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DTCWT Based EEG Biomarker Detection and Classification for Amyotrophic Lateral Sclerosis

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Abstract:

Amyotrophic Lateral Sclerosis (ALS) is the most common progressive neurodegenerative disorder reflecting the degeneration of upper and lower motor neurons. Motor neurons controls the communication between nervous system and muscles of the body. ALS results in the loss of voluntary control over muscular activities along with the inability to breathe and the maximum life expectancy of affected individual will be 3-5 years from the onset of symptoms. But the lifetime of affected people can be extended by early detection of disease. The usual methods for diagnosis are Electromyography (EMG), Nerve Conduction Study (NCS), Magnetic Resonance Imaging (MRI) and Magneto-encephalography (MEG). But some of these methods may erroneously result in neuropathy or myopathy instead of ALS and some do not provide any biomarker. EEG is comparatively least expensive method and it provides biomarker for ALS detection. ALS is always associated with fronto-temporal dementia (FTD). The spectral analysis of EEG will reveal the structural and functional connectivity alterations of the underlying neural network that occurs due to FTD and it can generate potential biomarkers for the early detection of ALS. A novel algorithm has been developed by exploiting the Dual Tree Complex Wavelet Transform (DTCWT) technique and it can overcome the short comes of existing methods for the analysis and feature extraction of EEG. Deterministic biomarkers were obtained from spectral analysis of EEG and the proposed algorithm provided 100% accuracy for all the test datasets.

Keywords — **Amyotrophic Lateral Sclerosis, DTCWT, EEG, PSD, NN**

I. INTRODUCTION

Amyotrophic Lateral Sclerosis (ALS) is a neurodegenerative disorder that is progressive muscular paralysis in nature. It belongs to a group of neurodegenerative disorders known as Motor Neuron Disease (MND). ALS affects motor neurons, which are nerve cells located in the brain, brain stem and spinal cord, meant for overall control and communication between the brain and voluntary muscles of the body. Motor neurons control the activities such as speaking, walking, breathing, swallowing and gripping. Step by step transmission of messages are necessary for the initiation of muscular activities and co-ordination of muscles; Messages from the upper motor neurons located at brain are transmitted to the lower motor neurons in the spinal cord and from there to particular muscles of the body. ALS especially affects lower motor neurons that reside in anterior grey column of the brain stem and spinal cord and also the upper motor neurons that are located in prefrontal gyrus, parietal cortex and premotor cortex. Prefrontal motor neurons are involved in planning and organizing the works of upper and lower motor neurons. The malfunctioning of the motor neurons gradually ruins the ability of the brain to start and control the voluntary movement. [1, 2]

Incidence of ALS is more in male than female (2:1) and usually affects the people aged above 40 years. About 5-10% of the cases in which the disease is inherited with genetic contribution of about 61% that requires any one of the parent carrying the respective genes causing ALS, called Familial ALS (FALS) and the remaining 90% of the cases are Sporadic ALS (SALS) that do not have any familial history of ALS [2]. There is a probability that some familial genes may also be involved in sporadic ALS. 13% of the ALS patients

exhibit a full blown fronto-temporal dementia (FTD). 40% of ALS patients show the presence of progressive cognitive and behavioral impairment. And 40% remain cognitively affected mildly and they exhibit a slower trajectory compared to those affected by cognitive impairment [2, 3].

Biomarkers are the biological measurements that help in identifying the rate of progression of the disease. The biomarkers will help in the early detection of ALS. ALS leads to structural and functional alterations of the neural network. Measurements of neural connectivity will obtain potentially useful biomarker for both motor and cognitive disorder [2, 3]. The usual methods for diagnosis are Electromyography (EMG), Nerve Conduction Study (NCS), Magnetic Resonance Imaging (MRI) and Magneto-encephalography (MEG). The irregularity patterns obtained from NCS and MEG may erroneously result in neuropathy or myopathy instead of ALS. MRI of ALS patients may be normal which do not provide any biomarker an it is an expensive method. These methods sometimes result in diagnosing errors that occurs in 5-10% of ALS cases. Electroencephalogram (EEG) is the easiest and non-invasive method to measure the electrical activities of brain. It gives a clearest view of brain functioning that helps in initial stage of diagnosis. It is the efficient, widely available and relatively inexpensive method to capture the activities in neural network. EEG data are related to real-time neural activity with a greater temporal resolution. The spectral EEG analysis is based on static relations with a known number of frequency bands that represents significant biological and patho-psychological characteristics [3, 4, 18].

In EEG based Brain Computer Interfacing (BCI), EEG act as the control signals. BCI is a bridging system for the communication between brain and physical world. The EEG acquisition system collects the brain waves underlying the scalp and then digitalizes it with a specific sampling frequency in order to store the data in computer. The microvolt level voltage potentials from electrodes are then amplified approximately ten thousand times for BCI purpose. The EEG can be classified into five frequency bands for BCI. These bands are Delta, Theta, Alpha, Beta and Gamma which are associated with specific brain activities. Delta waves represent the frequency range 0.5-4 Hz. It is primarily associated with deep sleep and waking state. The Delta waves reflects the defects in the brain. Theta waves lie in the frequency range 4-8 Hz. Theta waves are associated with emotional stress, creative inspiration and deep meditation. Alpha waves lie in the frequency range 8-12 Hz. Alpha waves are associated with relaxed awareness as well as inattention and these waves are strongest in occipital cortex and frontal cortex. Beta waves lie in the frequency range 12-35 Hz. Beta waves are associate with the motor activities and it is strongest over motor cortex. Beta waves decreases during motor movement or when there is an intention to move. Gamma waves lie in the frequency range 35 Hz and above. Gamma waves reflect the mechanism of consciousness [6,15].

The EEG signal processing has been completed by applying the most efficient methods for feature extraction and biomarker detection to overcome the drawbacks of existing methods. Eigenvector method produces frequency spectra of high resolution when the Signal to Noise Ration (SNR) is low. Eigenvector methods are best suiting only for EEG signals that contain many distinct sinusoids that are artifact dominant and also Pisarenko method which is one of the eigenvector method introduces spurious zeros that results in relatively poor accuracy of PSD. The Time and Frequency Domain (TFD) analysis requires good resolution in both time and frequency domain that is not always possible [7, 8]. Good results can be achieved only by using EEG signals without any artifacts and requires restricted pre-processing methods. Therefore Discrete Wavelet Transform (DWT) and its modified form called Dual Tree Complex Transform (DTCWT) are used for EEG signal processing to get efficient output.

II. METHODOLOGY

The block diagram in Fig.1 shows various steps in EEG biomarker detection and classification. The EEG signal processing was done in MATLAB using the digital signal processing toolbox and wavelet toolbox.

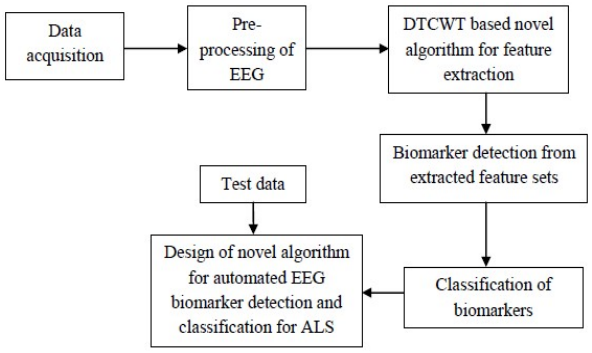

Fig. 1. Stages of EEG signal processing

A. Data Acqisition

EEG data sets of ALS patients are collected and motor imagery EEG data from people who do not have any known neural disorders are also collected from reliable sources.

In this module, the EEG data sets of two groups are considered for this project, 'Normal' group stands for EEG that is collected from people who does not have any known neural disease and 'Subject' stands for EEG collected from ALS patients. These data sets were collected from the database uploaded in the website of BNCI-Horizon-2020 by LADYBIRD, g.tec, Austria. The EEG signals from eight Subjects were collected with a mean age of 58±12. All channels were referenced to right earlobe and left mastoid [19] and the electrodes were placed according to 10-20 international standards. 4096 samples of EEG signals from central region: C_3, C_4, C_z and parietal lobe: P_z channels have been chosen for conducting experiments.

B. Pre-processing

Pre-processing removes artifacts from the input EEG signals. The artifacts can be introduced in EEG due to external noise in circuit, blinking of eyes, movements etc. Moving average filter operation followed by interpolation is used for preprocessing.

C. DTCWT based novel algorithm for feature extraction

DTCWT overcomes the drawbacks of the existing methods for EEG signal processing and the signal is reconstructed from the obtained coefficients

D. Biomarker detection from feature set of data

Power Spectral Density (PSD) analysis of EEG was done for feature extraction. PSD analysis using FFT, MEM and CPSD were done over the five frequency bands (feature set) of EEG signals: Delta, Theta, Alpha, Beta and Gamma the for biomarker detection

E. Classification of biomarkers

The measurements of PSD are used for classification that classifies ALS EEG signals from non-ALS EEG signals. This is done using Neural Network.

F. Design of novel algorithm for automated EEG biomarker detection and classification of ALS

DTCWT based algorithm takes any input EEG signal and readily gives output whether it is ALS or normal signal based on the calculated values of feature set. 2/3rd rule is applied here that gives output TRUE if any two out of the three Neural Network (NN) calculations are TRUE according to the given criteria.

G. Test Data:

Finally the algorithm is tested and validated for its efficiency and performance using different data sets.

III. WAVELET TRANSFORM TECHNIQUES

The basic wavelet analysis expresses a wavelet as an infinite series of wavelets, obtained by shifting and dilating one single function called mother wavelet [11]. The wavelet techniques considered in this module are DWT and DTCWT.

1. Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) uses multi-resolution decomposition method as shown in Fig 3. DWT decomposes an EEG signal into different resolution levels to extract the percentage of distribution of its feature over a particular frequency range. The low frequency component is important in detecting the biomarker.

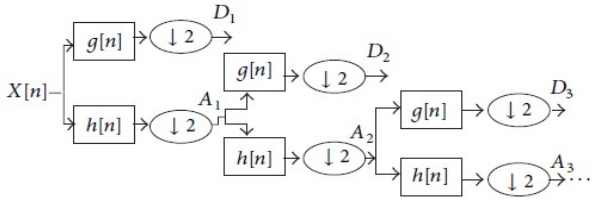

Fig. 3. Multilevel DWT decomposition [5]

The input signal X(n) is decomposed using two digital filters, g(n) & h(n) where g(n) is high-pass filter and h(n) is low-pass filter. The output at every stage consists of a detail (D) and approximation (A).Approximations (A) are the high scale, low-

frequency elements of the input signals whereas Details (D) are the low scale, high-frequency elements. The signal is then down-sampled with a sampling factor 2 and approximations are fed as input to next stage [7]. The relationship between low-pass filter and wavelet is given in Equation (1) and the high-pass filter's complementary z-transform is expressed as given in Equation (2) where $H(z)$ represents filter's h z-transform.

$$H(z)H(z^{-1}) + H(-z)H(-z^{-1}) = 1 \quad (1)$$

$$G(z) = zH(-z^{-1}) \quad (2)$$

DWT is most appropriate for signals with irregular patterns or transients that have impulses at different time instances. But it has some drawbacks such as: Inability for shift invariance, aliasing due to down sampling, imperfect reconstruction beyond level 1 and poor directional selectivity which is inability to distinguish between -45º and +45º spectral features [9, 10].

2. *Dual Tree Complex Wavelet Transform*

Dual Tree Complex Wavelet Transform (DTCWT) is a modified form of the DWT. It is used in this algorithm to overcome short comes of DWT. DTCWT provides perfect reconstruction along with all the properties of DWT. The DTCWT uses two real DWT trees to implement a real tree and an imaginary tree [9]. In Fig 4, *Tree a* generates real part of the transform and *Tree b* generates imaginary part of the transform.

Analytic filters are used for analysis in DTCWT. The input signal x is decomposed using the combination of high_pass and low_pass filters. H_{0a}, H_{1a}, H_{ob} and H_{1b} are the level1 filters. H_{1a} & H_{1b} are the high pass filters and H_{0a} and H_{0b} are the low pass filters. At every level, the output of the low pass filters will be fed as the input to next level of decomposition. Filters H_{00a}, H_{01a} along with the filters H_{00b} and H_{01b} will together form Kingsbury Q-shift filters with specific number of taps. The nearest hold-up of respective filters is displayed inside the parenthesis in Fig. 4 and q is ¼th of the sample period. In order to achieve a better symmetry between the two trees in the structure, odd and even filters are used from stage to stage. The filters are designed so as to reduce the minimum mean-square error such that the impulse response to x_{00a} and x_{00b} should be similar to the maximum extent. To achieve uniform intervals between the samples corresponding to both trees under level1, the delay in one tree should be essentially half a sample differs of the other [10]. In MATLAB, Farras' almost symmetric filters are used for the decomposition at level1 to generate symmetric bi-orthogonal wavelets with almost orthogonal behaviour and they obey the orthogonality property.

DTCWT decomposes a signal in terms of a complex shifted and dilated mother wavelet ψ(x) and scaling function φ(x). The real (r) and imaginary (i) parts of the wavelet and scaling functions The wavelet generated from the *Tree a* can be estimated using the Equation (3) and that generated from *Tree b* can be estimated using Equation (4)

$$\psi_r(t) = \sqrt{2}\sum_n H_{1a}(n)\,\varphi_r(2t-n) \quad (3)$$

$$\psi_i\, t = \sqrt{2}\sum_n H_{1b}(n)\,\varphi_i(2t-n) \quad (4)$$

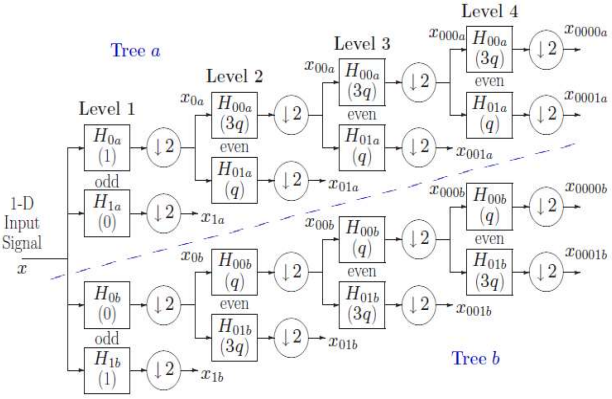

Fig. 4. 4-level Dual Tree Complex Wavelet Transform [7]

The scaling functions can be obtained from *Tree-a* and *Tree-b* using the equations (5) and (6) respectively.

$$\varphi_r\, t = \sqrt{2}\sum_n H_{0a}\, n\, \psi_r(2t-n) \quad (5)$$

$$\varphi_i\, t = \sqrt{2}\sum_n H_{0b}\, n\, \psi_i(2t-n) \quad (6)$$

The complex wavelet function ψ_c can be produced from the real and imaginary wavelet functions as shown in Equation (7).

$$\psi_c = \psi_r + j\psi_i \quad (7)$$

Dual Tree Complex Wavelet Transform has the following advantages over other wavelet techniques [10] are: Approximate shift invariance, Good directional selectivity for 2D and higher

dimensionality mD, Perfect reconstruction using short linear phase filters, Limited redundancy independent of number of scales, 2^m : 1 for mD.

IV. DESIGN OF ALS FEATURE EXTRACTOR & CLASSIFIER

A. Data Acqisition

Two input EEG signals from the same person will be fed as input data to the automated ALS feature extractor and classifier.

B. Moving Average Filter

The original EEG signals in time series can be decomposed into different trend components. Filters are used to obtain the trend component that changes one time series into another by modifying or eliminating some time components from the existing one. Moving average filter is a specific linear filter that takes the average of a number of points from the input signal and gives a single output. The smoothing action of moving average filter will decrease the noise in signal and extracts the brain waves from the input EEG signal.

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

The Equation (8) explains the moving average filter operation for 10 points. x[ ] is the input signal and y[ ] is the artifact-less EEG signal. The energy values of input EEG were calculated to verify the difference in input EEG data base that contains artifacts from the artifact-less EEG.

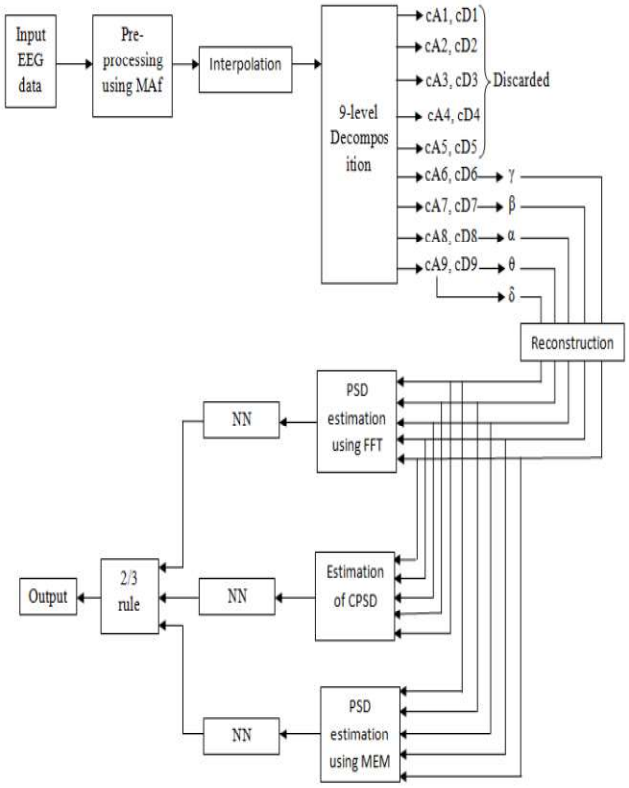

Fig. 5. Proposed algorithm

C. Interpolation

Interpolation reconstructs the artifact-less EEG signal by introducing new discrete data points inside closed set of familiar data points. A linear interpolation of the filtered EEG was accomplished using MATLAB. The missing information is calculated such that the mean of the data points will be considered as the new intermediate point. The 5-point interpolation was achieved by introducing 0's in place of missing information and then low pass filtering that sequence to get the artifact-free EEG signal with interpolated data at new frequencies. La-grange's equation, Equation (9) is used for the interpolation of 5-point sequence.

$$y = \frac{(x-x_1)(x-x_2)\dots(x-x_5)}{(x_0-x_1)(x_0-x_2)\dots(x_0-x_5)} y_0 + \frac{(x-x_1)(x-x_2)\dots(x-x_5)}{(x_1-x_0)(x_1-x_2)\dots(x_1-x_5)} y_1 + \dots + \frac{(x-x_0)(x-x_1)\dots(x-x_5)}{(x_5-x_0)(x_5-x_1)\dots(x_5-x_4)} y_5 \quad (9)$$

where x_1 to x_n are the known data points and y_0 to y_n are known values of interpolation.

D. 9-level Decomposition

The five frequency bands of the EEG contain the major characteristics of EEG spectrum. PSD is calculated by Fourier transforming the

reconstructed DTCWT coefficients. Fast muscular movements and the underlying neuromuscular signals are single events and the Fourier analysis of such transient signals can be physiologically informative which cannot be found in temporal signal [13]. Three types of PSD analysis of the P_z, C_3 and C_z signals are done here for feature extraction.

1) PSD using FFT

The signals are analysed using Fast Fourier Transform (FFT) which is the method of calculating Discrete Fourier Transform and gives frequency response. The data sequence is applied to data windowing which produces modified periodogram. The average power of PSD using periodogram is obtained from bandpower calculation. The number of points in the DFT is taken as the next power of two greater than the input signal length which is reconstructed from DTCWT coefficients [7, 12]. The FFT of *N* point input signal X(n) with period *T* and length *L* is calculated using Eqution (10)

$$x_i(\omega) = \sum_{n=0}^{N-1} x(n) e^{-j\omega nT} \tag{10}$$

The resulting periodogram is given in Equation (11),

$$P_{xx}(f) = \frac{1}{NU} \left| \sum_{n=0}^{N-1} x_i(n)\omega(n) e^{-j2\pi fn} \right|^2 \tag{11}$$

where U is the normalization power and ω (n) is the window function. It is given by Equation (12)

$$U = \frac{1}{N} \sum_{n=0}^{N-1} \omega^2(n) \tag{12}$$

The average of these modified periodograms is calculated using Equation (13)

$$P_{xx} = \frac{1}{L} \sum_{n=0}^{L-1} P_{xx}(f) \tag{13}$$

2) Cross Power Spectral Density

The cross spectral density analysis allows the determination of relationship between two time series as a function of frequency. In this module the cross spectral density is used to find the correlation in all five frequency bands of data from two different electrodes which are of the same person. The brain waves from P_z, C_3 and C_z are studied here. The CPSD of brain waves represent underlying connectivity of the neural network. CPSD is computed using Welch's averaged and modified periodogram method [16]. The complex cross spectrum of two time series x and y, P_{xy} (ω) is calculated using the Equation (14).

$$P_{xy}(\omega) = \sum_{m=-\infty}^{\infty} R_{xy}(m)\, e^{j\omega m} \tag{14}$$

where R_{xy} is is the cross relation sequence and it is estimated using the equation (15)

$$R_{xy}(m) = E\{x_n + m\, Y^*{}_n\} = E\{x_n Y^*{}_{n-m}\} \tag{15}$$

where E{ } denotes expected value of function operator, x_n and y_n are compound stationary-random-processes and *n* lie in the range -∞< n <∞.

3) PSD using Maximum Entropy Method

The Maximum Entropy Method (MEM) is used for PSD analysis because of its high resolution [10]. The Maximum Entropy power spectrum of a signal is calculated using the coefficients called the model parameters a_k, which are obtained from autocorrelation matrix. The PSD, X(f) using MEM will be a finite sequence of model parameters and it is calculated using [7,14] Equation (16).

$$P_{xx}(f) = \frac{\sigma^2{}_{wp}}{\left|1 + \sum_{k=1}^{p} \hat{a}_p(k)\, e^{-j2\pi fk}\right|^2} \tag{16}$$

where a_k stands for autocorrelation coefficients, k is the order of the filter and norm of $\sigma^2{}_{wp}$ will give the nearest lowest MSE of the p^{th} order predictor that is disposed in equation (17)

$$\sigma^2_{wp} = r_{xx}(0) \prod_{k=1}^{p} [1 - |a_k(k)|^2] \tag{17}$$

and the corresponding r_{xx} is given by the equation (18), where *m* should be greater than or equal to zero

$$r_{xx}(m) = \frac{1}{N} \sum_{N=0}^{N-m-1} x^*(n)\, x(n+m) \tag{18}$$

E. Reconstruction

After decomposition using DTCWT and DWT, the EEG signal as well as each of its components is reconstructed from the obtained wavelet coefficients. Thus the feature set consisting of γ, β, α, θ and δ was obtained and it was fed as the input to all three PSD estimation algorithms.

F. Neural Network Classifier

Neural networks (NN) models the activities of biological nervous system. The neural networks were trained for a pattern recognition based upon the weights assigned to the connection elements. The neural networks are usually trained to get a particular targeted output for a specific set of inputs

and supervised method trains the network based on the comparison made on outputs and targets until it approximate the function by matching the output and target elements. Feed-forward-back-propagation NN has been applied for the classification of ALS. Generalized Widrow-Hoff learning formula is applied to multi-layer networks and non-linearly distinguishable transfer functions to accomplish the gradient-descent-algorithm.

In NN, the sum of all the inputs which are approximately weighted (W_p) is biased with bias *b* and fed as the input to transfer function *f*. The output *a* of the neural function is estimated using [17] the Equation (19)

$$a = f(W_p + b) \tag{19}$$

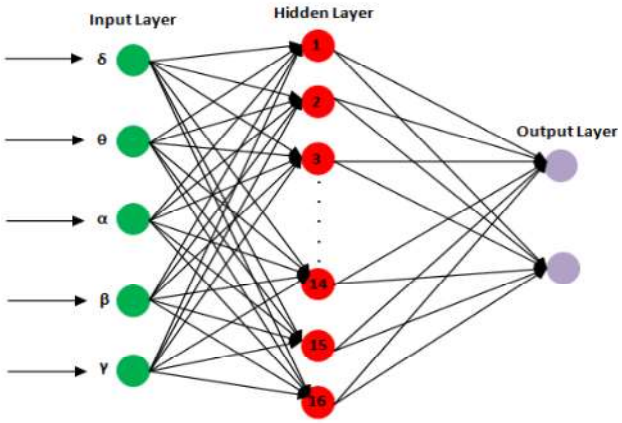

Fig. 6. Proposed NN

The proposed NN with 5-inputs, hidden layer of 16 neurons and two outputs are as shown in Fig. 6. All the three networks are created in the same pattern. Different PSD estimations which give the biomarkers were provided as the stimuli to the multi-layer NN. The NNs for classification of ALS have been created using tansig as the hidden layer's transfer function and purelin as the transfer function of output. Three NNs with different inputs have been created for ALS classification and each of the networks consists of a hidden layer and output layer. The hidden layer consists of 16 neurons each. Inputs were transmitted from nodes at input layer to the hidden layer nodes without performing any computation of inputs. The dimension of input matrix was five. The back-propagation-algorithm computes and updates the inputs and biases in the negative path of performance function. A looping of the back-propagation-algorithm is computed using Equation (20) to achieve better result, x_K stands for a vector of present weights and biases, α_K represents the learning rate and g_K stands for current gradient.

$$x_{K+1} = x_K - \alpha_K\, g_K \tag{20}$$

The *traingdm* mode used, provides a back propagation algorithm with faster convergence and steepest descent according to momentum. A fractional sum of the latest weight and the next weight nominated by back_propagation formula will account for change in weight or momentum. The effective change will be dependent on momentum constant such that effective change will be a number within 0 and 1. Gradient is ignored when momentum-constant is 1. The Levenberg-Marquardt algorithm (trainlm) was used as the training function in NN classifier for ALS and was assessed using the Equation (21)

$$x_{K+1} = x_K - (J^T J + \mu I)^{-1} J^T e \tag{21}$$

where *J* represents the Jacobian matrix that consist of the first derivatives of the NN errors corresponding to weights and biases and *e* represents an array of errors. This becomes gradient descent when μ is very large [17].

G. 2/3rd Rule and Output Classification

The networks are trained such that the output value should be 0.8 if the input EEG signals belong to Subjects group and the output should be 0.2 if the input EEG signals do not belong to Normal group or non-ALS. The output of the DTCWT based algorithm is accomplished on the basis of two by three rule, such that the output will be classified as ALS if any two pattern recognizing NNs generate output as ALS for given set of input signals, else the input EEG signals will be classified as non-ALS.

V. RESULTS

Power Spectral Density analysis on five frequency bands of the EEG signal, using three different methods are plotted and shown in the Fig.8.

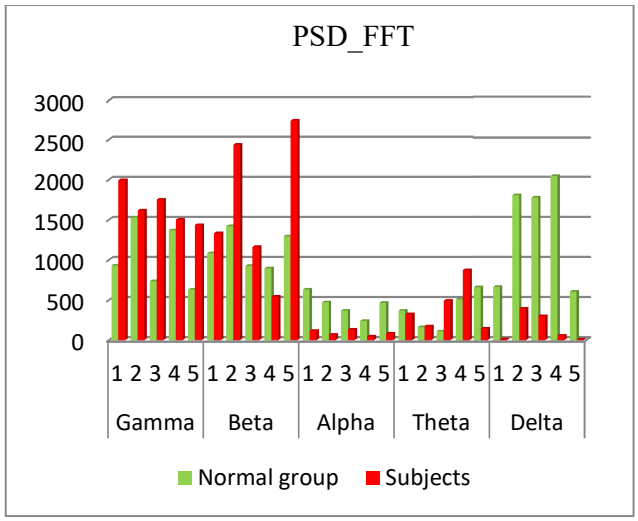

Fig. 8(a). PSD of normal group & subjects using FFT

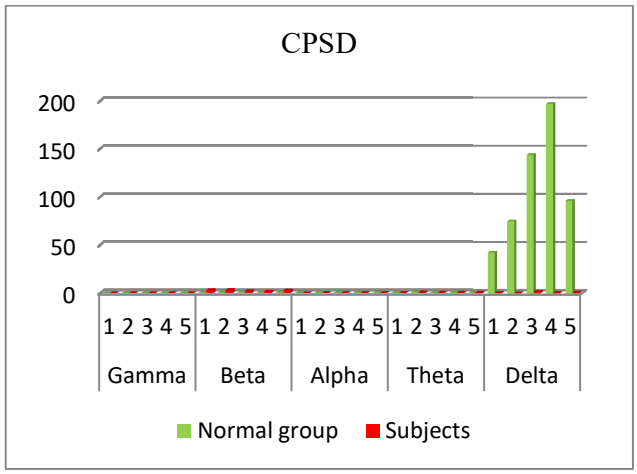

Fig. 8(b). PSD of normal group & subjects using CPSD

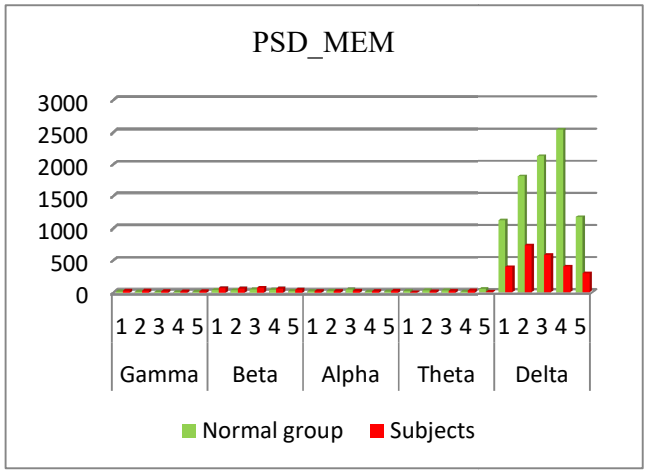

Fig. 8(c). PSD of normal group & subjects using MEM

All three PSD estimations & analysis show that the PSD of Delta band is relatively decreased in ALS patients. This reveals that the functional connectivity in Delta band is relatively very less in ALS patients than in normal group.

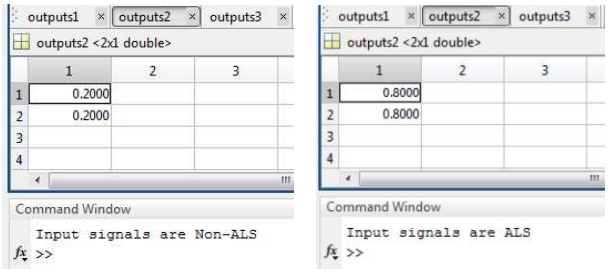

Fig. 9. Output of the DTCWT based algorithm for classification of ALS, when input signals are:
(a) Output when input signals are normal or Non-ALS.
(b) Output when input signals are ALS

The outputs were classified as ALS, if any two pattern recognizing networks generate output as ALS for given set of input signals. The final output of the algorithm will be either of the outputs as displayed in Fig. 9. It is found from the analysis that the DTCWT wavelet decomposition method is more efficient than DWT analysis for ALS EEG signal processing. The results are consistent while using DTCWT and the results are not consistent with DWT algorithm. The training of neural network with tansig-purelin transformations and by using PSD estimations of the feature sets obtained from DWT and DTCWT based algorithms are shown in Fig. 10. The target output is 0.2 and it has been achieved using DTCWT algorithm.

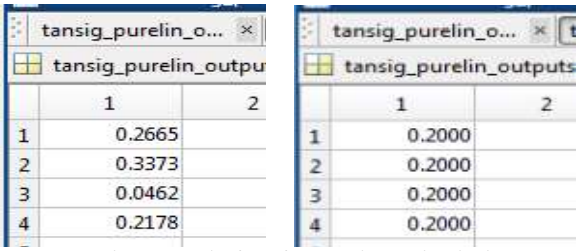

Fig. 10. Result of NN for normal EEG signal using:
(a) DWT and (b) DTCWT

VI. CONCLUSION

The proposed method based on DTCWT based algorithm is a novel algorithm for the consistent detection and classification of Amyotrophic Lateral Sclerosis at the earliest. From the analysis of proposed method it has been found that the PSD of Delta band is comparatively very less in ALS patients. The reduced activity of the Delta band reflects the structural and functional alterations occurred in the neural network of the affected person due to ALS. The average decrement in Delta

band activity of an affected person is approximately 60-90%. The maximum computation time for the proposed algorithm is approximately 9.5 seconds. The comparative study of DTCWT with DWT reveals that DTCWT is the efficient method that produces consistent result for biomarker detection as well as for classification of ALS EEG, even when multi-level decomposition using DWT also provides biomarkers to some extent. Therefore, PSD estimation of EEG signals based on DTCWT algorithm, especially that of the Delta band generates the potential biomarker and the proposed method can be used as the best algorithm for easiest and earliest detection and classification of ALS. 100% accuracy is achieved for the verification of the suggested algorithm with test datasets.

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