LSTM-based approach for Classification of Myopathy and Normal Electromyogram (EMG) Data

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Abstract— **Electromyograms (EMG) are recorded movements of nerves and muscles that help diagnose muscles and nerve-related disorders. It is frequently used in the diagnosis of neuromuscular diseases such as myopathy, which causes many changes in EMG signal properties. The most useful auxiliary test in the diagnosis of myopathy is EMG. Therefore, it has become imperative to identify computer-assisted anomalies with full accuracy and to develop an efficient classifier. In this study, a new machine learning method with a deep learning architecture that can score normal and myopathy EMG from the EMGLAB database is proposed. Using the discrete wavelet transform Coiflets 5 (Coif 5) wavelet, the EMG signals are decomposed into subbands and various statistical features are obtained from the wavelet coefficients. The success rates of the decision tree C4.5, SVM and KNN-3, which are traditional learning architectures, and the Long Short-term Memory (LSTM) algorithm, which is one of the deep learning architectures, were compared. Unlike the studies in the literature, with the LSTM algorithm, a 100% success rate was achieved with the proposed model. In addition, a real-time approach is presented by analyzing the test data classification time of the model.**

Index Terms— **Deep learning, EMG, Myopathy, Neuromuscular disorder, Wavelet.**

I. Introduction

MYOPATHY IS a critical type of neuromuscular disorder called neurological disorders in skeletal muscle [1]. It is a disease caused by the improper functioning of muscle fibers [1, 2]. In the later stages, it even affects the respiratory muscles and makes life difficult. Both the disturbances in the muscle cells and the disturbances in the nerve cells that stimulate these cells cause changes in certain symptoms. However, it also makes changes in Electromyogram (EMG) signals.

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EMG is a method that records the electrical activity occurring in muscle cells, that is, a large number of action potentials occurring in muscle tissue. Factors such as the variation of muscle structures from person to person and the degree of disease complicate the diagnosis of myopathy, which acts as a healthy EMG signal. Artificial intelligence algorithms are used to overcome these difficulties [2, 3]. Advanced artificial intelligence techniques have recently provided convenience in applications that will facilitate diagnosis. Because these techniques quickly summarize detailed and accurate information, they have allowed the development of tools to aid in diagnosis [5].

In the literature, there are various studies that include the classification of signals such as normal, myopathy and neuropathy from EMG data related to the diagnosis of neuromuscular diseases. Myopathy and Amyotrophic Lateral Sclerosis (ALS) signals in the EEGLAB database were classified by Bakiya A. et al. [6]. They applied the selected features to the deep neural network and artificial neural network using the bat algorithm. They compared the results of the classifier algorithms. In the study with the traditional single-layer artificial neural network, they reached an accuracy rate of 83,3%. Using the deep neural network modeled with layers 2 and 3 (neurons = 2 and 4), they achieved a 100% success rate in classifying abnormalities in EMG signals. Belkhou A. et al. [7] presented a new method for classifying normal and myopathy EMG signals in the EMGLAB database. They analyzed EMG signals with Symlet 6 (Sym6) wavelet using Continuous Wavelet Transform (CWT). Five features were obtained with CWT. Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), Discriminatory Analysis (DA) and Naive Bayes (NB) were used as classifier algorithms. It was revealed in the study that the KNN classifier reached the best performance with an accuracy of 93,68%. Patidar M. et al. [8] classified normal and myopathic EMG data with data obtained from Beth Israel Deaconess Medical Center. The data is sampled at 50 KHz. 60% of the data was used for training and 40% for testing. They achieved 96,75% success rate with the Neural Network Classifier. Jose S. et al. [9] classified healthy, myopathy and neuropathy EMG data using the EMGLAB database. They produced subsampled signals from the EMG signal using Lifting Wavelet Transform (LWT). They calculated Higuchi's fractal dimensions of the LWT coefficients in the lower bands. They used 10-fold cross validation. They achieved success rate of 99,87% using a combination of Multilayer Perceptron Neural Network (MLPNN) and Boyer-Moore majority vote (BMMV). Normal, myopathic and ALS data were classified by Belkhou A. et al. [10]. The features were obtained using the Mel Frequency Cepstral Coefficients (MFCC) technique. The size of MFCC vectors has been reduced using statistical values. SVM and KNN algorithms were used as classifiers. According to the F-measure evaluation metrics, the performances of the classifiers were evaluated. Normal-ALS and Normal-Myopathy binary classifications had 99,34% and 99,07% accuracy rates, respectively.

When the literature studies are examined; It is seen that traditional learning algorithms are mostly used in the classification of EMG data. For this reason, deep learning architecture is included in this study and high success rates are aimed. At the same time, traditional classification algorithm and deep learning method are compared. The continuation of the article is organized as follows: In the second part, information about the EEG data sets to be used and the methods and techniques used are given. In the third part, the results of the analysis of the article and the studies in the literature are discussed. In the fourth part, the studies that are planned to be done in the future according to the results of the analysis are included.

II. Materials and Methods

In this section, the methods and techniques used for feature extraction and classification from EMG data will be explained.

A. Subjects and data acquisition

The data were taken from the database that can be accessed free of charge on the EMGLAB.net website. There are 10 healthy and 6 myopathy patients' data in the database. Healthy people are between the ages of 21-37. There are no signs of neuromuscular disorders in the normal group of EMG data. People with myopathy are between the ages of 19-63. Myopathic patients have all the electrophysiological and clinical manifestations of myopathy. Although there are measurements from various muscles in the database, only the measurements taken from the Brachial biceps muscle were used to ensure homogeneity in this study. During the measurements, a concentric needle electrode was used and the low and high pass filter cut-off frequencies of the EMG recording device were adjusted to the range of 2Hz-10Khz. A total of 1196,5 seconds of EMG data were obtained from healthy subjects, all taken from the long head of the brachial biceps muscle. The number of measurements taken from this muscle group in the database is 3355,4 seconds for the myopathy group. The sampling frequency of the data is 23437,5 Hz [11].

B. Preprocessing

Various filter structures are used in order to remove unwanted electrical activities seen in the channel during recording, such as DC component, biological artifact and network noises that directly affect the signals [12, 13]. In this article, EMG signals were passed through a notch filter (50 Hz.) and a third order band stop Butterworth filter. The filter degree was chosen as three by trial and error process.

C. Feature extraction

In today's conditions, the concept of data is important. The amount of data is increasing day by day, so the concept of data has an important place. However, the raw form of the data is not a meaningful sum of information. In order to become meaningful, it must go through several processes. One of these processes is feature extraction. The raw data space may contain redundant elements, and the data can be difficult to manipulate due to its size. Therefore, feature extraction is provided in most machine learning applications [14,15]. In this study, the feature vector was calculated for each epoch with the discrete wavelet method and all feature vectors were combined to form the feature matrix. This obtained feature matrix is given as input to the classifier algorithms for classification.

D. Discrete wavelet transform (DWT)

Wavelet transform is a tool whose functions separate the data into its components at different frequencies and allow to work on each component separately [16]. Wavelet transform has been used frequently in the fields of mathematics and biomedical engineering recently. Figure 1 shows the 3-levels wavelet tree. H(n), g(n) generate wavelet coefficients at each stage. Approximation (A) is called approximation coefficients, Detail (D) is called detail coefficients. For the spectral analysis of non-stationary EMG signals, feature extraction was performed with wavelet transform, which aims to provide the best time-frequency resolution by using small size window at high frequencies and large size window at low frequencies [17,18].

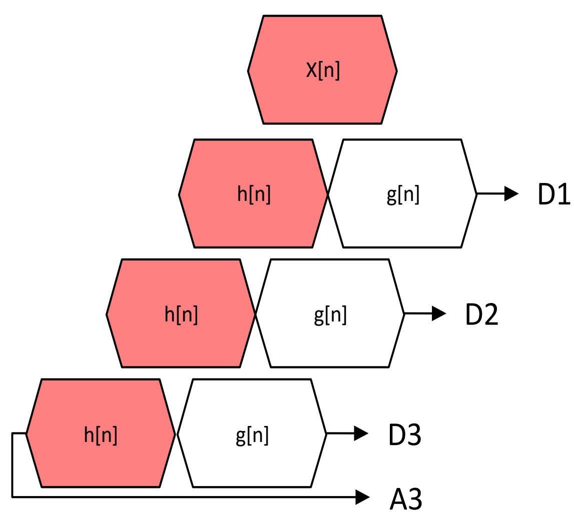


Fig.1. Wavelet decomposition tree with 3-levels

The most important parameter of the wavelet transform is the wavelet. The term wavelet is expressed as a wavelet defined as a window function of a certain length. There are many main wavelets with different properties and uses [19]. The drawing of the Coiflets (Coif5) wavelet form used in this study is given in Figure 2 [20].

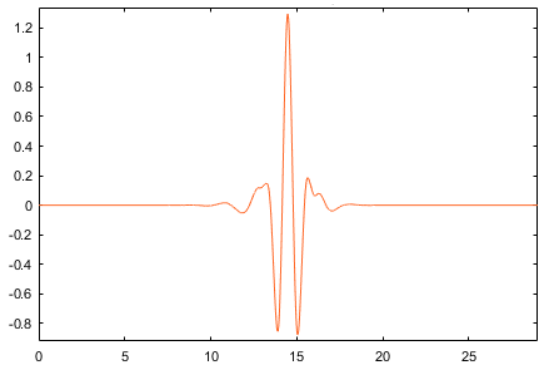


Fig.2. Plots of Coif5 wavelet function

E. Classification

In addition to extracting useful information from the data, it is also important to classify this information correctly. Classifier algorithms can make rational decisions in a very short time by evaluating all situations and examining millions of data very quickly. Millions of data bring great problems due to diversity, speed and volume [21]. Classifier algorithms prevent these problems by properly classifying big data [22]. In this study, traditional classification algorithms C4.5 decision tree, SVM, KNN-3 and deep learning algorithms LSTM were used.

1) C4.5 decision tree

Decision trees are one of the machine learning algorithms used for classification and value estimation. Many approaches have been proposed to construct decision trees. C4.5 decision trees method, which is one of these approaches, is frequently used in many areas. A decision tree structure consists of root, node, branch and leaf. The lowest part of the tree structure is called the leaf and the upper part is called the root. Each feature in the data set represents the nodes. The part that provides the connection between the nodes is called the branch. In this algorithm, the entropy of all columns in the data set is calculated according to Equation 1. Next, the entropy of each column in the dataset is divided by the entropy of the class to calculate the gain for each column. Finally, the information gain is calculated for each predictive variable/class. The root node with the highest gain is assigned as [23-26].

$$Entropi = -\sum_{i=1}^{n}(p_i log_2 p_i) \quad (1)$$

Where, n is the number of values that the target variable can take.

After the root node, the tree begins to branch. Thus, the data will be evenly distributed under each branch. After the first predictor variable is determined, the same process is calculated by repeating. This process continues until all predictive variables are placed in the tree [23-26].

2) Long short-term memory

Long short-term memory (LSTM), a sub-branch of recurrent neural networks (RNN), was developed to eliminate the problems in RNN. There are three gates in an LSTM structure: input, output and forget. The tasks of these ports are write, read and reset respectively. Changes in cell states are controlled by the three gates described. The task of the entrance gate is to control the information to be added to the memory, the task of the forget gate is to control how much of the old information will be transferred to the new data, and the output gate is to control how much of the information in the memory will be used at the output stage [27,28]. Figure 3 shows the structure and gates of the LSTM cell. Here, the input data at time t is xt and the output data from the previous cell is ht. The input at time t, xt, and the output of the previous step, ht-1, arrive at the forget gate. According to these values, forget gate makes a decision according to xt input and ht-1 output. The amount of information from the previous cell state information is checked in the cell at the current time t. At the input gate, it is decided how much of the newly incoming information as ht-1 and xt from the previous cell will be used in the memory cell. It can be understood from 0 and 1 outputs whether this information will be used or not. The output port, on the other hand, decides whether there will be an output. The output port also takes the inputs ht-1 and xt and decides whether to output 0 or 1 as in the input port. The state of the cell at time t is the sum of the information at t-1 and t times when it passes to the next cell (t+1 moment) [28,29].

3) Support Vector Machine

SVM is a pattern recognition method proposed by Vladimir Vapnik in the 1960s and whose algorithm was developed by Cortes and Vapnik in 1999 [30, 31]. The main principle of this method is to find the hyperplanes in the feature space that will allow to distinguish the two classes in the most appropriate way. It is aimed to complete the classification process by finding the most optimal hyperplane. In general, signals of non-physiological origin can be separated by a linear hyperplane, but it may be difficult to separate signals of physiological origin with a linear hyperplane. In order to overcome this difficulty, the data is transformed into a high-dimensional feature space [32].

4) KNN

KNN is one of the supervised data mining algorithms that classifies according to the distance between objects. This method makes the classification according to the proximity calculation. Its basic principle is based on the idea that objects that are close together in the sample space probably belong to the same category. The application steps of this method are given below.

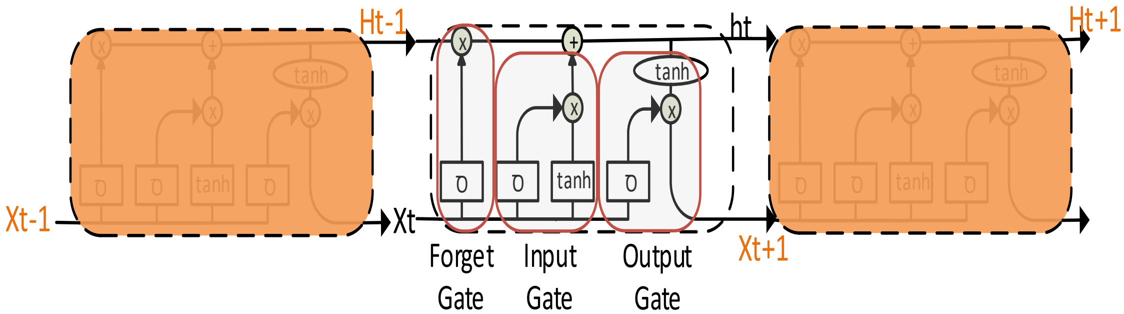


Fig.3. LSTM cell structure and gates

- The distance of the new observation to all the observations in the data set is calculated.
- The distance values are ordered.
- The k observations with the smallest distance are selected.
- In k observations, the majority voting category creates the class value [33].

III. RESULTS

This article presents a new machine learning algorithm for EMG signal analysis and classification. The flow diagram of the proposed algorithm is given in Figure 4. After the data was transferred to the Matlab environment, it was passed through a 3rd order band stop Butterworth filter (50 Hz) as a preprocessing step. After the preprocessing step, the EMG signal was subjected to a one-second windowing process to avoid overlapping and various features (19 features) were extracted in different frequency bands using DWT for each window. The obtained feature matrix was given as input to the classifier algorithms (C4.5, LSTM, KNN-3, SVM) and the results were discussed. Typical examples of EMG signals for the two groups (normal and myopathic) used in the article study are given in Figure 5.

After the preprocessing step, windowing was done and various features were obtained for each window. The obtained feature matrix was given as an input to the classifier algorithms and the results were discussed. Typical EMG signal examples for the two groups (normal and myopathic) used in the article study are given in Figure 5.

In the study, measurements taken from the Brachial biceps muscle in the EMGLAB database were used. The data used are given in Table 1. Biceps Brachii muscle data was not included in the M01 dataset, so it was not included in the study. In the study, the last 1,8 seconds of M07 myopathy data and the last four seconds of C10 Normal EMG data were excluded from the study for adjusting window sizes.
Features are obtained to classify each window data. The discrete wavelet method (Coif5 wavelet) was used to obtain the features. The lower frequency bands of the DWT used in this study are shown in Figure 7. With 10-levels wavelet transform, EMG signals are reduced to lower frequency bands and approximation and detail coefficients are calculated for each 1 second EMG data. Figure 7 shows the 10-levels DWT tree for obtaining the features. Various statistical features are obtained from all coefficients D1-A10.

The EMG data used in this study are divided into training dataset and test dataset. The training data represents 80% of the randomly selected dataset from the total data and is used to construct the classification model. Test data representing 20% of the total data are used to evaluate classifier performance. The distribution of records in the datasets for each class is presented in Table 2.

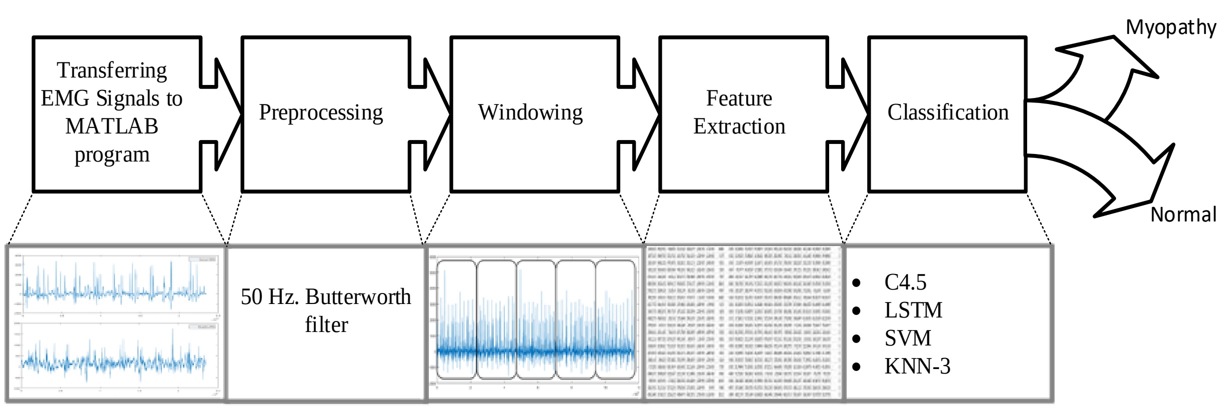
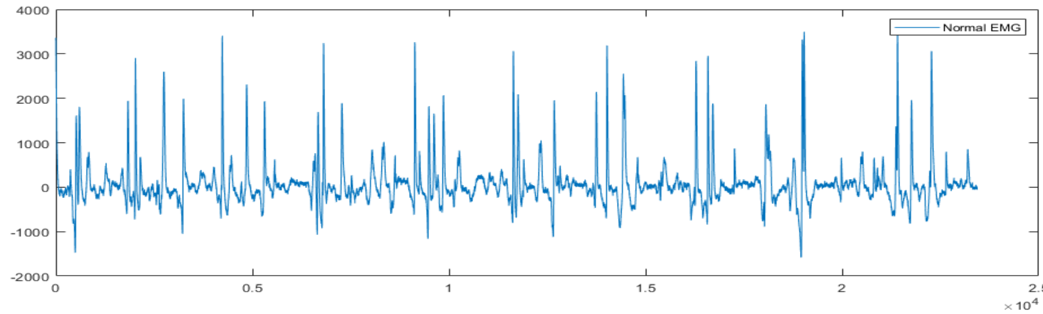
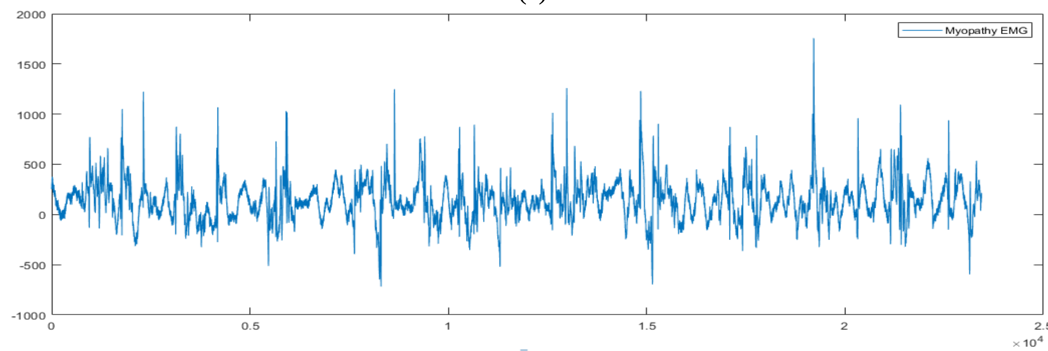


Fig.4. Schematic diagram of the signal processing



(a)



(b)

Fig.5. (a) Normal EMG (b) Myopathy EMG

TABLE I
EMG DATASET USED IN THE STUDY

Types	Patient	Number of patient	Type of Muscle	Time (sn)
Myopathy	M02, M03, M04, M05, M06, M07.	6	Biceps Brachii (long head)	1196,8
Normal	C01, C02, C03, C04, C05, C06, C07, C08, C09, C10.	10	Biceps Brachii (long head)	3355,4

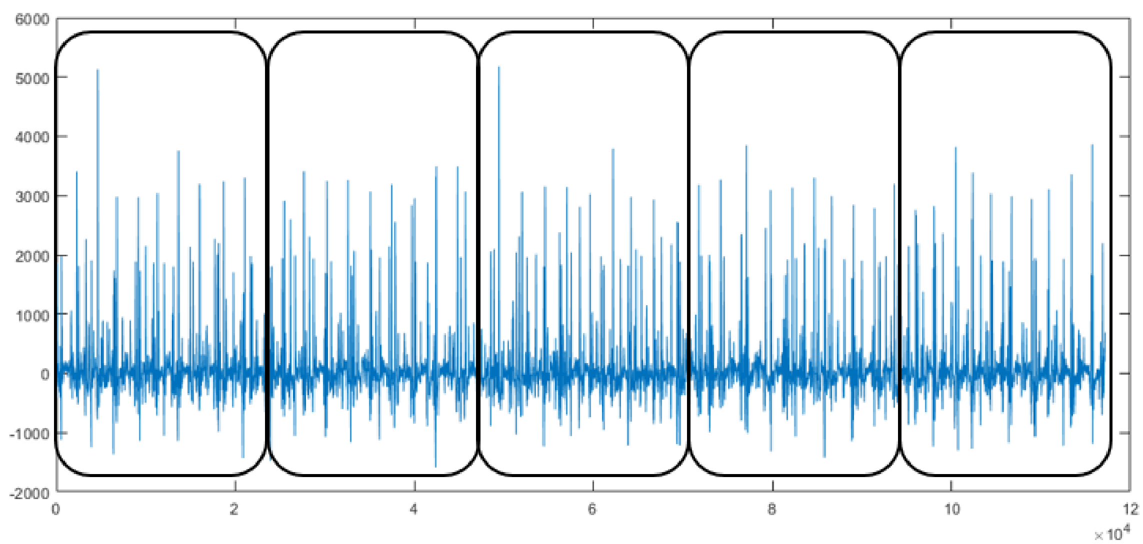


Fig.6. Dividing EMG data into 1-second epochs

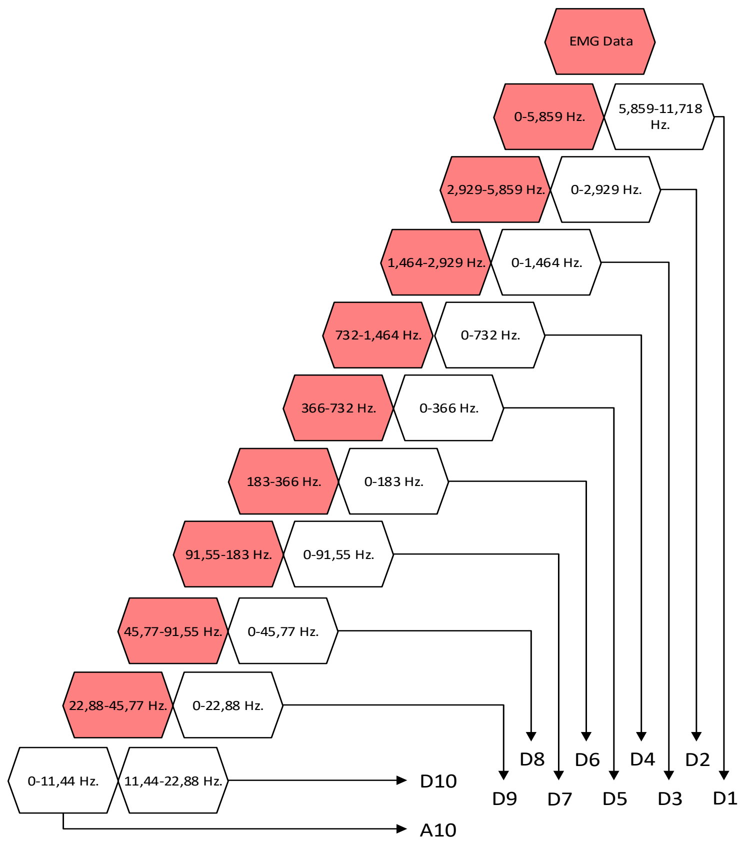


Fig.7. Wavelet decomposition tree with 10-levels

A10, D1, D2, D3, D4, wavelet coefficient variance value, energy value of all wavelet coefficients, maximum and minimum values of A10 wavelet coefficient, standard deviation values of D1, D2, D3, D4, D5, D6, D7, D8, D9, D10, A10 wavelet coefficients were calculated from the wavelet coefficients obtained from the EMG data in each epoch. A total of 19 features were extracted. The numbers 0 for normal EMG signals and 1 for myopathic EMG signals are set for the classifier response. The details of the obtained features are given in Table 3.

TABLE II
DISTRIBUTION OF RECORDS IN THE TWO DATASETS

Class	Training set (80%)	Test set (20%)	Total
Myopathy	956	239	1195
Normal	2684	671	3355
Total	**3640**	**910**	**4550**

As a result of the training carried out for the classification of healthy and myopathic signals, high success rates were achieved with the C4.5 decision tree and LSTM algorithms. In this article, the Confidence Factor (CF) coefficient used in the C4.5 decision tree algorithm was determined as 0,2, number of leaves: 7, size of the tree: 13, batch size: 50 in order to more effectively use the post-pruning process that prevents over-learning. Figure 8 shows the decision tree result screen for myopathy disease prediction of the C4.5 algorithm.

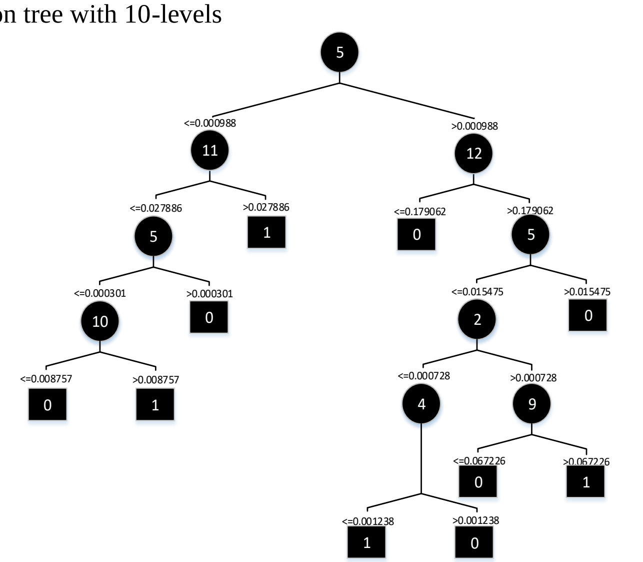


Fig.8. Decision tree created as a result of the study

According to Figure 8, if feature number 5 is greater than 0,000988 and feature number 12 is less than 0,179062, class 0 is assigned. If feature 5 is less than 0,000988 and feature number 11 is greater than 0,027886, class label 1 is assigned. Similarly, other situations occurring in the decision tree are given in Figure 8.

4-layer model (LSTM, dropout, activation and output layer) has been created for the LSTM algorithm. Algorithm parameters; optimizer: Adaptive Moment Estimation (ADAM), dropout rate: 0,2, batch size: 50, epochs: 50, 8 memory unit in LSTM layer. Learning rate of 0,001 was used with the ADAM optimizer.

The kernel function used in this study for the SVM algorithm is PUK. The mathematical representation of the PUK kernel function is given in Equation (2).

$$f(x) = \frac{H}{\left[1+\left(\frac{2(X-X_O)\sqrt{2^{\left(\frac{1}{W}\right)}-1}}{\sigma}\right)^2\right]^W} \quad (2)$$

The w ve σ parameters indicate the width of the function, and the H indicates the maximum peak level between the peak values. The Euclidean function was used as the distance function for the KNN algorithm used in this study, which determines which class the data belong to. The mathematical representation of the Euclidean function is given in Equation (3). In the study, k=3 neighbourhood was used.

$$d_{(i,j)} = \sqrt{\sum_{k=1}^{p}(X_{ik} - X_{jk})^2}$$
(3)

The confusion matrix resulting from the training of both classifiers is given in Table 4 and Table 5.

TABLE III
FEATURE LIST OBTAINED FROM EMG DATA

No.	Wavelet coefficient	Feature Name	No.	Wavelet coefficient	Feature Name
1	A10	Variance	11	D6	Standard deviation
2	D4	Variance	12	D7	Standard deviation
3	D3	Variance	13	D8	Standard deviation
4	D2	Variance	14	D9	Standard deviation
5	D1	Variance	15	D10	Standard deviation
6	D1	Standard deviation	16	A10	Standard deviation
7	D2	Standard deviation	17	All coefficients	Energy
8	D3	Standard deviation	18	A10	Maximum value
9	D4	Standard deviation	19	A10	Minimum value
10	D5	Standard deviation	Classifier Response		[0,1]

The calculation results from this confusion matrix are given in Table 4 and Table 5. Different metrics such as accuracy, precision, recall, Receiver Operating Characteristic (ROC) area were calculated to measure the success criteria of the models. While the time taken to classify data in deep learning architecture was 1.25 seconds, it was measured as 0,01 seconds (SVM) in traditional learning algorithms. Calculations were made on a computer with "Intel(R) Core(TM) i3-6006U CPU @ 2.00GHz and 4GB ram". Accuracy value is calculated by the ratio of correctly predicted data in the model to the total data set. Precision is the metric that shows how many of the data predicted as positive are actually positive. Recall is called as the metric that shows how much of the transactions we need to predict positively [34]. The ROC area is defined as the True Positive Rate / False Positive Rate ratio. It is basically a metric to understand whether the models established to solve the classification problems are working well. As the ROC value approaches 1, it means that the success of the model established to distinguish the classes increases [35]. According to Table 4, with the decision tree model, the accuracy rate was 98%, precision 98,20%, recall 98%, ROC value 0,99. With the LSTM model, the accuracy rate, precision and recall values were 100%, and the ROC value was 1.

According to Table 6, LSTM algorithm achieves more successful results, other algorithms It has been found that the performance is close to the LSTM model. As a result of the applications within the scope of the study, the deep learning architecture model, which has a 100% success rate, has been suggested for the classification of myopathy diagnosis because it has higher accuracy. At the same time, by examining the data in one-second windows, more data was classified separately, and the classification resolution was kept higher. When the data of Table 6 models are analyzed in terms of classification time; Traditional learning architectures achieved faster results than deep learning architecture. However, considering the classification time together with the success rate, we consider that 1,25 seconds is a feasible time for real-time applications. This study will shed more light on the investigation of deep learning architectures with high accuracy rates in future studies with EMG data. In addition, minimizing the need for physical consultation of the patients, blood tests etc. It will allow the design of a system or algorithm with high accuracy using only EMG signals without the need for operations.

Table IV
Confusion matrix (C4.5 and LSTM)

Classifier					
C4.5 (80% train, 20% test)			LSTM (80% train,20% test)		
Class Label	0	1	Class Label	0	1
0	688	18	0	706	0
1	0	204	1	0	204

Table V
Confusion matrix (SVM and KNN-3)

Classifier					
SVM (80% train, 20% test)			KNN-3 (80% train,20% test)		
Class Label	0	1	Class Label	0	1
0	703	3	0	699	7
1	1	203	1	8	196

Table VI
Success criteria and classification time of models

Classifier	Accuracy (%)	Precision (%)	Recall (%)	ROC Area	Classification time (sn.)
C4.5	98	98,20	98,00	0,99	0,03
LSTM	100	100	100	1	1,25
SVM	99,56	99,60	99,60	1	0,01
KNN-3	98,35	98,30	98,40	0,99	0,02

IV. DISCUSSION

From studies in the literature, Bue DB et al. [36] presented a methodology to predict the presence of myopathy from EMG signals in their study. They classified myopathic disease with an average success rate of 90%. Data were collected in the EMG lab. at the Baylor College of Medicine Department of Neurology in Houston, TX. Collected by James Killian. 15

EMG recordings were taken from 8 different subjects measured in one or more different muscles. EMG data were classified with SVM using Fourier transform. The performance of the model was measured at intervals of 0,05-2 seconds of the window duration. It was stated that the success rate increased with the increase of the window duration.

From studies using EMGLAB data; Belkhou A. et al. [7] studied myopathy disease classification. They obtained 5 features (the mean scale, the median scale, the mean coefficient, the minimum coefficient, the maximum coefficient) using the CWT together with the Sym6 wavelet. As a result of the classification made with SVM, KNN, DT, DA and NB algorithms, they reached a success rate of 93,68% with the KNN classifier algorithm. Belkhou A. et al. [37] have classified myopathy disease. 4 features (mean coefficient, minimum coefficient, mean scale, median scale) were extracted using CWT. As a result of the classification using KNN and SVM classifier algorithms, they achieved a success rate of 91,11% with KNN-9. ALS and Myopathy were classified by Bakiya A. et al. [6]. They obtained features in the time domain (seventeen time features) and Wigner-Ville transformed time-frequency domain (nineteen time-frequency features) from the data. Feature selection was made using the bat algorithm. The performance of the deep neural network is compared with the traditional neural network. It has been demonstrated that the deep neural network modeled with layers 2 and 3 (neurons = 2 and 4) using time domain features classifies abnormalities of EMG signals with higher accuracy. Dubey R. et al. [2] classified myopathy, ALS and normal EMG data. EMG signals were decomposed by the Empirical Mode Decomposition (EMD) method. The proposed methodology was tested on a dataset of more than 900 EMG signals from three classes. Empirical mode decomposition method is applied to decompose EMG signals. Appropriate intrinsic mode functions for feature selection are selected using the t-test-based approach and a complex plane graph is created. The proposed algorithm is trained and validated using Feed Forward Neural Network (FFNN), SVM and DT. When the algorithm was tested with FFNN, a maximum classification accuracy of 99,53% was achieved. Torres-Castillo JR. et al. [3] classified myopathy, ALS, and normal EMG data. Using the Hilbert Transform, 234 features are extracted in the time-frequency domain. Non-parametric statistical analysis and unrelated linear discrimination analysis were used for feature selection. After feature selection, 103 features were given to the classifier. The data were classified with the KNN classifier and a success rate of 99,4% was achieved.

Table 7 compares the results of this study with the results of other studies conducted with various data sets and classifiers in the literature. Bue DB. [36] achieved 90% success rate with the SVM classifier using the Fourier transform. Belkhou A. [7] achieved a success rate of 96,68% by using KNN, one of the traditional learning architectures, in their 2019 study.

Table VII
The proposed methodology and other exiting methodologies are compared

Work	Dataset	Method	Classifier	Acc.	Validation method	Classes
Bue DB. et al. [36]	Department of Neurology of the Baylor College of Medicine	Fourier transform	SVM	90%	10 fold cross validation	Normal and myopathy
Belkhou A. et al. [7]	EMGLAB	CWT	SVM, KNN, DT, DA, NB	93,68%	75%, 25%	Normal and myopathy
Belkhou A. et al. [37]	EMGLAB	CWT	SVM, KNN	91,11%	10 fold cross validation	Normal and myopathy
Bakiya A. et al. [6]	EMGLAB	Statistical features in the time and frequency domain	Developed deep neural network, conventional artificial neural network	100%	80%, 20%	ALS and myopathy
Dubey R. et al. [2]	PhysioBank, EMGLAB	EMD	FFND, SVM, DT	99,53%	85%, 15%	Myopathy, ALS and normal
Torres-Castillo JR. et al. [3]	EMGLAB	Ensemble-EMD	Latent Dirichlet allocation, DT, KNN	99,50%	3 fold cross validation	Myopathy, ALS and normal
Jose S. et al. [9]	EMGLAB	LWT	MLPNN-BMMV	99,87%	10 fold cross validation	Myopathy, ALS and normal
This work	**EMGLAB**	**DWT**	**LSTM,** DT (C4.5), SVM, KNN	**100%**	**80%, 20%**	**Normal and myopathy**

Belkhou A. et al. [37] achieved a success rate of 91,11% in the classification study. Jose S. et al. [9] classified the data with a success rate of 99,87%. Bakiya A. et al. [6] performed ALS and Myopathy classification in their study and achieved a 100% success rate. Dubey R. et al. [2] achieved a 99,53% success rate in myopathy, ALS and normal EMG classification. Similarly, Torres-Castillo JR. et al. [3] achieved a high success rate of 99,50% in the study, but too many (103) features were used in the study. This will naturally increase the processing load in a real-time application. When the studies in the literature are examined in terms of methods and techniques, in the study by Bue DB et al. [36], fast fourier transform was used and the signal was examined in the frequency domain. The performance of the model was tested with the classifier algorithm. In the study conducted by Belkhou A. et al. [7], it was concluded that the continuous wavelet method can be used on EMG data. Belkhou A. et al. [37] calculated the average absolute coefficient to reduce the size of the CWT coefficients. Thus, they tried to solve the size problem in CWT. Bakiya A. et al. [6] tried to improve the classification performance by extracting features in the time-frequency domain. A bat algorithm is used to select the best features from the time and time-frequency feature sets extracted by the Wigner-Ville transform. They concluded that the Wigner-Ville transform and the bat algorithm are suitable for classification of myopathy and ALS signals. Dubey R. et al. [2] using EMD method arranged the signals from high frequency to low frequency components and decomposed Intrinsic Mode Functions (IMF)'s. The features were obtained using the hilbert transform of the IMFs. The obtained features were classified by various classifier algorithms. They measured the statistical significance of the IMFs using the rule-based learning proposition (statistical values such as t, h, and p were calculated) in the feature extraction stage. Torres-Castillo JR. et al. [3] separated all signals into amplitude or frequency modulated subbands and extracted time-frequency features using Hilbert transform. Due to the large number of features, feature selection was made using linear discriminant analysis. Jose S. et al. [9] decomposed the signals using LWT. They calculated Higuchi's fractal dimensions (FD) of the LWT coefficients in the separated signals. The FDs of the LWT subband coefficients are combined in one dimension and given as input to the classifier algorithms. As stated above, studies have focused on high success rates. At the same time, the performances of different algorithms were compared and optimum models were proposed. In our study, lower frequency analysis of EMG signals was performed similar to the studies in the literature. Unlike the studies in the literature, wavelet method was preferred to examine the signal in lower frequency bands and features were obtained from the wavelet coefficients representing the signal form.

With this proposed study, the deep learning architecture, which is not available in most other studies, is tested on EMG data. At the same time, high success rates were achieved with 19 features. In addition, the results were compared with the traditional learning architecture. A better classification success rate (100%) was obtained in the diagnosis of myopathy with the deep learning architecture than the studies in the literature. According to the results obtained, the deep learning architecture LSTM model (4 layers: LSTM, dropout, activation and output layer) is proposed as the optimum model. At the same time, the parameters of the proposed model were determined as Optimizer: ADAM, learning rate: 0,001, dropout rate: 0,2, batch size: 50, epochs: 50, 8 memory units in a single layer.

V. Conclusion

The EMG signal is a non-linear, noisy signal. Therefore, it is difficult to distinguish various diseases from the EMG signal. In this study, a classifier algorithm from both traditional and deep learning architectures was used to diagnose neuropathy from the EMG signal. Numerous studies have classified neuropathy using traditional learning architectures. The proposed method has been effective in diagnosing neuropathy. Before extracting features from the EMG signals, the data were decomposed using the Coif5 wavelet. 19 features are obtained from wavelet coefficients and given as input to classifier algorithms. C4.5 decision tree, SVM and KNN-3 from traditional learning methods and LSTM model from deep learning method were used as classifiers. In this study, the focus is on achieving high accuracy rates. A higher success rate was obtained with the LSTM model compared to traditional learning methods. At the same time, the performance of traditional classifier algorithms is compared with deep learning architectures and the optimum model is proposed. A new contribution has been made to the literature with the application of deep learning architecture to the EMG dataset. It is considered important by us to be able to diagnose neuropathy using only EMG signals. It is possible to test this research article by increasing the number of data and classes. In future studies, the classification results of deep learning architectures can be evaluated by expanding the number of classes and data sets. Thus, it will be possible to provide more detailed and accurate information that can help medical professionals with machine learning methods.

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