | 98 |
| <b>B</b>  | 4   | 4   |      |      |      | 94 | -  |
| <b>8</b>  |     |     |      |      |      |    | 99 |
| <b>D</b>  | 0.9 | 0.9 | 0.94 | 0.97 | 0.06 | 0. | 98 |
| <b>B</b>  | 4   | 4   |      |      |      | 94 | -  |
| <b>9</b>  |     |     |      |      |      |    | 99 |
| <b>D</b>  | 0.9 | 0.9 | 0.94 | 0.97 | 0.06 | 0. | 98 |
| <b>B</b>  | 4   | 4   |      |      |      | 94 | -  |
| <b>10</b> |     |     |      |      |      |    | 99 |

the range of AUC values obtained from ROC plots for RF classifier with DB2 to DB10 wavelets decomposition is shown in table 2.

For RF the overall accuracy is 95%, precision is 95%, sensitivity is 95%, specificity is 98%, misclassification rate is 5%, F1-score is 95%. The AUC values are ranging from 98% - 99%.

The classification performance of XGBOOST classifier model with wavelet decomposition using DB2 to DB10 wavelets is shown in table 3

Table 3: Performance of XGBOOST Classifier Model

| <b>XG<br/>BO<br/>OS<br/>T</b> | <b>Average of Performance Values</b> |                            |                              |                              |                                            |                             | <b>A<br/>U<br/>C<br/>R<br/>an</b> |
|-------------------------------|--------------------------------------|----------------------------|------------------------------|------------------------------|--------------------------------------------|-----------------------------|-----------------------------------|
|                               | <b>Ac<br/>cur<br/>acy</b>            | <b>Pre<br/>cisi<br/>on</b> | <b>Sen<br/>siti<br/>vity</b> | <b>Spe<br/>cifi<br/>city</b> | <b>Misl<br/>assific<br/>ation<br/>Rate</b> | <b>F<br/>1-<br/>S<br/>c</b> |                                   |

|             |          |          |          |          |      | <b>o<br/>re</b> | <b>ge<br/>(<br/>%)</b> |
|-------------|----------|----------|----------|----------|------|-----------------|------------------------|
| <b>DB2</b>  | 0.9<br>8 | 0.9<br>8 | 0.9<br>8 | 0.9<br>9 | 0.02 | 0.<br>9<br>8    | 98<br>-<br>99          |
| <b>DB3</b>  | 0.9<br>8 | 0.9<br>8 | 0.9<br>8 | 0.9<br>9 | 0.02 | 0.<br>9<br>8    | 98<br>-<br>99          |
| <b>DB4</b>  | 0.9<br>7 | 0.9<br>7 | 0.9<br>7 | 0.9<br>9 | 0.03 | 0.<br>9<br>7    | 98<br>-<br>99          |
| <b>DB5</b>  | 0.9<br>7 | 0.9<br>7 | 0.9<br>7 | 0.9<br>8 | 0.03 | 0.<br>9<br>7    | 99<br>-<br>10<br>0     |
| <b>DB6</b>  | 0.9<br>8 | 0.9<br>7 | 0.9<br>7 | 0.9<br>9 | 0.02 | 0.<br>9<br>7    | 99<br>-<br>10<br>0     |
| <b>DB7</b>  | 0.9<br>7 | 0.9<br>7 | 0.9<br>7 | 0.9<br>8 | 0.03 | 0.<br>9<br>7    | 99<br>-<br>10<br>0     |
| <b>DB8</b>  | 0.9<br>7 | 0.9<br>7 | 0.9<br>7 | 0.9<br>8 | 0.03 | 0.<br>9<br>7    | 99<br>-<br>10<br>0     |
| <b>DB9</b>  | 0.9<br>7 | 0.9<br>7 | 0.9<br>7 | 0.9<br>8 | 0.03 | 0.<br>9<br>7    | 99<br>-<br>10<br>0     |
| <b>DB10</b> | 0.9<br>7 | 0.9<br>7 | 0.9<br>7 | 0.9<br>8 | 0.03 | 0.<br>9<br>7    | 99<br>-<br>10<br>0     |

the range of AUC values obtained from ROC plots for XGBOOST classifier with DB2 to DB10 wavelets decomposition is shown in table 3.

For XGBOOST the overall accuracy is 97%, precision is 97%, sensitivity is 97%, specificity is 98%, misclassification rate is 3%, F1-score is 97%. The AUC values are ranging from 98% - 100%.

The classification performance of KNN classifier model with wavelet decomposition using DB2 to DB10 wavelets is shown in table 4.

Table 4: Performance of KNN Classifier Model

| K<br>N<br>N | Average of Performance Values |                                   |                                             |                                             |                                   |                              | A<br>U<br>C<br>R<br>a<br>n<br>g<br>e<br>(<br>%) |
|-------------|-------------------------------|-----------------------------------|---------------------------------------------|---------------------------------------------|-----------------------------------|------------------------------|-------------------------------------------------|
|             | Acc<br>u<br>r<br>a<br>c<br>y  | Pre<br>c<br>i<br>s<br>i<br>o<br>n | Sen<br>s<br>i<br>t<br>i<br>v<br>i<br>t<br>y | Spe<br>c<br>i<br>f<br>i<br>c<br>i<br>t<br>y | Miscla<br>ssificat<br>ion<br>Rate | F<br>1-<br>Sc<br>o<br>r<br>e |                                                 |
| D<br>B<br>2 | 0.95                          | 0.94                              | 0.94                                        | 0.98                                        | 0.05                              | 0.94                         | 98 - 99                                         |
| D<br>B<br>3 | 0.95                          | 0.95                              | 0.94                                        | 0.98                                        | 0.05                              | 0.94                         | 98 - 99                                         |
| D<br>B<br>4 | 0.92                          | 0.92                              | 0.92                                        | 0.97                                        | 0.08                              | 0.92                         | 98 - 99                                         |
| D<br>B<br>5 | 0.93                          | 0.93                              | 0.93                                        | 0.98                                        | 0.07                              | 0.93                         | 98                                              |
| D<br>B<br>6 | 0.92                          | 0.92                              | 0.92                                        | 0.97                                        | 0.08                              | 0.92                         | 98                                              |
| D<br>B<br>7 | 0.91                          | 0.91                              | 0.91                                        | 0.97                                        | 0.09                              | 0.91                         | 98                                              |
| D<br>B<br>8 | 0.91                          | 0.91                              | 0.90                                        | 0.97                                        | 0.09                              | 0.90                         | 98                                              |
| D<br>B<br>9 | 0.90                          | 0.90                              | 0.90                                        | 0.97                                        | 0.10                              | 0.90                         | 97 - 98                                         |
| D           | 0.8                           | 0.9                               | 0.89                                        | 0.97                                        | 0.11                              | 0.97                         | 97                                              |

|         |   |   |  |  |  |    |         |
|---------|---|---|--|--|--|----|---------|
| B<br>10 | 9 | 0 |  |  |  | 89 | -<br>98 |
|---------|---|---|--|--|--|----|---------|

the range of AUC values obtained from ROC plots for KNN classifier with DB2 to DB10 wavelets decomposition is shown in table 4.

For KNN the overall accuracy is 92%, precision is 92%, sensitivity is 92%, specificity is 97%, misclassification rate is 8%, F1-score is 92%. The AUC values are ranging from 97% - 99%.

The better classification accuracy is achieved with XGBOOST classifier model compared to MLP, RF, and KNN classifier models.

The performance of classifier models indicate the better classification of normal and paralysis condition.

## V CONCLUSION AND FUTURE SCOPE

I. The normal muscular activity is very much essential for the movement of the body. There are many mechanisms in the human body which maintain the steady state conditions of the body. Muscular activity is controlled by the nervous system. When there is any impairment in the muscular activity, it results in paralysis. The complications related to paralysis are many, among them the prominent are myopathy, amyotrophic lateral sclerosis, and neuropathy. The time-frequency analysis by wavelet decomposition approach is carried out and the results show that better classification accuracy is achieved. Classifier models are employed for automated classification of normal and paralysed condition. In the proposed work time-frequency domain features derived from EMG with classifier models are able to classify the normal and paralysis condition with greater accuracy, precision, sensitivity, specificity, F1-score, AUC values from ROC plots, and lower misclassification rate. The results show that the present work yield greater performance values compared to existed research works. Hence the analysis of muscular paralysis is made efficiently with the methods described and performed in the present work. Future scope for the work includes development of portable system for acquisition and analysis of EMG, for the assessment of muscular activity, and quantification and assessment of EMG in paralysis condition, and finding the impact on

II. the neuromuscular activity, and developing model to classify paralysis and normal conditions.

## REFERENCES

- [ Kaplanis P. A., Pattichis C. S., Christodoulou C. I., Hadjileontiadis L. J., Roberts C.V., Kyriakides T., A surface electromyography classification system, IFMBE Proceedings of the 10th Mediterranean Conference on Medical and Biological Engineering and Computing, Vol.6, 2004, pp. 278-281 ]
- [ Güler N. F., and Koçer S., Classification of EMG signals using PCA and FFT, Journal of Medical Systems, Vol. 29, No. 3, 2005, pp. 241–250 ]
- [ 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 ]
- [ Haig A.J. , Jeffery B. G., Rechten J. J., Gitter A. J., The use of surface EMG in the diagnosis and treatment of nerve and muscle disorders, Muscle Nerve, Vol.22, no.8,1999, pp. 239-242 ]
- [ Fuglsang-Frederiksen A., The Role of Different EMG Methods in Evaluating Myopathy, Clinical Neurophysiology, Vol. 117, No. 6, 2006, pp. 1173– 1189 ]
- [ 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. ]
- [ JamilehYousefi, Andrew Hamilton-Wright, 'Characterizing EMG data using machine-learning tools', Computers in Biology and Medicine, Volume 51, 2014, Pages 1-13, ISSN 0010-4825, https://doi.org/10.1016/j.combiomed.2014.04.018. https://www.sciencedirect.com/science/article/pii/S0010482514001048 ]
- [ https://www.webmd.com/brain/paralysis-types ]
- [ 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 ]
- [ https://www.healthline.com/health/paralysis ]
- [ https://www.verywellhealth.com/paralysis-5224673 ]
- [ https://www.medindia.net/patientinfo/diagnosis-of-paralysis.html ]
- [ https://www.mayoclinic.org/tests-procedures/emg/about/pac-20393913?p=1 ]
- [ https://www.brighamandwomens.org/medical-resources/emg-test ]
- [ https://www.medicalnewstoday.com/articles/281472#who-gets-it ]
- [ https://my.clevelandclinic.org/health/diseases/17256-myopathy ]
- [ 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 ]
- [ A. Phinyomark , C. Limsakul, and P. Phukpattaranont, "Application of Wavelet Analysis in EMG Feature Extraction for Pattern Classification", MEASUREMENT SCIENCE REVIEW, Volume 11, No. 2, 2011. https://www.researchgate.net/publication/241475036\_Application\_of\_Wavelet\_Analysis\_in\_EMG\_Feature\_Extraction\_for\_Pattern\_Classification ]
- [ SomarKarheily, Ali Moukadem, Jean-Baptiste Courbot and DjaffarOuldAbdeslam, "Time-frequency Features for sEMG Signals Classification", In Proceedings of the 13th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2020) - Volume 4: BIOSIGNALS, pp: 244-249 ISBN: 978-989-758-398-8; ISSN: 2184-4305. DOI: 10.5220/0008971902440249. https://www.scitepress.org/Papers/2020/89719/89719.pdf ]
- [ Elamvazuthi, N.H.X. Duy, Zulfiqar Ali, S.W. Su, M.K.A. Ahamed Khan, and S. Parasuraman, "Electromyography (EMG) based Classification of Neuromuscular Disorders using Multi-Layer Perceptron", 2015 IEEE International Symposium on Robotics and ]

Intelligent Sensors (IRIS 2015).

- [ M. Fındık, Ş. Yılmaz and M. Koseoglu,  
2 "Random Forest Classification of Finger  
1 Movements using Electromyogram (EMG)  
] Signals," 2020 IEEE SENSORS, 2020, pp. 1-4,  
doi:10.1109/SENSORS47125.2020.9278619.
- [ S. Samui, A. K. Mukhopadhyay, P. K. Ghadge  
2 and G. Kumar, "Extreme Gradient Boosting  
2 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.
- [ H. Küçük, C. Tepe and İ. Eminoğlu,  
2 "Classification of EMG signals by k-Nearest  
3 Neighbor algorithm and Support vector  
] machine methods," 2013 21st Signal  
Processing and Communications Applications  
Conference (SIU), 2013, pp. 1-4, doi:  
10.1109/SIU.2013.6531240.
- [ Database of Clinical Signals. Nikolic M,  
2 Rigshospitalet, Copenhagen, DK, dataset  
4 N2001 at <http://www.emglab.net>  
]