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Novel Method for Early Detection and Classification of Neuro Degenerative Disorder Amyotrophic Lateral Sclerosis

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Abstract*: *The most common progressive neurodegenerative disorder in the fetal nature is amyotrophic lateral sclerosis (ALS). The ALS incidence is approximately 2 per 100 000, with the maximum life span being two to three years after the start of symptomatic growth. However, premature identification may increase the lives of the impacted people. EEG is the most convenient and cheapest technique for measuring brain electrical activity. Automated EEG can be used as the coherent identification biomarker technique which is always connected with fronto-temporal dementia (FTD) in seconds to detect ALS in previous phases of growth. The EEG spatial assessment will show spatial and behavioral structure changes in the fundamental cellular network resulting from FTD and may produce prospective biomarkers for premature identification of ALS. The use of the Dual Tree Complex Wavelet Transformation (DTCWT) technique has developed a novel algorithm. DTCWT can solve the abbreviation of current EEG removal functionality techniques. The spectral leakage is reduced by a ideal rebuilding of the DTCWT measurements, so the suggested algorithm has led to an effective and coherent ALS ranking with a Neural Network (NN). For analyzes, eight EEG datasets, each of the Normal Group and Subject were used, and spectral EEG analysis provided a source of definite biomarkers. The proposed algorithm produced 100 percentage accuracy with respect to the dataset considered in this analysis.

Keywords*: *Amyotrophic Lateral Sclerosis (ALS); Fronto-temporal dementia (FTD); DTCWT; Neuro Degenerative Disorder; EEG.

I. INTRODUCTION

The most widespread neurodegenerative disease of today is amyotrophic lateral sclerosis (ALS), characterized by progressive muscle paralysis. The motor neuron disease (MND), which has an effect on the motor neurons in the brain, brain stem and Spinal Cord, forms part of the neurodegenerative disorder group. The term ' Amyotrophy ' relates to muscle fiber atrophy, the term ' Lateral' to the region in the heart which initiates muscle physical activities, and the term "Sclerosis" relates to the degeneration of the processes of the Cortico-Spinal Nerves by MNs in the region[1]. The nerve cells are engine neurons intended to regulate communication between your brain and your body's voluntary muscles. Motor neurons regulate certain actions of the brain, including walk, grip, swallow, breathe and talk. Step by phase, message delivery is essential for muscle activity introduction and muscle cooperation. Two kinds of mNs are: I the middle neuron engine (UMN) in the brain, and (ii) the bottom neuron of the reduced engine (LMN) in the backbone. Communication signals are transferred from and to the particular tissues of the organ from UMNs to LMNs. ALS impacts engine cells in one or more cellular network components [2]. This especially affects LMNs in the foreground of the brain and the backbone and the top motor neurons in the prefrontal gyrus, parietal cortex and premotor cortex [3]. The effect of these conditions is particularly severe. The scheduling and organization of the work of the middle and smaller neurons is carried out by prefrontal motor neurons. The capacity of the brain to activate and regulate voluntary muscular activity is progressively ruined by the malfunction of motor neurons. The nerves are deserved because the respective degenerate front nerve cells contribute to muscle weakness and fasciculation, thus preventing the person from moving, speaking and breathing [4]. The leading causes of degeneration and death of ALS-cause nerve cells are high glutamate concentrations (glutamate is a chemical which transmits the message from neuron to neuron), sporadic ALS changes in the nucleic acid can be caused by acquired nucleic acid, nerve cells misprocessing protein and oxidative damage can accumulate abnormal proteins causing the nerve cells to die [5].

Both ALS kinds are I sporadic (SALS) and (ii) family (FALS) families. FALS is related to ALS or MND's community background while SALS is not linked to the disease's community history [6]. In 5–10% of the instances, genetically modified FALS needs approximately 61% for any child bearing the mutations that cause ALS. Some familial genes are thought to also participate in sporadic ALS. 2:1 and the probability of incidence of ALS is greater in men than women, and in individuals above the age of 40. As the era rises, sporadic ALS is more likely to develop because nuclear acid accumulates. The 13 percent of people with ALS have a full-length frontal dementia. In 40% of ALS patients there is a progressive cognitive and behavioral deficiency [7]. Low-impact cognitive ALS nurses demonstrate a faster course to ALS than cognitive impairments nurses.

Neuronal communication requires the type of chemical and electrical messages. Each electrical signal at synapse becomes a chemical stimulus and returns when the message hits the next neuron [8].

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The stimulus is transferred from one axon neuron to the recipient neuron dendrite. A non-invasive technique called electroencephalogram (EEG) is used to measure the electrical function of the body.

It offers the most clear perspective of the workings of the brain that enables the original diagnostic phase. Brain waves can be registered using conductive fluid to place electrodes on the person scalp and EEG can be compared with appropriate technology. Figure 1 shows the 10–20 norm for positioning of electrodes. Figure 1, symbols F, C, T, O and P represent EEG indications, respectively, for the Front, Central, Temporary, Occipital or Parietal lobes. Figure 1 (a) shows an electrode system from the right shoulder, while the electrode layer from the top of the neck is illustrated in Figure 1 (b). EEG is the cost-effective and widely available method for capturing the neural network's activities. EEG information is strongly linked to high-temporal processing in real-time brain operation. The temporal resolution of EEG enables resonance assessment centered in linear interactions with a recognized amount of biological and psychological features representing frequency channels [9].

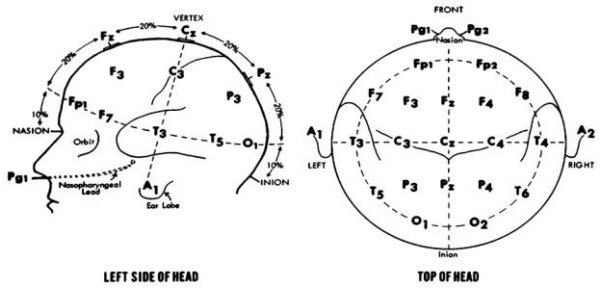

Fig. 1 Standard electrode placement

Spectral analyzes are known to classify EEG in various bands and are carried out via Fourier transform. The functional connectivity is based on activities on various brain regions and is measured by similar statistics. Effective connectivity refers to the data relation between regional activity and to the extent to which each regional activity has an influence on the other. A spectral EEG analysis may be used to find functional and effective brain connectivity. The human brain is collected by the peripheral nervous system to control and coordinate human activities in billions of pulses per second [10].

Human brain processes billions of pulses per second from the peripheral nervous system to monitor the activity of man and to coordinate it. The EEG control signals act as Brain Computer Interfacing (BCI). Brain computer interface is a communication mechanism for physical and intellect world. In order to display the information on the desktop the EEG acquisition framework gathers and digitizes intellectual vibrations at the bottom of scalp with a special sample frequency. The electrode micro voltage capacity was then enhanced for BCI reasons by about 10 000 occasions. The EEG can be classified in 5 BCI frequency ranges. These groups are Delta, Theta, Alpha, Beta and Gamma, which are linked to particular body operations. ALPEA bubbles in the occipital cortex and frontal cortex are comfortable, carefree and most strong. Beta bubbles have a frequency of 12-35 Hz. Beta pulses are associated with engine exercise and cortex engine is highest. Beta waves will decrease during motor movement or when movement is planned. Gamma waves are within 35 Hz and higher frequencies. Waves of the gamma reflect the consciousness mechanism [11].

II. LITERATURE REVIEW

Parameshwaram Iyer et. al [12] in its paper, the spectral EEG detection analysis for biomarkers in patients with ALS is present. This paper discusses the importance of functional, structural and efficient connectivity measurements in spectral analysis of the underlying neural network and fronto-time dementia associated with ALS. ALS EEG was presented in this paper as a cross-spectral analysis. It has been found that the ALS patients with cognitive and behavioral impairment and significant traits were found in the alpha band with a more disruptive network. The levels of the grouping coefficients (p=0.02) of the alpha and gamma bands have increased in ALS. Ajmed S. Al-Fahoum et. al [13] discussed conventional feature abstraction methods through a linear EEG frequency and TFD study. The following paper presents a detailed study and a comparison of the performance of various techniques, like Times and Frequency Domains (TFD), Fast Fourier Transform (FFT), Eigen vector methods (EM), Wavelet Transform (WT) and Auto Regression mode (AR). Yunfeng Wu et. al [14] proposed the classification of ALS EEG signals is presented by a Fisher Linear Discriminant Analysis (FLDA) and the Least Squares Support Vector Machines (LS SVM). The two methods were evaluated with cross-validation method and the performance was compared to provide the best method for classification of the pattern. Their conclusion was that LS SVM generated 89.66 percent with sigmoid kernels with an operating curve area of 0.9729. Stafford Michahial et. al [15] In order to extract EEG signals characteristic, recommend Discrete Wavelet Transform (DWT). This paper describes deriving features of the EEG waves that belong to the patients with ALS paralyzed to develop BCI applications and further pattern classification. Takashi Kasahara et. al [16] describes the desynchronization event-related (ERD) of EEG parameters in ALS patients during motor imaging. A comparative analysis is done in this document on the ERD of normal patients and the ALS in order to find the correlation between motor imaging and ERD using the coefficient of Spearman correlation. Indu Sekhar Samant et. al [17] talk about the difference between other cognitive disorders and memory impairment in ALS patients. The study focuses primarily on two distinct ALS and Alzhimer's disease cognitive disorder groups and finds a distinct and characteristic memory impairment with fronto-time dementia in ALS patients. This article shows how important it is to differentiate ALS from other neural disorder subtypes. Cuneyt Judith Machts et. al [18] Present various methods for the EEG estimation of power spectral density. Classification accuracy is analyzed and compared in this paper using different methods, such as FFT, Welch and Autoregressive. They found that neural networks achieved the highest test classifications with FFT at 79.92%, with the Welch method 75.64% and with the method 66.32,%. Cuneyt Yucelbas et. al [19] describes Dual Tree Complex Wavelet Transformation (DTCWT) as a way to reduce shift variance and improve directional selectivity that dominates the Wavelet Transformation technique when retaining other characteristic dimensions of methods already used.

III. METHODOLOGY

The block diagram for feature extraction and pattern classification of the EEG for ALS is shown in figure 2.

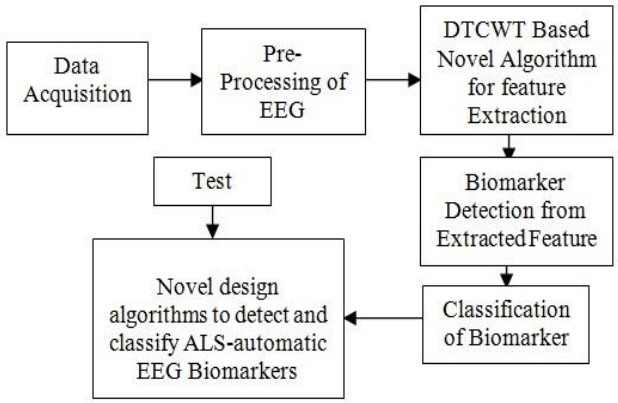

Fig. 2 Block diagram representation of suggested work

The proposed work is implemented in MATLAB software provided by Math works. Wavelet toolbox, DSP toolbox and NN tool are utilized for elemental extraction of characters and pattern classification. The methodology of the suggested work is explained in the following steps:

1. ***Data acquisition:*** EEG information collections from individuals with ALS are gathered, and EEG information from people without recognized neuronal conditions are also obtained.
2. ***Pre-processing of EEG signals:*** The artifacts were removed from the EEG signal input prior to processing. External noise, blinking of the eye, motion, etc can put artifacts in the EEG. Average filtering and interpolation operation for pre-processing.
3. ***DTCWT based novel algorithm for feature extraction:*** DTCWT eliminates the inconvenience of existing EEG signal processing methods and reproduces the signal from the received coefficients.
4. ***Biomarker detection from featured set of data:*** EEG screening is carried out for feature extraction (PED). FFT, MEM and CPSD analyzes are carried out for biomarker identification.
5. ***Classification of biomarkers***: PSD measures are used for the classification of ALS EEG transmissions in the non-ALS EEG network.
6. ***Classification of ALS-automatic EEG Biomarkers***: The DTCWT-based Algorithm provides an entry message, which can readily decide whether the calculated numbers are ALS or ordinary. The 2/3 Rule relates here, which provides TRUE performance when TRUE is based on the specified requirements for two of the three ANN calculations.
7. ***Test Data:*** Finally, the algorithm is tested and validated with different performance and efficiency datasets.

IV. DESIGN OF ALS FEATURE EXTRACTOR AND CLASSIFIER

The algorithm based on the DTCWT is proposed to extract the feature so that the EEG signal is fully reconstructed and changed invariantly. The imaginary part of the wavelet coefficients is taken into account as well. The potential biomarker of ALS can only be provided by the PSD EEG evaluation. The PSD is therefore calculated using 3 methods in the DTCWT-extracted feature set with the frequency components. Figure 3 illustrates the system architecture of the proposed method.

Details of each step in this flow chart are described in each subsections of this chapter. The main steps in EEG processing using the proposed method are described as follows.

Data Acquisition

This project takes into account the EEG data groups of two groups, the Normal Group and the Subject Group. Normal implies an EEG that is gathered from individuals without any recognized illnesses and is recognized as a topic for an EEG gathered from ALS nurses. The subject of these information collections has been added to the BNCI-Horizon-2020 site by LADYBIRD, g.tec, Austria. The EEG signals were collected from 8 subjects with an average age of 58±12. The right ear section and the left mastoid were referenced by each electrode channel. All electrodes have been placed in accordance with 10-20 international standards and 4096 EEG samples have been selected for experimentation in C3, C4, Cz and Pz channels. The EEG recording was performed during engine imaging tasks so that the right and right legs could move in replaceable time.

Moving Average Filter

The time series were broken down into different characteristic components. Filters have been estimated to estimate such a component without approximate parameters. Filter changes a time series with a clarified template to generate a new time series or even to remove some of them. The Moving Average Filter (MAf) is a desired linear filter for the proposed work. The principle behind MAf is that the average is calculated from the input EEG signal for a number of points and produces a unique output. The MAf operation uses low-pass filters. The filter will reduce the impact of artifacts in the EEG signal by smoothing operations. The fluidity also diminishes the intensity of the EEG signals ' peaks and boards. The sum of the decrease is equal to the square root of the points norm. The artifacts are reduced by a gradient of 20 by 200 points MAf. Move the 10-point filter's average filter operation with equation 1 is calculated.

$$y[i] = \frac{x(i) + x(i+1) + x(i+2) + x(i+3) + x(i+4) + x(i+5) + x(i+6) + x(i+7) + x(i+8) + x(i+9)}{10} \quad (1)$$

where x[] is a signal of the ISG input and y[] a signal that is without artifacts. The filter functions on its columns, as the input is matrix. For the entire operation of EEG signals with 4096 samples, the frequency of sampling (fs) of the 4500 shall be used. The fs are detected by manual9-level decomposition calculation. A 10-by-1 array of the numerator coefficient was

used and the denominator coefficient was taken as the average filtering of 1 to 10 points.

The EEG input values have been computed to check the input EEG database difference which contains artifacts from the artifacts-free EEG. The artifact-less EEG has been found to have lower amplitude energy values.

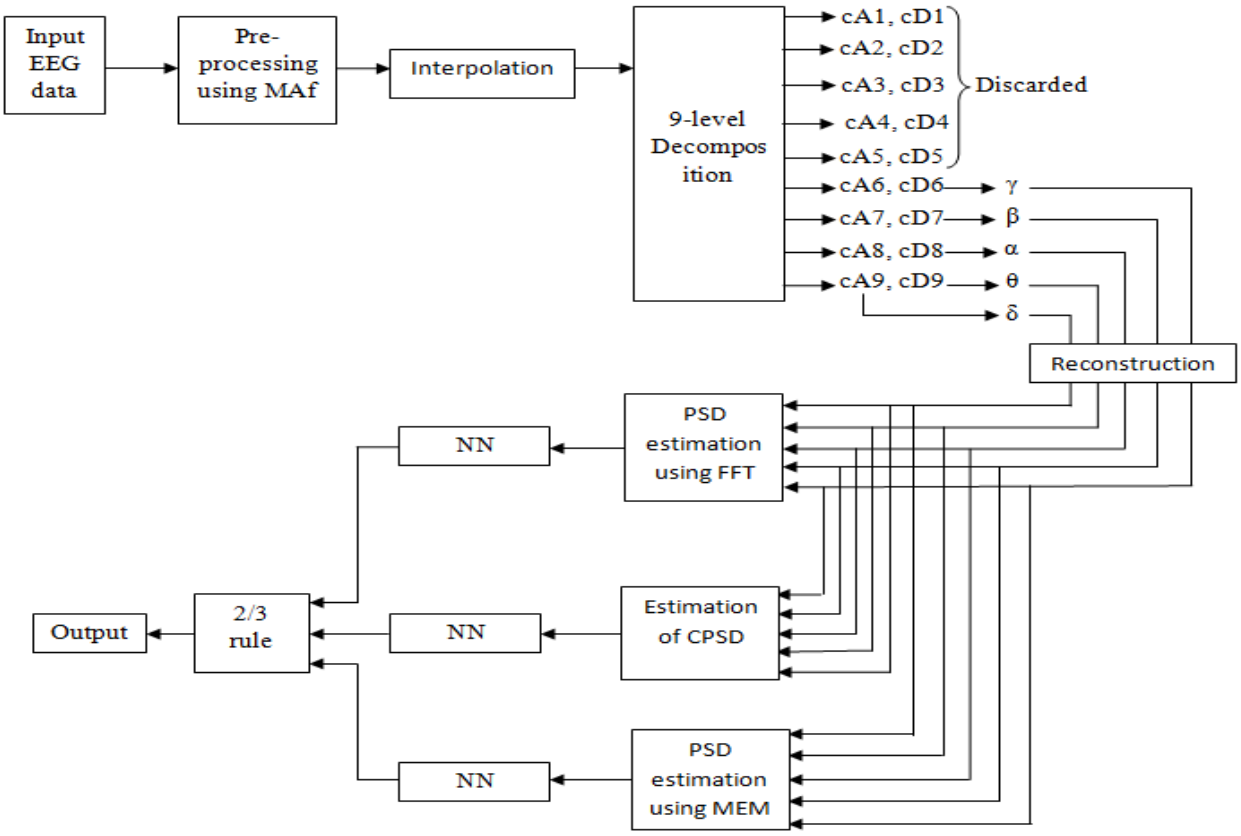

Fig. 3 Proposed method system architecture

Interpolation

Interpolation is the way to rebuild a signal through the introduction of new, discrete data points within closed data points. Middle data points from the known data points shall be estimated. Interpolation method maintains the original EEG signal harmonics without introducing an aliasing above the Nyquist signal limit. MATLAB can be used to conduct a linear interpolation of the filtered EEG. The signal sampling rate will be increased by interpolation at a higher sample rate. The lacking information is calculated as a fresh starting stage for the average of the data scores. At MATLAB, five-point interpolation has been performed by adding 0 instead of lacking data and scanning the low-pass series to achieve a fresh frequency, interpolated data artifact-free EEG message. La-grange equation 2 is used to interpolate5-point series. Where x_1 to x_n are the known data points.

$$y = \frac{(x-x_1)(x-x_2)\dots(x-x_5)}{(x_0-x_1)(x_0-x_2)\dots(x_0-x_5)}y_0 + \frac{(x-x_1)(x-x_2)\dots(x-x_5)}{(x_1-x_0)(x_1-x_2)\dots(x_1-x_5)}y_1 + \dots + \frac{(x-x_0)(x-x_1)\dots(x-x_5)}{(x_5-x_0)(x_5-x_1)\dots(x_5-x_4)}y_5 \quad (2)$$

V. PSD ESTIMATION FOR BIOMARKER DETECTION

Fast muscle movements are a transitory occurrence and the subsequent neuromuscular recordings can physiologically inform the analysis of such transients that can not be discovered on the time EEG signals [20]. In order to find the biomarker of ALS EEG spectrum, characteristic of each EEG frequency band were analyzed from three types of PSD estimations. The three PSD estimation methods used are:

- ✓ PSD estimation using FFT
- ✓ Cross Power Spectral Density (CPSD)
- ✓ PSD estimation using MEM.

PSD Estimation using FFT

Data Windowing is applied to a data sequence in order to decompose it into frequency components and to create modified periodogrids in order to achieve DFT. Fast Fourier Transformation is the method of estimating discrete Fourier transform in the generation of frequency response. FFT is achieved by using Cooley-Tukey algorithm in MATLAB. This algorithm initially estimates N1 transform of size N2 and then estimates N2 transform of size N1. Using one of the machine-generated, fixed-sized codelets, the decomposition is recursively applied to both N1 and N2 [21].

The PSD of DTCWT wavelet coefficients were estimated over frequency ranges of desired sub-bands (δ, θ, α, β, γ) of EEG. The modified periodogram was accomplished from the average of band power calculated for each frequency bands. The number of DFT estimation points has been taken as two power points larger than the input signal length of the DTCWT coefficient signal reconstructed. The FFT of a N-point signal x(n) is calculated using equation 3 with period T and length L.

$$x_i(\omega) = \sum_{n=0}^{N-1} x(n)\, e^{-j\omega nT} \quad (3)$$

The resulting periodogram is given in equation 4.

$$P_{xx}(f) = \frac{1}{NU}\left|\sum_{n=0}^{N-1} x_i(n)\, w(n)\, e^{-j2\pi fn}\right|^2 \quad (4)$$

where w(n) is the windowing function and U is the normalization power estimated using the equation 5.

$$U = \frac{1}{N}\sum_{n=0}^{N-1} w^2(n) \quad (5)$$

The average PSD of modified periodogram is estimated using equation 6.

$$P_{xx} = \frac{1}{L}\sum_{n=0}^{L-1} P_{xx}(f) \quad (6)$$

Spectral Density of Cross Power

The assessment of the Cross Power Spectral Density makes the discovery of the state as a frequency task between two time series. The CPSD is the power / unit frequency disperson. The two-channel CPSD estimate of the EEG signals will estimate both signals ' correlations[22]. A biomarker potential for ALS is the correlation between EEG signals in the motor region. CPSD method was used to find and estimate the correlation of EEG signals in all five frequency bands from C3, Cz and Pz. Applying Welch's averaged and changed periodogram mode, CPSD was calculated on MATLAB. Equation 7 estimates the CPSD of two different time signals x & y.

$$P_{xy}(\omega) = \sum_{m=-\infty}^{\infty} R_{xy}(m)\, e^{j\omega m} \quad (7)$$

where R_{xy} is the sequence of the cross relation, and t is estimated by equation 8.

$$R_{xy}(m) = E\{x_n + m\, Y^*_n\} = E\{x_n Y^*_{n-m}\} \quad (8)$$

The expected function operators value of E { } is indicated here; x_n and y_n are the stationary-random compound processes. The complex x and y inputs generate two-sided PSD [23].

VI. NEURAL NETWORK CLASSIFIER

The ALS classification was requested by Feed-forward-back-propagation NN. In order to achieve back-propagation[24], a generalizing Widrow-Hoff learning method applies to the multi layer networks and non-linear transferring functions. The basis of the gradient descending algorithm is the ideal rear propagation. Weight of the network was driven downward to achieve the Widrow-Hoff learning rule, which is called the gradient downward algorithm. Each neuron consists of a number of inputs followed by a transfer function in neural network classifier.

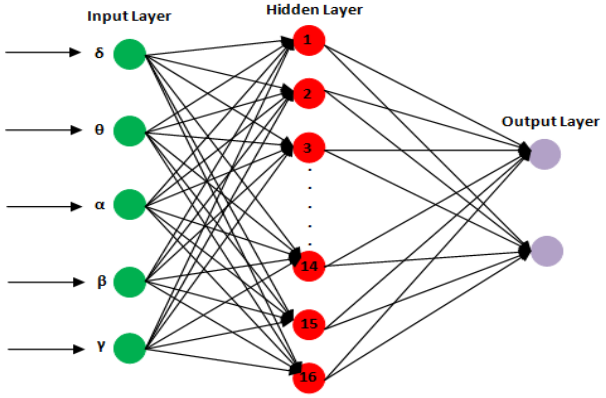

Fig. 4 Proposed NN

Tan-sigmoid (tansig), purelin and log-sigmoid (logsig) can be transported. Figure 4 'w' provides the common pattern of the neuron with inputs R as weighted approximately by each input. The partial sum of the inputs is supplied as the f input. The suggested NN with five variables, 16 concealed layer neurons and two outputs is shown in Figure 4. The three networks are all built in the same method [25.

The Levenberg-Marquardt algorithm (trainlm) was used to provide training in NN classification for ALS. The secondary ordering training speed excluding the need for the Hessian matrix is an algorithm [26]. When a double-model system is able to recognize the DTCWT-based algorithm output as ALS for certain input signals, the DTCWT-based algorithm is performed by three rules for two, the EEG signal otherwise input will be categorized as non-ALS.

VII. RESULTS AND DISCUSSIONS

In MATLAB, a number of EEG data sets are tested for the functioning of DTCWT based algorithm for classification of ALS. The data sets include EEG from ALS patients, normal EEG sets with motor imagery as well as without motor imagery. Only two data sets of EEG are considered here for analysis of results. This chapter gives analysis of different results obtained.

The interpolated EEG signal was given as the input to a wavelet transform algorithm. DWT and DTCWT techniques are used for this and a comparative study has done. Nine levels of decomposition were done for both DWT and DTCWT techniques. The nine level wavelet decomposition obtained for an EEG signal in MATLAB is shown in figure 5. The Delta and Theta, Alpha, Beta and Gamma sub bands for the development of functional sets (cD6, cD7, cD8, cD9 and cA9), have the desired frequency ranges shown in figure 5(b), depending on the maximum frequency obtained from each level. All other wavelets will therefore be discarded.

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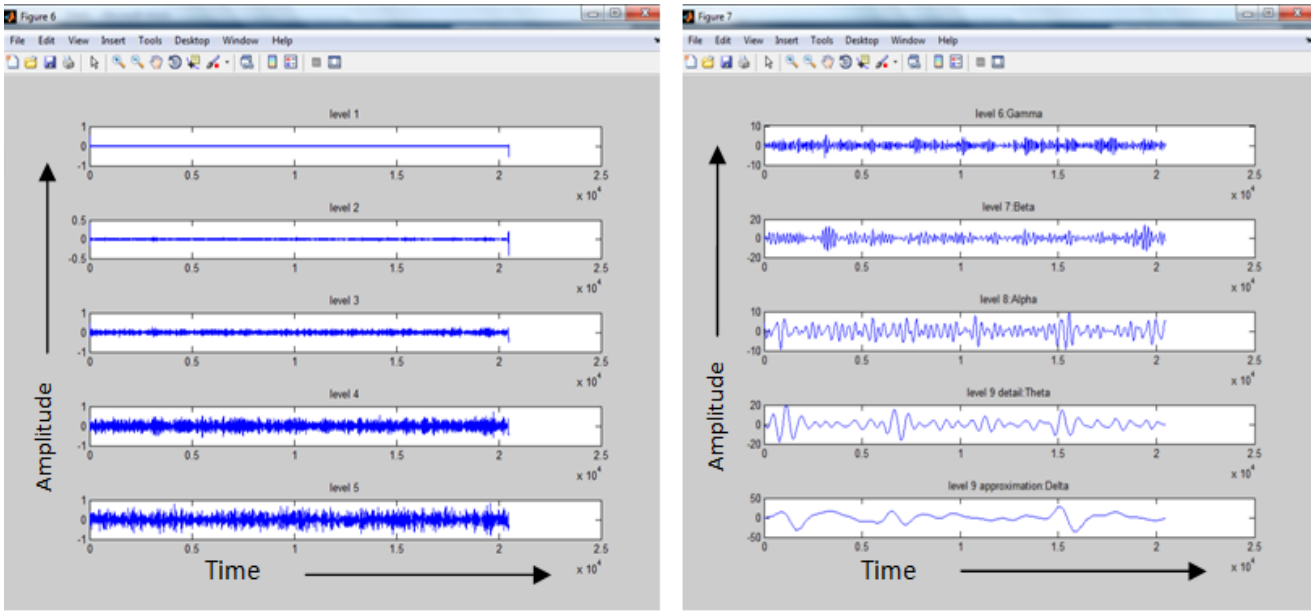


(a) (b)

Fig. 5. Plots for 9-level DWT decomposition of EEG. (a) cD 1-5 levels (b) cD 6-9 levels and cA9

The declining levels were achieved by checking for the maximum frequency of each wavelet, as illustrated in Fig. 6.4. For the detection of wavelets of biomarker and other wavelets, only the sub-bands Delta (δ), Theta (θ), Alpha (α), Beta (β) and Gamma (γ) are considered. The frequency of the components at each level is achieved by reconstructing the coefficients of the waves and then changing Fourier each of them.

```
Command Window
  level 1 detail:Maximum occurs at 1999.20 Hz
  level 2 detail:Maximum occurs at 975.20 Hz
  level 3 detail:Maximum occurs at 463.20 Hz
  level 4 detail:Maximum occurs at 230.40 Hz
  level 5 detail:Maximum occurs at 66.80 Hz
  level 6 detail:Maximum occurs at 48.80 Hz
  level 7 detail:Maximum occurs at 25.60 Hz
  level 8 detail:Maximum occurs at 10.00 Hz
  level 9 detail:Maximum occurs at 4.60 Hz
  level 9 approx:Maximum occurs at 3.40 Hz
fx >>
```

Fig. 6 Maximum frequency of EEG signal at each level

1-D DWT tree is used for decomposition using DWT. The different DWT techniques were established using different filters such as Haar, biorthogonal, daubechies-4 and daubechies-8. A comparative study was carried out on the wavelet coefficients generated by using the wavelet-coefficients obtained using DWT techniques with different filter banks. The nine levels of DWT decomposition of an EEG signal that belongs to an EEG from Subject is tabulated using different filter banks as shown in table 1. The low and high values of coefficients at each level are tabulated and shown in table I.

The db8 filters are found to have the better performance and therefore DWT decomposition using DWT-db8 has been used for the wavelet analysis. Forward real and complex double density dual tree is accomplished in MATLAB. Two1-D DWT trees were used for the construction of DTCWT tree; one for real part of signal decomposition and another one for imaginary part. An ‘Fdf’ filter was used for first stage of decomposition is a 1-by-2 cell array of vectors another filter ‘df’ was used for the subsequent levels of decomposition. Both these types of filters include a collection of filters with a low pass and a high pass. The filter ' Fdf' was Farras almost symmetrical filter and the Kingsbury Q-shift filter' df' filter was composed of ten taps. The low-pass filter forms the first column in MATLAB and is the second column in a high-pass (wavelet). The DTCWT produces high-frequency components and low frequency approximations Details.

Table. I High and Low coefficients using different filter banks in DWT technique

D/A	Haar		Biorthogonal		db4		db8	
	High	Low	High	Low	High	Low	High	Low
cD1	0.450398	-0.50576	0.028959	-0.04252	0.010968	-0.00879	0.049534	-0.03456
cD2	1.270289	-1.43315	0.279583	-0.31151	0.117719	-0.20221	0.078603	-0.09913
cD3	3.586437	-4.00413	0.535931	-0.50434	0.298841	-0.27057	0.268597	-0.29501
cD4	9.878282	-10.4278	0.8832	-1.44102	1.525653	-1.3807	0.689102	-0.57576
cD5	22.98418	-29.0882	9.038396	-9.34471	15.83712	-10.9419	9.647216	-7.49292
cD6	61.23804	-57.125	45.37647	-48.4324	56.67133	-52.6556	55.65992	-51.216
cD7	89.53926	-117.256	93.48065	-78.3455	120.974	-133.236	129.1801	-105.528
cD8	67.22823	-61.1795	68.37879	-91.607	92.52832	-72.4531	72.82493	-90.1789
cD9	100.8941	-108.521	120.4375	-111.92	110.0399	-116.47	120.1171	-109.673
cA9	68.9942	-83.1745	72.03894	-297.863	114.6062	-289.963	91.38674	-318.545

Table II PSD estimation of features using DWT

Sl. no	Normal					Subjects				
	Gamma	Beta	Alpha	Theta	Delta	Gamma	Beta	Alpha	Theta	Delta
1	894.71	2216.83	289.09	1259.02	147.40	4786.67	429.83	190.18	0.70	44.17
2	1144.22	1154.56	310.48	4607.69	10537.19	2091.24	3758.81	258.28	1726.84	553.85
3	614.30	8067.55	2939.49	100.96	1111.22	3211.87	1097.48	341.50	95.81	1829.39
4	1153.83	759.54	869.26	28.18	7790.03	1352.70	437.20	128.90	476.23	3347.72
5	422.43	231.84	212.52	127.35	6918.24	2248.56	76.49	110.54	8.15	454.11
6	404.63	1393.13	328.34	6.09	4124.70	1851.32	1035.05	536.64	13.87	112.85
7	3245.60	870.82	14.59	3425.35	37608.23	691.75	1088.55	148.19	429.12	337.57
8	7429.50	3771.58	103.23	166.77	14063.83	1431.52	2932.24	46.38	32.41	1314.29

The decomposition of signal using DWT has done and the PSD values are estimated using FFT for comparison of DTCWT with DWT. The PSD values are tabulate in table 2 for eight signals from normal and subjects. A graph is plotted for the data.

The feature extraction using DWT is providing significant variation in Delta band activity in Subjects when compared with Normal group. The decrement has found to be around 95%.

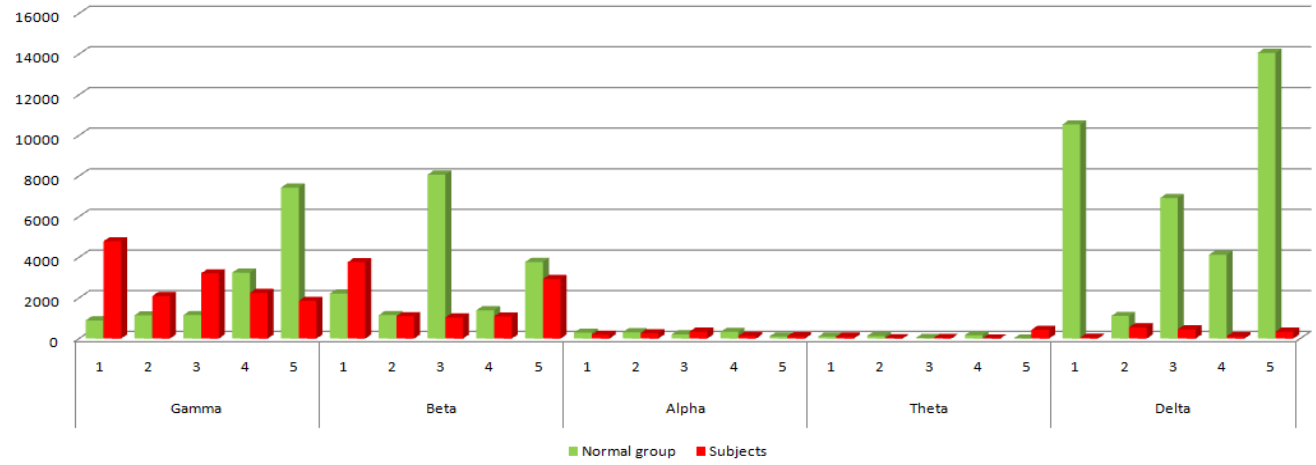


Fig. 7 Graph showing PSD estimated for features using DWT

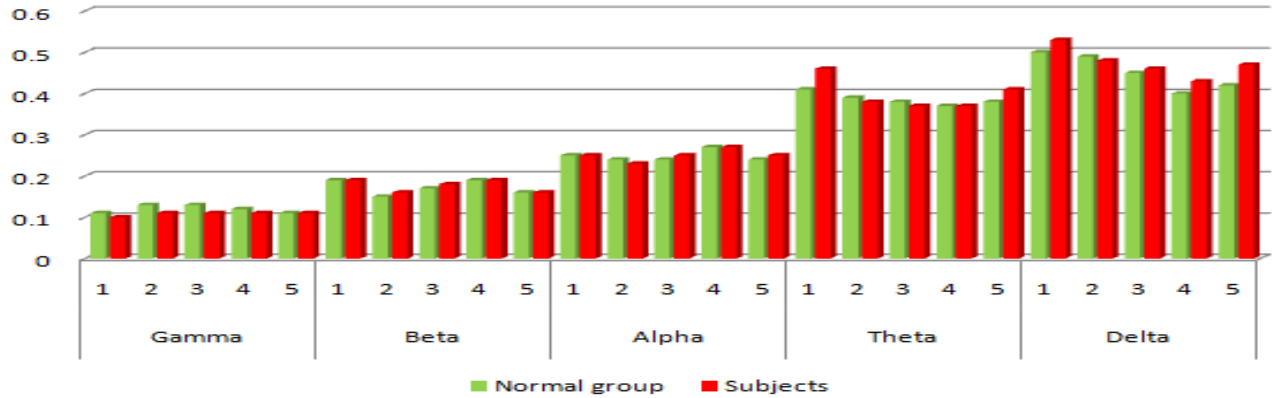
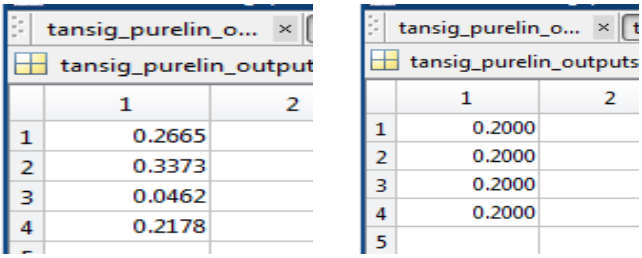


Fig. 8 Graph showing the Shannon entropy estimation of features

Entropy values of EEG feature sets have been calculated for detection of biomarkers. Shannon entropy method has been used for this. The average values of entropy for the feature sets have been calculated and the graph is plotted as shown in fig 7.

When using DTCWT, the results are consistent and the results are not DWT compliant. Figure 9 shows the training of neural networks with transformations of the tansig-pureline and the use of PSD estimates of feature sets derived from DWT and DTCWT-based algorithm. The target output of the DTCWT algorithm is 0,2 and has been achieved.



(a) (b)

Fig. 9 Results of Neural Network based on its normal EEG signal for the: (a) DWT and (b) DTCWT

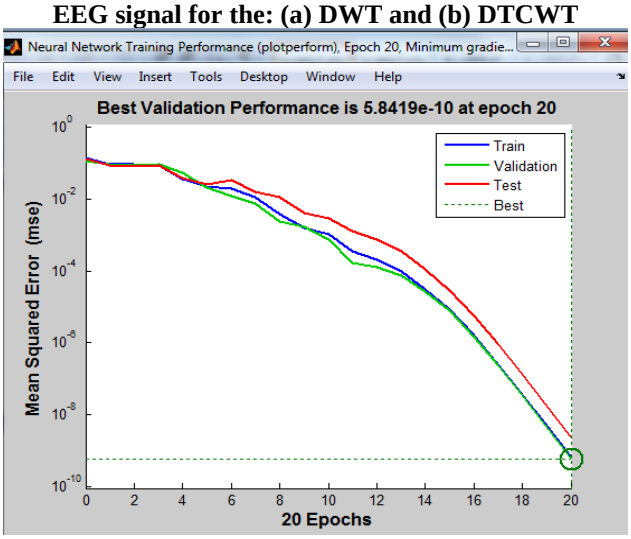


Fig. 10 Best validation performance curve for an NN after training

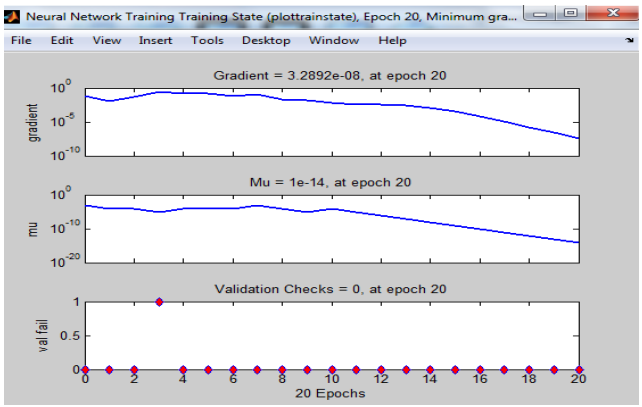


Fig. 11 Plots for the estimation of training states

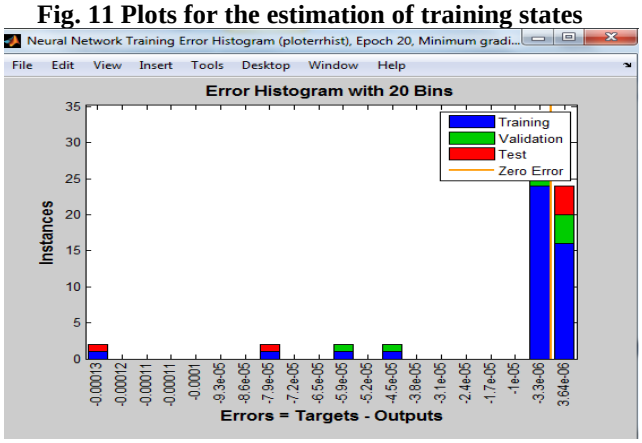


Fig. 12 Histogram showing NN training errors

Using DTCWT algorithm, perfect reconstruction can be achieved from wavelet coefficients than from the DWT algorithm. Using DWT, it cannot be achieve beyond level1. After training the neural network, the best performance validation rate, network training state and the training error are estimated from the plots as depicted in following figures. Fig 10 reflects the best validation performance curves with MSE for an NN that obtained minimum gradient at epoch 20. The curves in fig 11 show the estimation of training states at epoch 20. Errors after NN training are plotted as histogram in fig 12.

VIII. CONCLUSION

The proposed DTCWT based algorithm is a new algorithm to detect and classify Amyopathic Lateral Sclerosis as consistently as possible.

The PSD at the delta group in ALS nurses was discovered to be significantly less through the evaluation of the suggested technique. Decreased Delta group exercise represents organizational and behavioral modifications in the neural network of the person caused by ALS. The median reduction in exercise in the impacted person's Delta group is 60-90%. The peak period for calculation of the suggested algorithm is about 9.5 seconds. The DTCWT algorithm's PSD estimate of EEG signals, in particular the delta band producing the potential biomarker, is therefore useful to identify and classify ALS as easily as possible. DTCWT is the effective technique for the identification and classifying of biomarkers of DWT even where multi-level decomposition using DWT also gives biomarkers, as shows the comparison analysis of DTCWT with DWT. The testing of proposed algorithms with sample data sets achieves 100 per cent precision.

Real-time analysis of EEG signal for ALS classification using DTCWT algorithm and the Development of Graphic User Interface (GUI) for ALS classification by using the proposed algorithm are the further enhancement of this study and analysis.

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