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Energy Density Feature Extraction using Different Wavelets for Emotion Detection

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ABSTRACT

Electroencephalography (EEG) is a technique which is used to record the electrical activity of the brain.EEG measures voltage fluctuations occurred from classic current flow within the neurons of the brain. In this Research the EEG data collection was performed by using 10-20 Electrode Placement System and the database was collected from Columbia Asia Hospital. In this paper, new features are extracted using Discrete Wavelet Transform (DWT) and further the emotions were classified using EEG signals.Feature Extraction is performed by using DWT and the Decomposition of EEG signals is extracted for 8 levels. Features like Energy Density, Entropy are extracted.Energy Density was calculated for “Bior 5.5”,“db4”,“db8” and “Haar wavelet”, and the energy density is compared to analyse the better wavelet. The feature extracted signals are then classified using Artificial Neural Network (ANN) and the neural system is trained, evaluated and the classification is performed which can be compared for emotional states classification.

Keywords: Electroencephalogram (EEG), Emotion detection, Energy density,Feature extraction, Discrete Wavelet Transform (DWT), Daubechies wavelet(db4),Artificial Neural Network (ANN)

INTRODUCTION

Researchers are finding ways to focus on Human computer interaction to empower computers to understand human emotions. Emotion Recognition (ER) is the first and one of the most important issues. Affective computing brings forward and plays a dominant role in the effort to incorporate computers, and generally machines, with the ability to interact with humans by expressing cues that postulate and demonstrate Emotional Intelligence (EI) related attitude. Successful ER will enable machines to recognize the affective state of the user and collect emotional data for processing in order to proceed toward the terminus of emotion-based HMI, the emotional-like response [1].Emotion is one of the most essential features of humans. It analyses the mental status of mind. The state of feeling of emotions is complex and it causes physical and psychological changes that influence behavior of individuals. The emotional experiences can be sub-divided into two dimensions called as valence and arousal. These two dimensions are depicted on a 2-dimensional co-ordinate map [3].Parts of the brain activated for different Emotion sets Happy - The left side of the frontal lobe - the left prefrontal cortex. Sad The right side of the frontal lobe –the right prefrontal cortex. Laughter and humor - Temporal lobe and hypothalamus Anger - Limbic center of the brain The small structure within the limbic system is termed as the amygdale. Fast eye moment sleep - It is the cerebral cortex. The most famous model is the representation of emotions in two or three dimensional spaces of valence-arousal space. The valence ranges from negative to positive and arousal extends from calm to excite. The 2-D valence arousal model is shown in Figure 1.

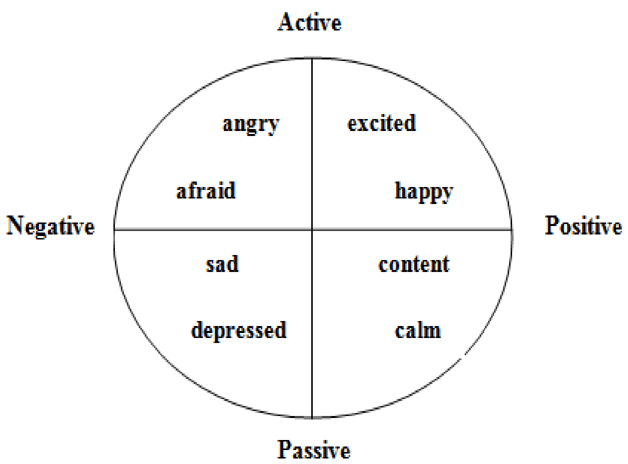

Figure 1. 2-Dimensional Valence-Arousal Model

Many methods are used for estimating human emotions in the past. Some of the authors have implemented different methods for feature extraction and classification which is been discussed.

The author in [2] analysed that emotion perception relates to similar thinking, learning and remembering a consequent of complicated brain activity.These detected emotions can be used as a user input to the brain computer interface system. Researchers on human EEG signal reveal that brain activity plays a major role in the effective way of implementing brain computer interfaces**.** In paper [3] relates the studies related to an important functional activity of EEG signals. Many methods are used for estimating human emotions in the past. Different researchers have carried out different methods for feature extraction and classification which is been discussed. In [4], the author has proposed a novel approach for the Classification of BCI signals. In this work Discrete Wavelet Transform (DWT) was implemented for feature extraction using Daubechies wavelet db4, for a 5 level Decomposition of EEG signals. They have considered 100 samples in a single channel EEG at a sampling rate of 173.61 Hz. The features computed were mean of the envelope spectrum in each sub-band**,** energy, Standard Deviation, maximum value of the envelope spectrum in each sub-band**.** The classification of EEG signals was performed based on bagging method. In this method a Neural Network Ensemble (NNE) Algorithm was developed for the classification of EEG signal by implementing the N-class classification into N independent 2-class classification, which uses Classification accuracy of about 98.78% was achieved. In [5] two feature extraction methods namely DWT and Wavelet Packet Decomposition methods were implemented.

Both these methods generate several sub-band signals from which six different statistical features, including higher order statistics were extracted. A sampling rate of 100 Hz was considered by using Symlet 4 wavelet. Classification of BCI signals was implemented using K nearest neighbor (K-NN) algorithm and an average classification accuracy of 92.8% was achieved. In [6] a human emotional state from bio-signal system was developed to recognize human emotional state from biosignals.Two methods were proposed namely Multimodal Bio-signal Evaluation and Emotion recognition using Artificial Neural Network. An accuracy of 85.9% was obtained for Back Propagation. The study results can help emotion recognition studies to improve recognition rates for various emotions of the user in addition to basic emotions. In [7], the author has performed the feature extraction of EEG signals using Daubechies Wavelet by considering 32 channels. The physiological signals were recorded at 512 Hz sampling rate and down sampled to 256 Hz, for a 5 level decomposition to obtain the detailed and approximate co-efficients with a sampling rate of 512 Hz to capture the information from signals as it provides good results for nonstationary.The experiments were performed to classify different emotions from four classifiers namely, Support Vector Machine (SVM), Multilayer Perceptron (MLP), K-Nearest Neighbor (K-NN) and Meta Multiclass (MMC).The average accuracies obtained were 81.45%,74.37%,57.74% and 75.94% for SVM, MLP, KNN and MMC classifiers. In [8] the accuracy of EEG signal classification using different classifiers namely multi layer perceptron Neural network (MLPNN), Probabilistic neural network (PNN) and Multi-class support vector machine (M-SVM) was compared for four different emotions. Lyapunov exponents and wavelet transform is used for feature extraction.SVM and PNN gives a greater accuracy of 99.28% and 98.05% respectively of classification than MLPNN which is 93.63%..

An application of an artificial neural network (ANN) technique with an feature extraction method was proposed in [9] by using wavelet transform for the classification of EEG signals.Three classes of EEG signals were used: Normal, Schizophrenia (SCH), and Obsessive Compulsive Disorder (OCD).The architecture of the artificial neural network used in the classification is a three-layered feed forward network which implements the Back propagationa Learning Error algorithm.After training, the network with wavelet coefficients was able to correctly classify over 66% of the normal class and 71% of the schizophrenia class of EEG signal.In [10] a classification model using Neural Network for epilepsy treatment. An EEG data of about 100 single channel EEG signals were considered which was decomposed into sub-bands by using db2.The decomposition was performed for 11 levels. The wavelet coefficients were clustered using the K-means algorithm for each frequency sub-band. Wavelet coefficients obtained from EEG segments with 4097 samples were clustered by K-means algorithm. In this work, the MLPP Model is supported by the Levenberg–Marquardt (LM) algorithm by considering a single hidden layer of 5 hidden neurons resulting in classification of the EEG segments. Classification accuracy of 95.60% was achieved for normal and abnormal patients using the test data.From the above related works,in our Research, feature Extraction is performed using Daubechies 4 Wavelet, the features are extracted and are classified for two different emotional states,In this paper, Classification of EEG signals is proposed using artificial neural network using Feedforward Back-Propagation Algorithm

DISCRETE WAVELET TRANSFORM (DWT)

DWT is a time scale representation of the digital signal which is obtained using digital filtering techniques and is based on sub-band coding. The signal to be analyzed is passed through filters with different cut off frequencies at different scales. In DWT, a signal can be analyzed by passing it through an analysis filter bank followed by a decimation operation. When a signal passes through these filters, it is split into two bands.

The low pass filter, which corresponds to an averaging operation, extracts the coarse information of the signal. The high pass filter, which corresponds to a differencing operation, extracts the detail information of the signal. The output of the filtering operations is then decimated by two. Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal as shown in Figure 2**.**This is called the Mallat's algorithm or Mallat-tree-decomposition. At each decomposition level, the half band filters produce signals spanning only half the frequency band. This doubles the frequency resolution as the uncertainty in frequency is reduced by half. In accordance with Nyquist's rule if the original signal has a highest frequency of ω, which requires a sampling frequency of 2ω radians, then it now has a highest frequency of $\omega/2$ radians. It can now be sampled at a frequency of ω radians thus discarding half the samples with no loss of information. The decimation by 2 halves the time resolution as the entire signal is now represented by only half the number of samples. Thus, while the half band low pass filtering removes half of the frequencies and thus halves the resolution, the decimation by 2 doubles the scale. The filtering and decimation process is continued until the desired level is reached [11].The maximum number of levels depends on the length of the signal.

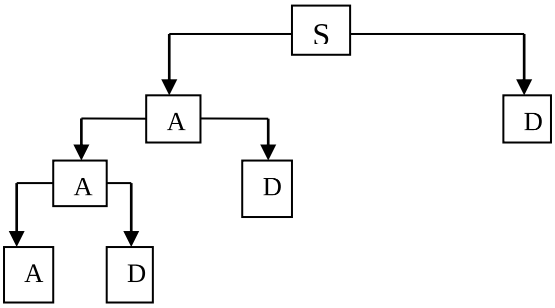

Figure 2. Mallats Tree Decomposition

The low pass filter (LPF) and high pass filter (HPF) decomposes the signal into different scales. The output co-efficient gained by the low pass filter is the approximation co-efficient. The scaling function output is in the form of:

$$\Phi\,(t) = 2\sum_{q=0}^{M} h(q)\,\Phi(2t-q) \quad \text{..............} \; (1)$$

The output of the high pass filter is the detailed co-efficient. The wavelet function output is the in the form of:

$$w(t) = 2\sum_{q=0}^{M} g(q)\,\Phi(2t-q) \quad \text{..............} (2)$$

The approximation co-efficient is consequently divided into new approximation and detailed co-efficients. By choosing the mother wavelet the co-efficient of such filter banks are calculated.This decomposition process is repeated until the required frequency response is achieved from the given input signal. The selection of an appropriate wavelet function has been a challenge in this research.

Table 1, represents the Energy values calculated for four different wavelets namely Bior 5.5, db4, db8 and Haar wavelet. From the above Energy table, Daubechies 4 wavelet is having a higher energy density compared to other wavelets. This is represented in the following graph shown in Figure 3.

Among different wavelets Daubechies wavelet has been chosen as they have a maximal number of vanishing moments and hence they can represent higher degree polynomial functions.

Table 1. Energy Values of Different Wavelets

Bior 5.5	Db4	Haar	Db8
28.2849	185.96	10.2701	129.1491
55.4622	257.028	109.2775	120.1251
73.5089	121.216	61.9483	63.4327
48.3495	159.329	86.827	72.6479
60.1156	85.998	38.569	45.0794
32.5086	87.407	43.4727	67.9186
27.6603	90.995	37.4688	47.9579
37.6693	42.123	30.1919	38.4824
23.8043	54.708	35.4021	65.2777
46.2647	42.756	50.8233	66.668
16.8454	50.926	36.9348	80.8556
22.0555	28.438	21.3817	48.9944
21.714	22.915	24.2226	28.9318
26.0667	18.769	21.3639	46.2955
24.3186	32.07	38.0919	54.3242
37.6455	49.301	50.1058	55.4126

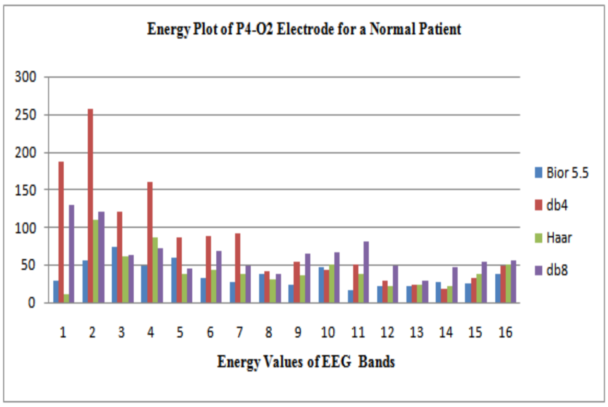

Figure 3. Energy Graph of Normal Patient representing different wavelets

The number of vanishing moments is what decides the wavelet's ability to represent a signal.Daubechies family of wavelets has been chosen because of their high number of vanishing moments making them capable of representing complex high degree polynomials.Thus Daubechies 4 wavelet provides a good signal output.

DAUBECHIES 4 WAVELET (Db4)

The Daubechies wavelet transforms are defined in the same way as the Haar wavelet transform by computing running averages and differences via products with scaling signals and wavelets the only difference between them consists in how these scaling signals and wavelets are defined. For the Daubechies wavelet transforms, the scaling signals and wavelets have slightly longer supports, i.e., they produce averages and differences using just a few more values from the signal.

The Daubechies D4 transform has four wavelet and scaling function co-efficients. The scaling function co-efficients are:

$$\{h_0 = \frac{1+\sqrt{3}}{4\sqrt{2}}\ ;\ h_1 = \frac{3+\sqrt{3}}{4\sqrt{2}}\ ;\ h_2 = \frac{3-\sqrt{3}}{4\sqrt{2}}\ ;\ h_3 = \frac{1-\sqrt{3}}{4\sqrt{2}}\}\ldots\ldots.(3)$$

Each step of the wavelet transform applies the scaling function to the data input , if the original data set has N values and the scaling function will be applied in the wavelet transform step to calculate N/2 smoothed values in the ordered wavelet transform and the smoothed values are stored in the lower half of the N element input vector.The wavelet function co-efficient values are:

$$\{g_0 = h_3\ ;g_1 = -h_2\ ;\ g_2 = h_1\ ;\ g_3 = -h_0\ \}\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

The wavelet transform applies the wavelet function to the input data if the original data set has N values. The original data set has N values and the wavelet function will be applied to calculate N/2 differences. The scaling and wavelet functions are calculated by taking the inner product of the co-efficients and four data values. The equations are shown as: Daubechies D4 scaling function:

$$a_i = h_0 s_{2i} + h_1 s_{2i+1} + h_2 s_{2i+2} + h_3 s_{2i+3}\ \ldots\ldots\ldots\ldots\ldots\ldots..(5)$$

$$a[i] = h_0 s[2i] + h_1 s[2i+1] + h_2 s[2i+2] + h_3 s[2i+3]\ldots..(6)$$

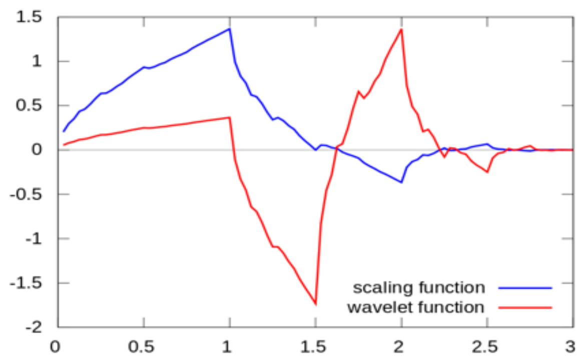

Figure 4. Daubechies Wavelet representing scaling and wavelet

Daubechies D4 Wavelet function:

$$c_i = g_0 s_{2i} + g_1 s_{2i+1} + g_2 s_{2i+2} + g_3 s_{2i+3}\ \ldots\ldots\ldots\ldots\ldots\ldots..\ (7)$$

$$c[i] = g_0 s[2i] + g_1 s[2i+1] + g_2 s[2i+2] + g_3 s[2i+3]\ \ldots..(8)$$

Each iteration in the wavelet transform step calculates a scaling function value and a wavelet function value.

IMPLEMENTATION

The proposed work describes the raw EEG which is acquired by using 10-20 electrode placement system. Though there are multiple acquisition system, the acquisition is done using 10-20 electrode placement system and it is found that 10-20 system is the best for the data acquisition with respect to the data consistency. Since it is a standard system for measuring the electrical activity of a brain with respect to all the standard positions on the scalp,therefore it is considered as the most suitable method for EEG signal acquisition.The acquired EEG signal which is in the format of .xls is loaded to the MATLAB workspace and converted to .csv format for further processing.The formatted EEG dataset is analyzed by using Daubechies 4 wavelet transform to extract all the fundamental frequency components of EEG signal i.e. alpha, beta, gamma, delta and theta.EEG frequency bands which relates to various brain states.The extracted EEG bands are further decomposed. After further decomposition, prominent features like Energy, Entropy are computed. The features extracted are fed as input for Classification using Artificial Neural Networks.The proposed Block diagram is shown in Figure 5.

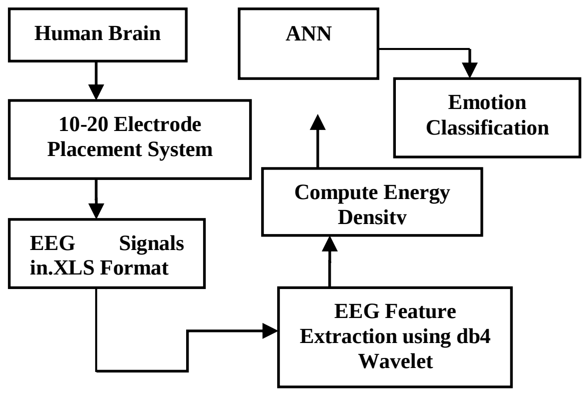

Figure 5. Proposed Block Diagram of Emotion Recognition System

The wavelet decomposition of any signal x(t) is represented in terms of its decomposition coefficients given by the equation:

$$x(t)=\sum_{k=-\infty}^{\infty} A(k)\varphi_k(t)+\sum_{j=0}^{\infty}\sum_{k=-\infty}^{\infty} D(j,k)\,\psi_{j,k}(t)\ \ldots\ldots\ldots\ldots\ldots(9)$$

In this work, “db4’’ wavelet is chosen for decomposition, db4 wavelet is known for its orthogonality property and its smoothing features and it is useful for detecting the changes in EEG signals.The raw EEG signal x(n) is decomposed by a sampling frequency of 500Hz which is shown in Figure 6.

Table 2. Decomposition of EEG Signals and their frequency range in Hz

Decomposition Levels	EEG Bands	Frequency Range (Hz)
D5	Gamma	37-56 Hz
D6	Beta	11-37 Hz
D7	Alpha	6-11 Hz
D8	Theta	4-6 Hz
A8	Delta	0-4 Hz

The multi-resolution analysis is decomposed using "db4" for eight levels of decomposition, which yields five separate EEG sub-bands. The main objective of the proposed method is the division of the original EEG signals into different frequency bands. Table 2, shows the decomposed EEG bands lying at their frequencies after decomposition.The feature which is obtained after Frequency decomposition, is Entropy. Entropy is calculated for the five EEG Bands for six different electrodes. Table 3, describes the entropy values extracted for the sub-bands CD5, CD6, CD7, CD8 and CA8 after decomposition.

Table 3. Entropy values of EEG Bands

Subject	Electrodes	cD5	cD6	cD7	cD8	cA8
		Entropy				
Normal Subject	FP2-F4	0.20	0.45	0.48	0.55	0.58
	F4-C4	0.19	0.38	0.51	0.55	0.59
	FP1-F3	0.19	0.27	0.41	0.53	0.51
	F3-C3	0.21	0.25	0.47	0.61	0.64
	P3-O1	0.19	0.33	0.45	0.57	0.45
	P4-O2	0.26	0.34	0.43	0.53	0.54

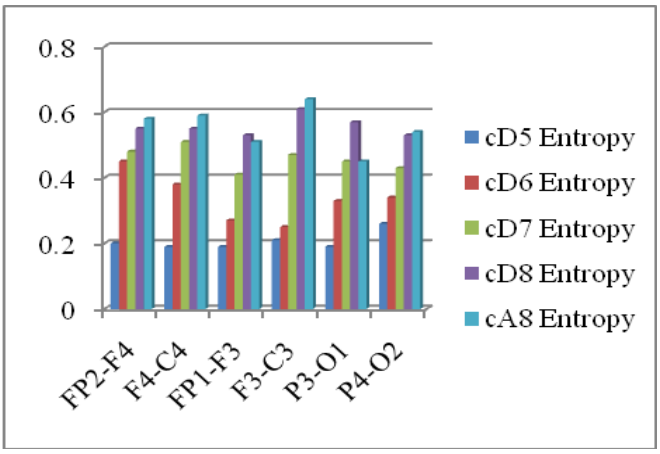

Figure 6. Shows the entropy graph of EEG Bands for different electrodes

CLASSIFICATION USING NEURAL NETWORKS

A typical ANN consists of large number of neurons, units, cells (or) nodes that are organized according to a particular arrangement. Each neuron is connected to other neuron by means of directed communication links, each with an associated weight. The weights represent information being used by the net to solve the problem.Each neuron has an internal state, called its activation (or) activity level, which is a function of the inputs it has received.Typically a neuron sends its activation as a signal to several other neurons. It is important to note that a neuron can send only one signal at a time, although that signal is broadcast to several other neurons.

Neural networks are adjusted or trained, so that a particular input leads to a specific target output. Such a situation is shown in Figure 7.The network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network.

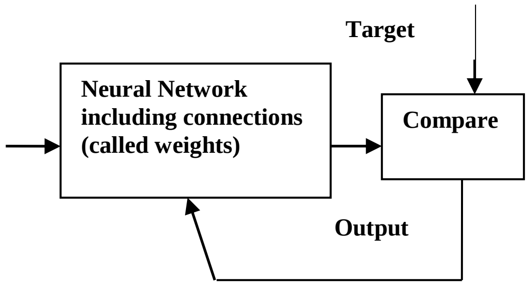

Figure 7. Neural Network Model

MULTI-LAYER FEED FORWARD NEURAL NETWORKS (MLP)

MLP consists of at least three layers of nodes. Except for the input nodes, each node is a neuron that uses a nonlinear activation. MLP utilizes a supervised learning technique called back Propagation for training. Its multiple layers and non-linear activation distinguishes MLP from a linear perceptron. This class of networks consists of multiple layers of computational units, usually interconnected in a feed-forward way.

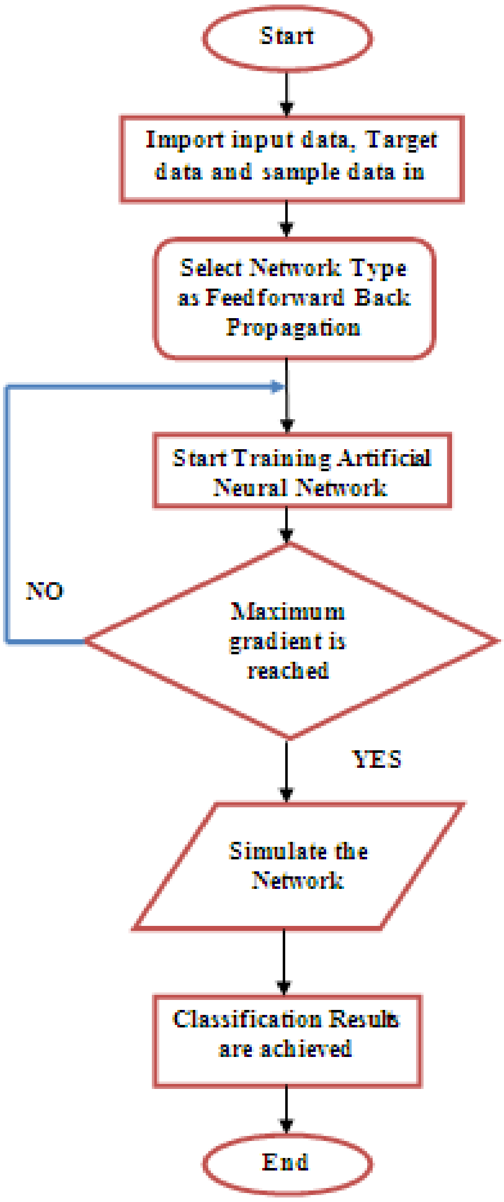

Figure 8. Flowchart of Neural Network Design

Each neuron in one layer has directed connections to the neurons of the subsequent layer. Back-Propagation neural network forms a mapping between inputs and desired outputs from the training set by altering the weighted connections within the network.The Neural Network Toolbox is designed to allow many kinds of networks. Neural network design flow is explained in the following flowchart, which represents the complete procedure of NN design in Figure.8.Feedforward Back Propagation Neural Network (FFBPNN) are appropriate for solving problems that involve learning the relationships between a set of inputs and known outputs**.**

RESULTS AND DISCUSSION

Classification of emotions is performed using FFBPNN training algorithm is implemented using neural network Toolbox.In this work, training is opted for considering two subjects namely normal and abnormal subjects.The energy graph of both Normal and Abnormal Subjects shown in Figure 9. and Figure 10.

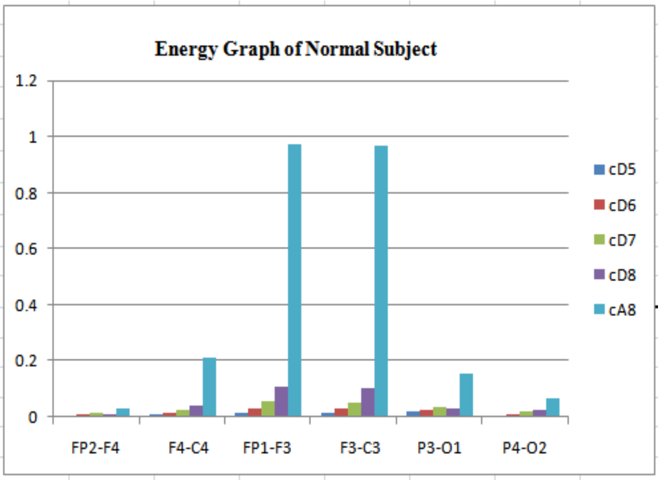

Figure 9. Energy Graph of Normal Subject of EEG Bands

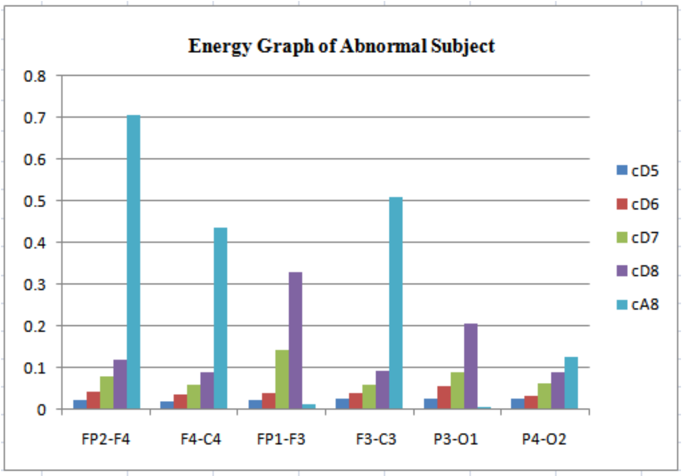

Figure 10. Energy Graph of Abnormal Subject of EEG Bands

Figure 9, represents the varying energy values of normal subject.From the energy graph,FP1-F3 and F3-C3, shows a greater energy density value compared to other electrodes. F3-C3 is a region which lies in the frontal and central parts of the brain lobes. The frontal lobe is located at the front of each cerebral hemisphere and positioned in front of the parietal lobe and above and in front of the lobe. The frontal and parietal lobes is associated with movement, recognition, reasoning and problem solving. Figure 10, represents the varying energy values of abnormal subject. From the energy graph, FP2-F4 in this the lobe is seen in the frontal part of the brain and it is associated with conceptualize plan and emotions.

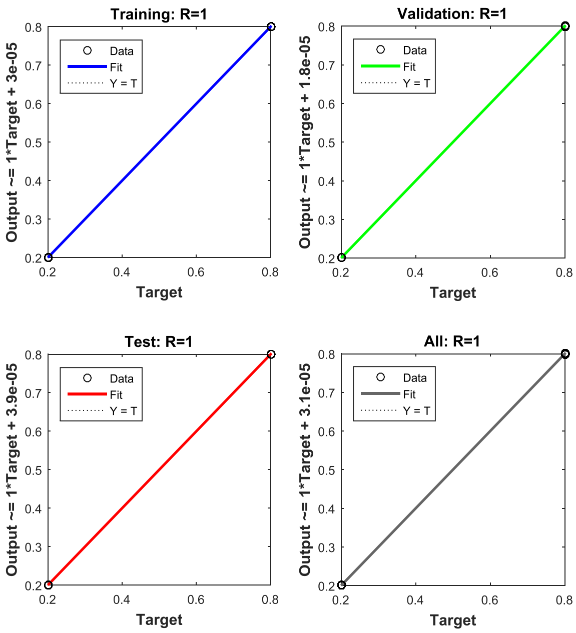

Figure 11. Snapshots of Training States

The Plot Performance shows the best validation performance with 19 epochs. The plot train state shows the system state after training based on the Plot regression which shows the plot between and training samples, between output data and validation samples and between output data and test samples (R value shows the correlation between output and target values).In the Neural network training stage, input data and sample data are fed to the neural network Classifier, where the targets are set as 0.2 for normal and 0.8 for abnormal subjects.

The energy density of these two subjects is calculated and fed to the NN toolbox for classification to analyze its performance. The performance of neural network is analyzed by considering the input values and the target values which are set. The performance graph, regression plot is achieved, which gives an optimal solution for better classification accuracy in terms of efficiency. The MATLAB software enables training with different convergence criteria, tolerance level, activation functions and number of epochs. The neural network models studied in this investigation uses transfer function = 'TANSIG' as activation function. After this the network model is ready for prediction of desired output.The plots namely plot Performance, Plot Regression are shown in Figure 11 and Figure 12.The performance graph, regression plot is achieved, which gives an optimal solution for better classification accuracy in terms of efficiency.Table 4 represents the performance value, the number errors and the number of epochs for two different networks, where the epoch of Network 1 is 19 and the epoch of Network 2 is 18.The classification accuracy for each type of network is achieved which can be compared with one another, for both normal and Abnormal subjects.

Table 4. Training and Simulated output results

Network Type	Performance	Epochs	Gradient	Errors	Classification Accuracy (%)	
					Normal Subject	Abnormal Subject
Network 1	0.00014	19	0.00094	5	98%	86%
Network 2	0.00028	18	0.00228	12	100%	66%

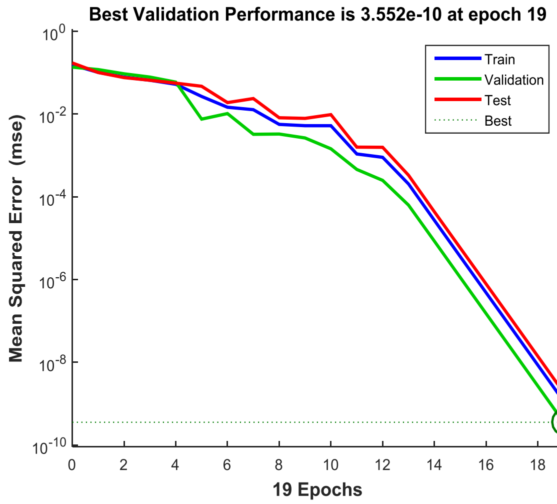

Figure 12. Snapshot of Best Validation Performance

Network 2, gives an optimal accuracy of 100% to normal subject and 66% to abnormal subject compared to Network 1, Network 1 achieves an accuracy of 98% to normal subject and 86% to abnormal Subject.Thus the classification accuracy is performed for two emotional states.

CONCLUSION

The proposed method in this paper highlights the performance of ANN Classification. A novel method is implemented by choosing a better wavelet for feature extraction. The classification performance is performed by achieving an optimal accuracy of 86% for network 1 for abnormal subject and network 2 achieves an accuracy of 66% .In the future more number of emotional states can be implemented with different classification algorithms

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