Classification of EMG Signals for Assessment of Neuromuscular Disorder using Empirical Mode Decomposition and Logistic Regression

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***Abstract*— The electromyographic (EMG) signal generated in muscle fibers has been the topic under substantial research in immediate past years as it provides fairly large amount of information for assessment of neuromuscular diseases particularly amyotrophic lateral sclerosis (ALS). Besides this, the design of an accurate and computationally efficient diagnostic system remains a challenge due to variation of EMG signals taken from different muscles with different level of needle insertion. This study offers a complete framework for accurate classification of EMG signals which includes denoising by empirical mode decomposition (EMD), feature extraction from both the time and frequency domains and classification by logistic regression (LR) and support vector machine (SVM). The presented work efficiently discriminates between EMG signal of healthy subject and patient with ALS disease independent of which muscle is used for EMG signal acquisition and what insertion level of needle is. Performance evaluation measures such as sensitivity, specificity, F-measure, total classification accuracy and area under ROC curve (AUC) are used to validate the performance of both classifiers. LR classification technique shows superlative performance with a classification accuracy of 95.1%. These results shows the competence of proposed diagnostic system for classification of EMG signals. Moreover, the proposed method can be used in clinical applications for diagnoses of neuromuscular diseases.**

Keywords*— *electromyography (EMG), amyotrophic lateral sclerosis (ALS), empirical mode decomposition (EMD), logistic regression (LR), support vector machine (SVM).

I. INTRODUCTION

Amyotrophic lateral sclerosis (ALS) is a growing paralytic, neuromuscular disorder which results in deterioration of motor neurons present in both the brain and the spinal cord [1]. According to ALS association, an average of 15 people is detected with ALS every day which means more than 5,600 people per year. The statistics shows that 30,000 Americans are affected by ALS at this time. The expected life of a person with ALS disease is about 2 to 5 years after screening of symptoms. These awful conditions are mainly due to unavailability of cure for this disease. Early detection of ALS helps to design proper treatment before the condition worsened. In this regard, a systematic and quantitative analysis of electromyography (EMG) signal is made to classify normal person and ALS patient.

The study of the electrical properties of the activities of muscle fibers is commonly termed as electromyography (EMG). Motor neurons transmit electrical signal to control muscle activity i.e. contraction or relaxation. EMG is used to translate these signals into numeric values known as electromyograms. EMG signal is made up of several Motor Unit Action Potentials (MUAPs) that provide significant source of information for comprehensive analysis of EMG signals to diagnose disorders like ALS. More purely, MUAP is a complex signal that gives information about activities of muscle.

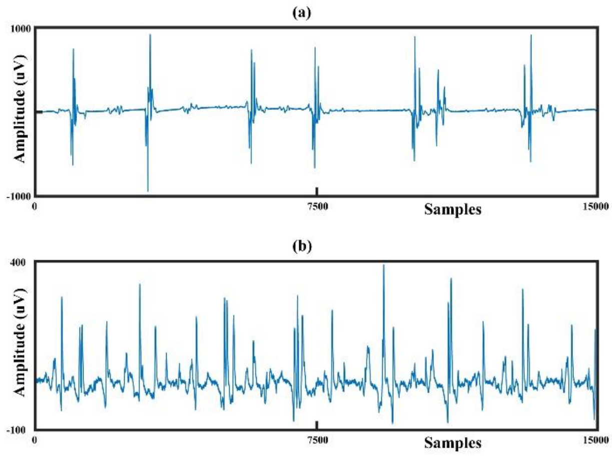

Fig. 1. EMG signals taken from: (a) medial vastus of ALS patient and (b) brachial biceps of normal person.

Recently, several methods have been proposed but still design of an accurate analytic system remains a challenge due to huge variability of EMG signals. A comprehensive review of existing methods was discussed in [2]. In [3], authors presented comparative work using multilayer perceptron neural network (MLPNN), adaptive neuro-fuzzy interface system (ANFIS) and dynamic fuzzy neural network (DFNN) for classification of neuromuscular diseases and found that ANFIS is more reliable due to having more recognition rate. In another work [4], support vector machines (SVM), K-nearest neighbor (KNN) were used in conjunction with multiscale amplitude and frequency modulation features. In [5], SVM tuned with particle swarm optimization (PSO) algorithm was used along with statistical features mined from detailed and approximation coefficients of wavelet transform.

In another research, neural network was also employed to accurately classify EMG signals with 96% accuracy [6]. In

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[7], authors used decision tree algorithms for classification of EMG signals with multi-scale principle component analysis for signal denoising and discrete wavelet transform was used as feature descriptor. Extreme Learning Machine (ELM) classifier was used in year 2016 for detection of neuromuscular diseases [8]. Classification accuracy of 88% was achieved by using this technique. Most recently, two stage cascaded SVM classifier is used [9]. Signal analysis was performed by extracting time domain features to achieve a classification accuracy of 95.7% and 91% for first and second stage respectively.

A research study in [10] proposed a method based on bagging ensemble for automatic classification of EMG signal with wavelet-based features. MFCC based feature extraction scheme was also proposed in [11] with k-nearest neighbor (kNN) as classifier. In [12], feature extracted from selected coefficients of wavelet transform were fed to kNN classifier to reduce computational cost of diagnostic system. In [13] neural network classifier was used with characteristic features. Some other research studies include power spectral density (PSD) method for comparative analysis of EMG signal [14]. In [15] authors proposed a method based on Auto-regressive Moving Average (ARMA) feature extraction for classification of EMG signals through Linear discriminant Analysis (LDA) as classifier.

The objective of this paper is to propose an accurate diagnostic framework for classification of EMG signals that can handle massive unpredictability in EMG signals. The proposed method discriminates between two classes namely healthy and ALS. In order to remove motion artifacts from EMG signals, empirical mode decomposition (EMD) is employed as preprocessing. Time as well as frequency domain features are extracted to train the two classifiers i.e. logistic regression (LR) and SVM in different experimental settings. To validate the performance of classifiers, different measures such as accuracy, sensitivity, specificity and some other are used. LR classifier provides best performance with making no assumptions about input EMG signals. Fig. 2 presents the block diagram of proposed framework.

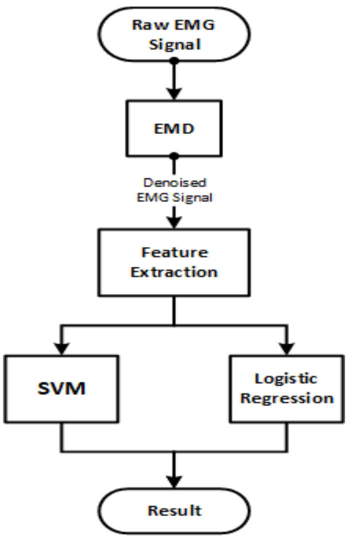

Fig. 2. Block diagram of proposed methodology.

The rest of the paper is organized as follows. The section II is designated for proposed framework for classification in detail. First, we give information about dataset and conditions of data acquisition. Then pre-processing stage and details of extracted features is discussed. A brief overview of both the SVM and LR classifier is given at the end of this section. Section III provides complete detail of classification results including performance evaluation using statistical parameters and performance comparison with other techniques. Lastly, section IV summarizes and concludes the paper.

II. MATERIALS AND METHODS

A. Dataset

In this work we use publicly available EMG dataset [16] for experimental purpose. This dataset consists of two classes namely normal and ALS subjects. The control or normal class consist of data from 10 healthy subjects including 4 females and 6 males that have age between 21 and 37 years. According to their medical history, 6 out of 10 had good physical health and the remaining were in overall good shape with the exception of one. None of them had symptoms of any kind of neuromuscular disease such as ALS or myopathy in their medical history.

EMG signal dataset of patients with ALS disease consist of 8 patients with equal number of male and female subjects aged from 35 to 67 years. All of them had clear signs of ALS disease and 5 of them died after a few years. The signals were taken mainly from two muscles that are brachial biceps and medial vastus.

The EMG signals were recorded under the following conditions;

- Low voluntary and constant level of contraction was maintained while recording EMG signal.
- The quality of EMG signals was observed by visual and audio feedback.
- Needle electrode of standard form was used to record the signals with same center.
- Three levels of insertion were used to acquire signals from five places in the muscle.

B. Preprocessing

In general, when studying EMG signals, every single component in the signal other than MUAPs is considered as noise. An EMG signal, contaminated with different types of noises and artifacts, lost its identity as it originates from muscle. The most common type of noise that cause irregularities in EMG data is baseline noise. Baseline noise or Motion Artifacts are low frequency components introduced into EMG signals by movement of cables used for data acquisition.

In order to remove motion artifacts from EMG data we use Empirical Mode Decomposition (EMD) that has newly been introduced by Huang et al. in [17] in order to represent signals adaptively, especially non-stationary signals. Along with wavelet decomposition, EMD is used in [18] for filtering EMG signals. The key factor in use of EMD is that it can decompose complex data set into Intrinsic Mode Functions (IMFs) which are of finite number or typically small number, through the process of sifting [19]. IMFs are the representation of signal in different time-scales that have different frequency bandwidths. Fig. 3 shows signal with motion artifacts and denoised EMG signal

Consider a raw EMG signal represented by $EMG_{(raw)}$ is fed to EMD. Through the process of sifting, it decomposed

$EMG_{(raw)}$ into constituent IMFs and final residue. The $EMG_{(raw)}$ can now be stated as linear summation of IMFs and final residue as shown in (1).

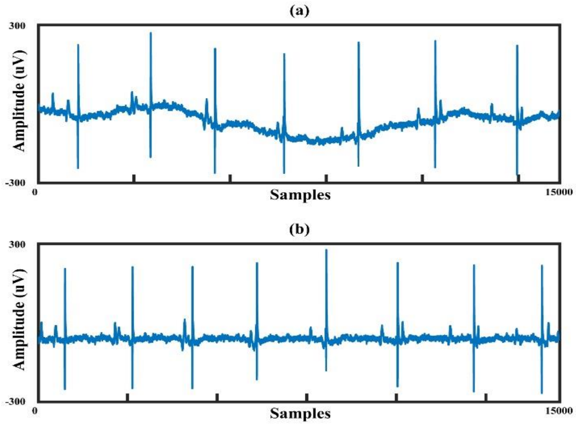

Fig. 3. EMG signal: (a) with baseline noise and (b) without baseline noise.

$$EMG_{(raw)} = \sum_{i=1}^{N} IMF_i + r_f \tag{1}$$

Where N is total number of IMFs, IMF_i is i^{th} IMF and r_f is final residue. The last n number of IMFs and r_f consist of low frequency components i.e. motion artifacts. The denoised signal can be constructed by linear sum of first N-n IMFs as stated in (2).

$$EMG_{(denoised)} = \sum_{i=1}^{N-n} IMF_i \tag{2}$$

C. Feature Extraction

For a signal classification system to exhibit better performance, feature extraction plays a critical role. The process of feature extraction is used to figure out a feature vector that contain useful information hidden in raw EMG signal. This feature vector is then fed to Classifier to achieve better success rate. Some feature descriptors are discussed by authors in [20]. In this study, the following time and frequency domain features were used to improve classification accuracy.

Let EMG_i be EMG signal at i^{th} sample and N be total number of samples then;

1) Mean: Mean is most common time domain feature and calculates the average of EMG Signal's amplitude values over sample length of signal. Equation (3) shows its calculation.

$$mean = \frac{1}{N}\sum_{i=1}^{N} EMG_i \tag{3}$$

2) Kurtosis: Kurtosis is measure of peakness of a probability distribution and shows the way the value is bundled across center of distribution. Equation (4) defines the kurtosis of a distribution as

$$kurtosis = \frac{\frac{1}{N}\sum_{i=1}^{N}(EMG_i-\mu)^4}{\sigma^4} \tag{4}$$

where μ represents the mean of signal and σ is the standard deviation of EMG signal.

The kurtosis of the normal distribution is called Mesokurtic and has a value of three while distributions with kurtosis of less than three are known as Platykurtic and distributions with kurtosis greater than three are known to be Leptokurtic.

3) Peak to Peak: The amplitude difference between maximum value and minimum value of EMG signal is commonly termed as Peak to peak.

$$Peak\ to\ Peak = max(EMG) - min(EMG) \tag{5}$$

4) Shape Factor: Shape factor is a dimensionless quantity that describes the shape of signal regardless of its size. It is the ratio of root mean square value to that of mean absolute value. It is a normalized quantity and have values ranges from 0 to1. Mathematical expression for shape factor is shown in (6).

$$Shape\ Factor = \frac{RMS}{MAV} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(EMG_i)^2}}{\frac{1}{N}\sum_{i=1}^{N}|EMG_i|} \tag{6}$$

5) Energy: The energy of a signal is measure of its strength and is given by (7).

$$Energy = \sum_{i=1}^{N}(EMG_i)^2 \tag{7}$$

6) Jitter: The variation of signal's periodicity from its target or actual frequency is know is jitter. The jitter is calculated by taking the difference between samples in EMG signal.

7) Zero Crossing Rate: Zero crossing rate is defined as the rate at which the amplitude of signal changes its sign from positive to negative or vice versa is know as zero crossing rate. It gives information about frequency of a signal while staying in time domain. Its calculation is given by (8).

$$ZCR = \frac{1}{N}\sum_{i=1}^{N-1} \begin{matrix}[sign(EMG_i \times EMG_{i+1}) \dots \\ \dots \cap |EMG_i - EMG_{i+1}| \geq threshold]\end{matrix} \tag{8}$$

Where

$$sign(EMG) = \begin{cases}1, & if\ EMG \geq threshold \\ 0, & otherwise\end{cases} \tag{9}$$

The threshold condition is used to avoid low voltage fluctuations and background noises.

8) Spectral Skewness: Spectral skewness is the measure of the symmetrical behavior of the surface eccentricities about the mean reference line.

9) Spectral Kurtosis: The spectral kurtosis is a statistical tool which can designate the occurrence of series of frequencies and their places.

10) Spectral Centroid: Spectral centroid is used in signal processing for the characterization of a spectrum. It shows us where the center of mass of a spectrum is located.

11) Spectral Flux: Spectral flux is the measure of the spectral alteration between two consecutive frames and is caculated from short length spectral frames as the squared difference between the magnitudes, having values from -1 to 1, of the spectrum of the two succeeding frames.

12) Spectral Roll Off: The spectral roll off is defined as the fequency in power spectrum of signal below which 85% of the spectral magnitude is situated. *Spectral Flatness:* Spectral Flatness is the measure of ratio of Arithmetic and Geometric mean of a signal powers spectrum.

13) Spectral Crest: The spectral crest measurement which is also known as peak factor, offers a process to measure the quality of a signal. It is calculated as a ratio of the peak value of a signal to the RMS value of the same signal. *Spectral Decrease:* Spectral decrease describes the average spectral slope and is helpful in extracting information from low frequencies.

14) Spectral Spread: The spectral spread describes the average deviation of signal around its centroid and is associated with the bandwidth of the signal. Signals with noise have large spectral spread as compare to other normal signals. Feature values ranges between 1 and 0.

15) MFCC: Mel-Frequency Cepstral Coefficients are an interesting variation on the linear cepstrum, which are widely used in speech and music analysis. They are the most extensively used features in speech recognition, mainly due to their ability to efficiently represent the audio spectrum. The mean values of MFCCs are used as features. The steps performed on their computation are mentioned in Fig. 4. More details about MFCC can be found in [21, 22].

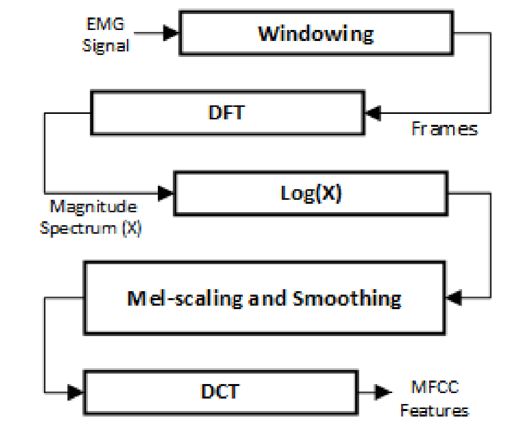

Fig. 4. Steps involved in calculation on MFCC.

D. Support Vector Machine

Support vector machines were firstly introduced to solve the problems of function approximations [23]. SVM are supervised learning models used for classification of data. The foremost benefit of using SVM instead of other classifiers is that SVM can classify data that is not linearly separable by making a hyper plane or a combination of hyper planes in space of high dimensionality. Significant degree of separation is accomplished by a hyperplane that has maximum distance to the adjacent training data point from any of class. The higher the width the better is the hyper line for precise classification.

The algorithm of SVM finds the points closest to the hyper plane from both the classes known as support vectors. The distance between the line and the support vectors is called margin and it must be maximized in order to perform better classification as shown in Fig. 5.

There is a kernel trick in SVM that converts the input feature data into the desired high dimensionality space. The

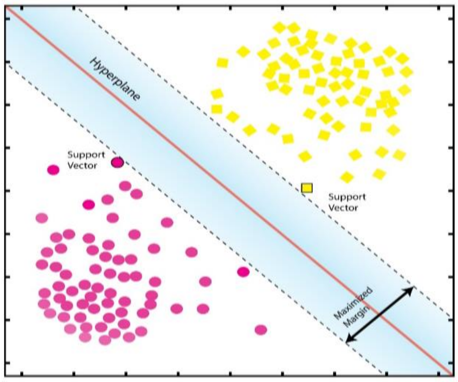

Fig. 5. SVM classifier.

most common types of kernel functions include linear, sigmoid, polynomial and radial basis function (RBF), that are used by different SVM algorithms. For transferring feature data to a higher kernel trick that is the dot product of data in that higher dimensional space is used. More details about SVM classifier can be explored in [24].

E. Logistic Regressions

Logistic regression (LR) is an analytical examination and is used to explicate the association between variables from which one variable can be dependent binary variable and the others are nominal, interval, ordinal or ratio-level independent variables. LR is a powerful statistical technique used is machine learning [25] for classification problems.

Similar to the linear regression model, logistic regression uses an equation as the depiction. Input features are joint in a linear manner using weights or coefficient values to forecast an output result. The output value in LR method is between 0 to 1 rather than a numeric value as defined by linear regression [26]. More detail about LR can be seen in [27].

III. Results and Discussions

The EMG signal classification is studied noticeably by researchers as machine learning problem. The variability of EMG signal within a class increases because of different levels of needle insertion, different level of contraction and different muscles used for signal accusation which results in a decrease in classification accuracy. A diagnostic system with several assumptions about EMG signals will fail to classify wide selection of EMG signals. For a computerized diagnostic system to use in clinical applications, it must have capability to perform well under different situations of signal acquisitions.

In this study, we suggest a method based on LR and SVM classifiers to discriminate between healthy subject and ALS patient independent of conditions of signal procurement. The feature vector is extracted from denoised EMG signals as mentioned in section II. ALL algorithms were implemented on MATLAB 2018b. The dataset consists of total 899 samples out of which 425 belongs to normal class and 474 are from ALS patients. 5-fold cross validation is used for testing of both classifiers. The available dataset is taken with three different level of needle insertion and from four different muscles.

For evaluation purposes, statistical parameters including sensitivity, specificity and total classification accuracy were used. These parameters are widely used for analysis of diagnostic systems. *Sensitivity* is defined as ratio of total number of properly classified subjects affected from ALS to that of total number of subjects affected from ALS.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \times 100 \qquad (10)$$

Where TP (true positive) defines the number of subjects correctly identified as ALS and FN (false negatives) defines the number of falsely detected ALS subjects as normal. *Specificity* is defined as ratio of total number of correctly classified healthy subjects to that of total number of healthy persons.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \times 100 \qquad (11)$$

Where TN (true negative) defines the number of correctly detected healthy/normal subjects while FP (false positive) defines number of falsely identified healthy subjects as ALS. *Total Classification Accuracy* is defined as ratio of number of correctly detected subjects to that of total number of subjects.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \times 100 \qquad (12)$$

F-measure is another parameter used for evaluation of performance of classifier and is calculated by (12),

$$\text{F} - \text{measure} = \frac{2\text{TP}}{2\text{TP+FP+FN}} \times 100 \qquad (13)$$

Receiver operating characteristic (ROC) curve is attained by plotting true positive rate verses false positive rate and is also used for evaluation purpose [28]. Classifier performance is evaluated by calculating area under the ROC curve (AUC).

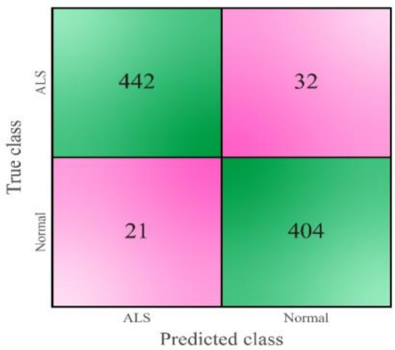

Fig. 6. Confusion Matrix of SVM classifier.

A. Results of SVM Classifier

Fig. 6 shows confusion matrix of SVM classifier. SVM correctly classifies 404 samples of normal subjects out of total

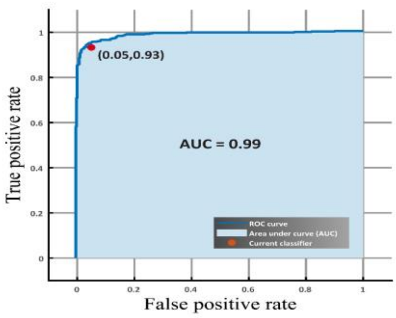

Fig. 7. ROC of SVM classifier.

425 and 21 are erroneously predicted as ALS patients i.e. FN. Similarly, out of 474 samples of ALS patients, SVM correctly predict 442 samples which is TN and remaining are incorrectly predicted. The total classification accuracy of SVM is found to be 94.1% according to above parameters. Other evaluation measures such as sensitivity, specificity and f-measure are 95.06%, 93.25% and 93.84% respectively. The AUC is measured to be 0.99 is case of SVM classifier and shown in Fig. 7.

B. Results of LR Classifier

For LR classifier, the confusion matrix is shown in Fig. 8 which shows correctly classified samples of normal subjects are 408 and ALS patients are 447 out of total of 425 and 474 respectively. From this, TP, TN, FP and FN are found to be

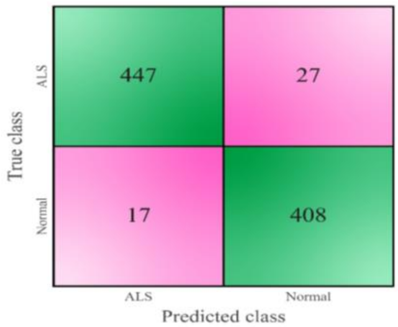

Fig. 8. Confusion Matrix of LR classifier.

408, 447, 27 and 17 correspondingly. LR classifier shows best performance with total classification accuracy of 95.1%.

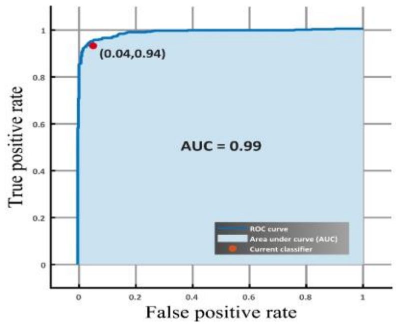

Fig. 9. ROC of LR classifier.

Specificity, Sensitivity, f-measure and AUC are calculated as 94.3%, 96%,94.88% and 0.99. The bar graph in Fig. 10 shows evaluation parameters of both the classifiers.

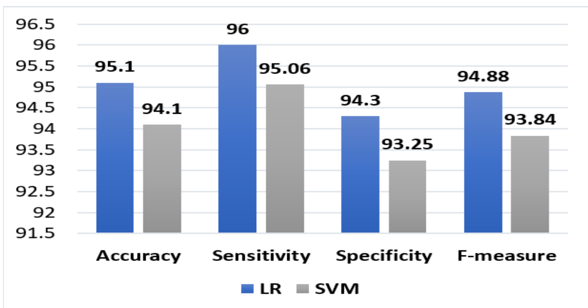

Fig. 10. Bar graph showing performance evaluation parameters of both classifiers.

For the purpose of comparison, we consider four approaches that used the same publicly available data set. The diagnostic procedure presented in [11] is a MUAP based method in which MFCC feature extraction scheme was proposed to classify ALS and normal subjects. K-nearest neighbor (KNN) is used as classifier to get a classification accuracy of 92.5%. Characteristic features of EMG signal were used in [13] along with neural network as classifier. Similarly, S. A. Fattah in [12] used DWT based features to

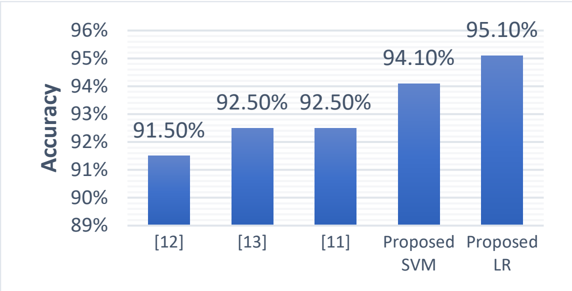

Fig. 11. Comparison with other techniques in terms of accuracy

TABLE I: COMPARISON WITH OTHER TECHNIQUES

Studies	Approach	Performance		
		Acc.	*Sen.*	*Sp.*
[12]	DWT based features KNN classifier	91.50%	74%	97.33%
[13]	Neural Network classifier	92.5%	-	-
[11]	MFCC based features KNN classifier	92.50%	76%	98%
Proposed	**SVM**	**94.10%**	**95.06**	**93.25**
Proposed	**LR**	**95.10%**	**96%**	**94.3%**

feed KNN classifier. Table I shows performance comparison of proposed method with other two techniques based on accuracy, sensitivity and specificity. Graphical comparison with recent studies in terms of classification accuracy is presented in Fig. 11. The observations clearly show the aptitude of proposed method for assessment of neuromuscular disease.

IV. CONCLUSION

The presented work introduced a framework for classification of EMG signals by SVM and LR. The proposed diagnostic system has an edge over other methods as it makes no prior assumption about conditions of signal acquisition. The results of evaluation parameters clearly show the viability of proposed automated system in clinical applications. LR classifier, along with EMD based denoising and proposed feature vector, categorize EMG signals with a high degree of accuracy. This can help for diagnosing proper treatment of ALS patients to increase their life expectancy. The huge distortions in EMG signals are removed by EMD which helps to extract valuable and convenient information to form feature vector. The total success rate of classifier increases due to feeding powerful feature set consisting of time and frequency domain features.

Finally, the signal classification technique presented in this work can be used as diagnostic decision support system which has the capability and reliability to use in clinical atmosphere. In future, we are looking forward to reduce the dimensionality of feature vector to make the diagnostic framework more computationally efficient.

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