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A COMPARATIVE ANALYSIS OF EPILEPTIC EEG SIGNALS

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ABSTRACT

Epilepsy is a perilous neurological disease covering about 4-5% of total population of the world. Its main characteristics are seizures which occur due to certain disturbance in brain function. During epileptic seizures the patient is unaware of their physical as well as mental condition and hence physical injury may occur. Proper health care must be provided to the patients and this can be achieved only if the seizures are detected correctly in time. In this paper, a system is designed using wavelet decomposition method and different training algorithms to train the neural network for classification of the EEG signals. The results showed that when Levenberg-Marquardt training algorithm was used the accuracy comes out to be 93.9%, which is better than other training algorithms.

KEYWORDS: Electroencephalogram, Epilepsy, Wavelet Transform, Energy Distribution, Neural Network

INTRODUCTION

After stroke, epilepsy is the second most common neurological disorder affecting approximately 4-5% of the world's population [1], [2], [3]. Epilepsy is a neurological anarchy manifest by impulsive intermittent episodes of sensory commotion. Persistent, uncontrolled, spastic seizure activities are the main characteristics of epilepsy. It is the result of a sudden disturbance of brain function and These are mainly result of certain unwanted and asynchronous firing in cerebral neurons.

The medical condition of epilepsy is as old as human existence [3]. There have been many strategies to detect such firing or seizure activities in the brain. Electro-Encephalo-Gram (EEG) is the most common technique for detection of these electrical activities [18]. It is a non-invasive technique used to acquire electrical impulses travelling through scalp. Although there are certain techniques for continuous detection of these seizures such as Epilepsy Monitoring Unit (EMU), electro cardio graph, accelerometry and electro dermal systems but these are very costly and time consuming method and hence not much preferred.

Even though anti-epileptic drugs have been helped many patients but roughly one-third of them are unresponsive to those too [4]. So, researchers and doctors came together to find such a elucidation which can help both doctors and patients to perceive as well as help to envisage seizures even before they occur. This can be done on an account of the brain areas involved during seizures.

EEG is one of the most common means used for detection of these seizures in humans. EEG is very informative and easy to access clinical tool to evaluate human brain activities. Though time domain recognition is also possible for EEG analysis but it is inadequate which results in the intercession of some automation and computer techniques for this purpose.

Many applications have been developed regarding analyses and classification of electrical activities of the brain. The working models or applications involve various complex methods such as signals acquirement, pre-processing of that acquired signal, decomposition of the EEG signal and then the classification of the extracted features. Many models are in existence for detection of seizures.

Leach et.al.[5] used three different protocols for acquisition of EEG signals: r-EEG, after sleep deprivation EEG, and after oral temazepam and concluded that sleep deprived EEG is much suitable in case of seizures. The author concluded that sleep deprived EEG have better sensitivity and it is better than those of r-EEG and DI-EEG. Shoeb et.al.,[6] used wavelet decomposition method with support vector machine as a classifier and spatial distribution method is also used in their model. Their system detected 131 out of 139 EEG signals but also declared 17 false detections. Rosso et.al.[7] proposed a system which used wavelet energy and wavelet entropy for the analysis of EEG using classifiers based on Shannon and Trellis code tree. The authors also reviewed that quantifiers based on wavelet decomposition tools and also self organized rate is triggered by epileptic focus.

Srinivasan et.al.[8] proposed a model using Elman network, recurrent neural network. The network used both time and frequency domain features of EEG signals and it was concluded that result obtained by this network with single input were much higher than that using multiple inputs. Srinivasan et.al. [9] designed a system that used approximate entropy as an input feature and neural network classifier is used for classification purpose. Zandi et.al.[10] designed a wavelet based system which used moving window analysis. G.Chen [11] used dual tree complex wavelet-fourier features. The author demonstrated an EEG seizure detection method by using the dual-tree complex wavelet fourier features. EEG database from the University of Bonn was used to test the system.

Shoeb et.al. [12] proposed a system that used machine learning approach for patient specific classifier that detect onset of epileptic seizures. Omerhodzic et.al.[17] proposed an algorithm for classification of EEG signal based on. DWT used with the MRA is applied to decompose EEG signal at resolution levels of the components of the EEG signal then feed forward neural network is used for classification according to the percentage distribution of energy features and their results shows that the proposed classifier has the capability to recognize and classify EEG signals correctly.

This paper is an extension of [17] and also presents a novel approach for classification of EEG signals of epileptic and healthy subjects. The decomposition of EEG signals has been done with the help of debauches five decomposition technique (db5) and dissimilar parameters such as energy distribution, current gradient are detected. The support artificial neural network has been used for classification of signals with different training algorithms and their regression and overall accuracy is compared accordingly.

This paper is organized as follow. The brief introduction and related literature survey has be covered in Section I. Section II of the paper includes the proposed methodology. The simulation setup and results are given in Section III. In Section IV, conclusion of the paper is given.

EEG Signals

EEG signal acquisition is the most important and most informative tool used these days due to its advantages over other acquisition techniques [13]. The electrical activities of the cerebral neurons spread throughout the head. These electrical signals also reach the scalp and can be easily detected by electroencephalogram (EEG) by placing the electrodes over the scalp in 10-20 International system of electrodes placement recognized all over the world. The EEG shows patterns of normal or abnormal brain electrical activity. Some anomalous patterns may occur with a number of unlike conditions.

EEG signals can be categorized into different frequency bands according to their frequency such as alpha (α), beta (β), gamma (γ), delta (δ) and theta (θ). Table I gives a brief description of these frequency bands [14].

International 10-20 System

This system of electrode placement is a recognized system which describes the location of electrodes to be placed over the scalp for the acquisition of the EEG signals. Figure 1 depicts the different points for the location of the electrodes. The numeric '10' and '20' are written which means the electrodes must be placed either 10-20% of the total front-back or right-left distance of the human skull.

Table 1: Brief Description of Different Frequency Bands of EEG Signals [14]

Signal	Brain Location	Frequency Band	Description
Delta (δ)	Frontal(adults) Posterior(children)	Below 4Hz	Sleep time, frequent in babies. Active in attention tasks.
Theta (θ)	Different locations	4-8Hz	Mostly found in young children Active in drowsiness or arousal in older children and adults Idle state Found to be spike when a person in attempting to repress action or response
Alpha (α)	1.Posterior, both sides 2.Higher in amplitude on dominant side 3.Central sites at rest	8-12Hz	Relax or Reflecting state Closing of eyes.
Beta (β)	Both on left & right side of brain Symmetrical distribution activity Most evident frontally	12-30Hz	Alert or focused, active, busy state
Gamma (γ)	Both left & right sides of brain, midline to front and back	30-100Hz	Sensory processing Short term memory activities

The different letters have been assigned to different locations for the ease of identification of lobe and hemisphere of the brain. The odd number describes left hemisphere whereas the even number describes the right hemisphere of the skull. This system uses two reference points, one at nasion (above the nose) and other at inion (the bony lump at the base of the skull).

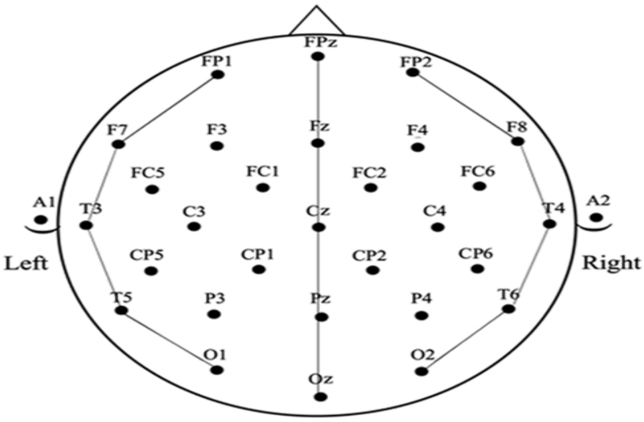

Figure 1: International 10-20 System for Electrode Placement Over Scalp

Wavelet Transform

The decomposition of the signals can be done with different decomposition techniques according to the type of the signal, stationary or non-stationary signal. If the signal does not vary much with respect to time that is if the signal seems to be ideal over long period of the time then it is said to be stationary signal and if it varies with respect to time it is referred as non-stationary signal [15]. For stationary signals Fourier transform is the generalized technique being used for decomposition. But it is not suitable for signals like EEG signals as it is a non-stationary signal. EEG signals contain a number of non-stationary characteristics. Its decomposition can be done using wavelet decomposition method. Figure 2 views the wavelet decomposition tree of EEG signal. The signals are passed through low-pass and high-pass filters for decomposition and the filter outputs are decimated by the factor of two to obtain approximated (A1) and detailed (D1) coefficients. Further, approximated coefficients are sent to next stage for repetition of the procedure and it is carried out repeatedly till the signal is decomposed at desired level.

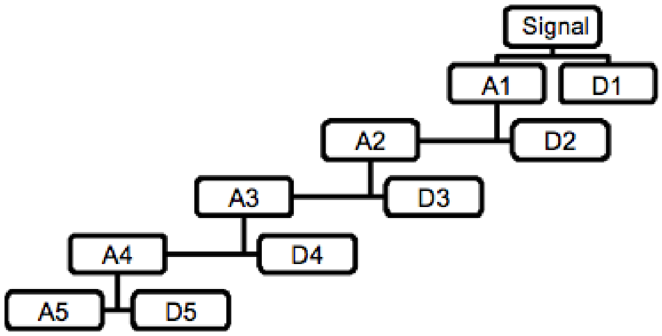

Figure 2: Wavelet Decomposition Tree [15]

In wavelet transform, decomposition is done on the basis of time-scale as well as frequency-scale and further compression of the signal is also done. Wavelet transform uses a mother wavelet to derive its different sets of wavelet functions.

Wavelet Families

There exist different wavelet families, daubechies (db), coiflets (coif), symlets (sym), biorthogonal (bior), which are described briefly in Table 2.

Table 2: Different Wavelet Families

Wavelet Families	Wavelets
Daubechies	db1 or haar, db2,db3……db45
Coiflets	coif1, coif2, coif3, coif4, coif5
Symlets	sym2, sym3, sym4,…….sym45
Biorthogonal	'bior1.1', 'bior1.3', 'bior1.5' 'bior2.2', 'bior2.4', 'bior2.6', 'bior2.8' 'bior3.1', 'bior3.3', 'bior3.5', 'bior3.7' 'bior3.9', 'bior4.4', 'bior5.5', 'bior6.8'

The decomposition matrices L and H are given as:

$$L_{N/2,N}=\begin{bmatrix} l(1) & l(0) & ... & 0 \\ l(3) & l(2) & l(1) & l(0) \\ 0 & l(L-1) & ... & l(0) \end{bmatrix}$$

$$H_{N/2,N} = \begin{bmatrix} h(1) & h(0) & \dots & 0 \\ h(3) & h(2) & h(1) & h(0) \\ 0 & h(H-1) & \dots & h(0) \end{bmatrix}$$

Also the initial signal ‘x’ is decomposed into two sequences $h = Hx$ and $l = Lx$ after passing it through high-pass and low-pass filters respectively and hence their components are saved in h and l respectively. Then the coefficients are chosen which are used as feature vectors.

Energy Distribution

Energy distribution (ED_i) of the decomposed EEG signals is identified using Parseval’s Theorem. The theorem states that energy of the deformed signal can also be partitioned at different resolution levels, i.e.,

$$ED_i = \sum_{j=1}^{N} \left|D_{ij}\right|^2, i = 1,2, \dots, l \tag{1}$$

$$EA_l = \sum_{j=1}^{N} \left|A_{lj}\right|^2 \tag{2}$$

where l is the level of decomposition of the signal [17] and ED_i represents the energy distribution of the detailed coefficients at different decomposition levels and EA_l represents the energy distribution of approximated coefficients.

Artificial Neural Networks

Artificial neural network is a mathematical tool that mimics some functional aspects of a biological neuron network. It consists of groups of interconnected artificial neurons. The low-level executions of cerebral neurons are replicated by cells and their networks depicting exact functioning synthetically is done using artificial neural networks.

The different neural networks have different learning algorithms and architectures. They also vary fundamentally in the way they learn or work. The most frequently used training algorithm in classification is back propagation algorithm which uses supervised learning technique. The main aim of this algorithm is to reduce errors and train the network continuously until it learns the data. One iteration of this algorithm can be written as $X_{K+1} = X_K \alpha_K g_k$, where X_K is a vector of current weights and biases, g_K is current gradient and α_K is learning rate of the network.

Multilayer Feed Forward Network

Multilayer Feed Forward network, as the name suggests, is a feed forward network with multiple layer. There exist three kinds of neurons in this network, i.e. input neuron, hidden neuron and output neuron. The computational units of hidden layer are called hidden units or hidden neurons. The weights and input layer neurons are connected to hidden layer and the hidden layer neurons and weights are further connected to output layer neurons.

Learning in Neural Network

There exists different method to train our neural network, i.e. there exists learning algorithms for neural network for its training which are classified as supervised learning, unsupervised learning and reinforcement learning. When an input vector is prearranged at inputs together with a set of preferred responses, one for each node, at the output layer this type of learning is called supervised learning. A forward pass is done and the errors between the desired response and actual response are deliberated for each node. These errors are then used to determine the weight changes according to the prevailing learning rule. In unsupervised learning, the weights and biases are modified in response to network inputs only.

There are no target outputs available and most of these algorithms perform clustering operations. This type of learning has applications such as vector quantization.

Back-Propagation Learning Algorithm

In this learning algorithm, artificial neurons are arranged in layers and send their signals forward but the errors are propagated backwards. In neural network there exist three layers mainly such as input layer, output layer and hidden layer. Some of the neural networks may also include one or more intermediate hidden layers. Back-propagation learning algorithm is a supervised learning algorithm which has main aim to reduce error until the network learns the training data perfectly. The simplest execution of back-propagation learning updates the network weights and biases in the path in which the performance function declines most hastily, the negative of the gradient.

Since the error is the difference between the actual output and the preferred output, the error depends on the weights and we must alter these weights in order to diminish this error. The network error is the sum of the errors of all the neurons on the output layer. This algorithm envisages how the error depends on the output, inputs and weights and we can easily amend the weights using method of gradient descendents.

Levenberg-Marquardt Algorithm was designed to approach second order training speed without having to compare the Hessian matrix. The Hessian matrix, when the performance function is in form of a sum of squares, can be written as $H = J^TJ$ and the gradient can be written as $g = J^Te$ where e is a vector of network errors and J is the Jacobian matrix. This matrix contains first derivates of the network errors with respect to the weights and biases. It can be computed through standard propagation technique. The Levenberg-Marquardt Algorithm uses following Newton-like update $X_{K+1} = X_K^-[J^TJ + \mu I]-1J^Te$. In this algorithm, when the scalar μ is large this method turns out to be gradient descent with diminutive step size. Newton's method is much more precise and faster. M is decreased with each successful step and is only increased when a tentative step would increase the performance function.

Bayesian Regularization Algorithm

The main aim of this algorithm is to minimize a combination of squared errors and weights and determines the correct combination so as to produce a network that generalizes well. It also modifies the linear combination. The Bayesian regularization takes place within the Levenberg-Marquardt Algorithm. BP is used to estimate the Jacobian jX of the performance with respect to the weights and bias variables X. Also each variable is adjusted according to Levenberg-Marquardt, jj = jX*jX, je = jX*E, dx = -(jj + I*mu)\je where E is all the errors and I is the identity matrix.

One Step Secant Algorithm

The one step secant (OSS) method is an attempt to bridge the gap between the conjugate gradient algorithms and the quasi-Newton (secant) algorithms. The storage of complete Hessian matrix is not required in this algorithm; it assumes that at each iteration the previous Hessian was the identity matrix. Also in this algorithm the new search direction can be calculated without computing a matrix inverse.

This method finds a root that uses a succession of roots of secant lines to better approximate a root of a function. This method can also be thought of approximation of Newton's method. The MATLAB command for this method is trainoss.

METHODOLOGY

The algorithm block diagram for the proposed system is shown in figure 3. It is divided into three main stages: acquisition stage, feature extraction stage and the classification stage.

In data acquisition stage, the brain electrical impulses are detected by placing electrodes on scalp. The head box used in acquisition may also perform noise reduction; the pre-processing stage prepares the signals in a suitable type of signal so that it can be further processed in desired form. The feature extraction stage maps the pre-processed signals onto a vector which contains effectual and discriminant features. The last stage, i.e., the classification stage uses the feature vectors and arrange them in different classes as per desired by the system.

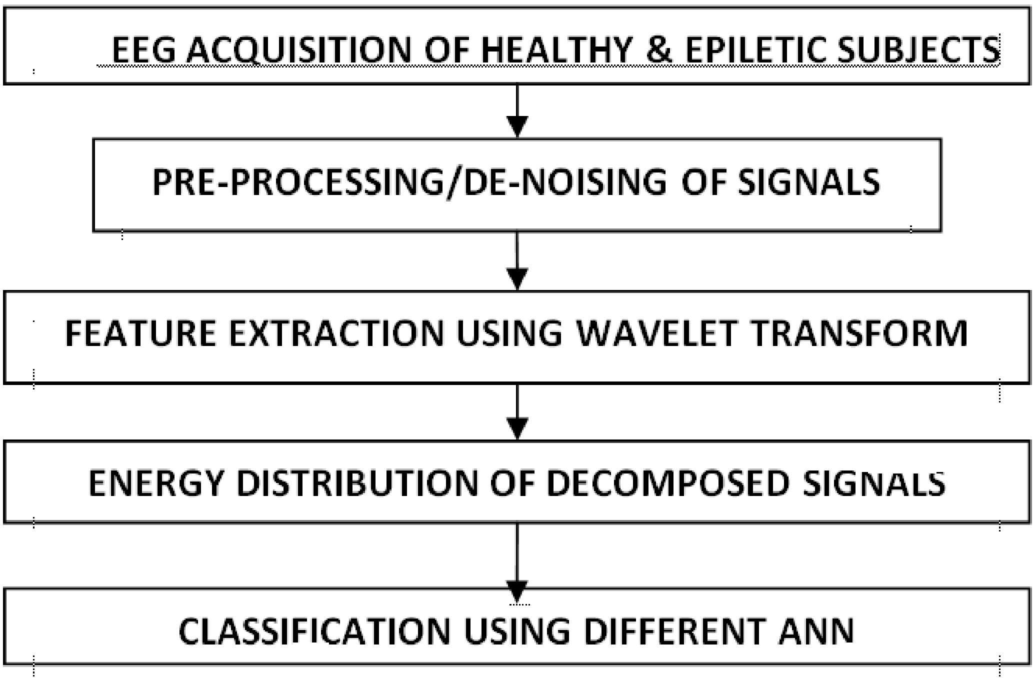

Figure 3: Algorithm for the Proposed System

METHODS

Participants

30 healthy subjects and 30 epileptic patients participated in this study. The ethical statement was taken before acquiring the signals. Their vision was normal or corrected to normal vision. The age ranged from 21 years to 28 years, with a mean of 23.65 years. No one of them was naive to the BCI equipment and paradigm. EEG was recorded in relaxed state continuously for 4 minutes. Each session contains 20 trials. Subjects were required to maintain full visual concentration

Apparatus

RMS EEG-32 Super Spec system was used to extract EEG signals of different subject. The system ensures high resolution, authentic data acquisition through its software and head-box. This system includes the head-box, the adapter, the connecting cables, the electrodes and PC as shown in figure 5.

The head-box is used for connecting electrodes from the scalp to the hardware unit. The signal generated is amplified and then sent to adapter box for signal conditioning. The digital signal generated is then displayed on Super Spec software designed for EEG signals.

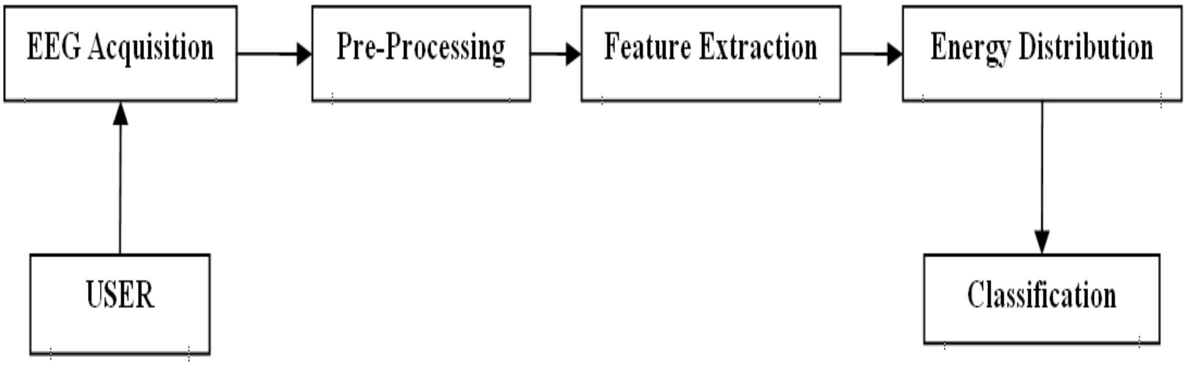

Figure 4: Block Diagram of the Proposed System

The head box minimizes noise pickups. The total integration of analog and digital processing in compact head box gives excellent signal to noise ratio. It can acquire simultaneously 32 channel raw data and also checks true AC impedance online. The brain mapping colour coding can also be done with the head box as per international standard.

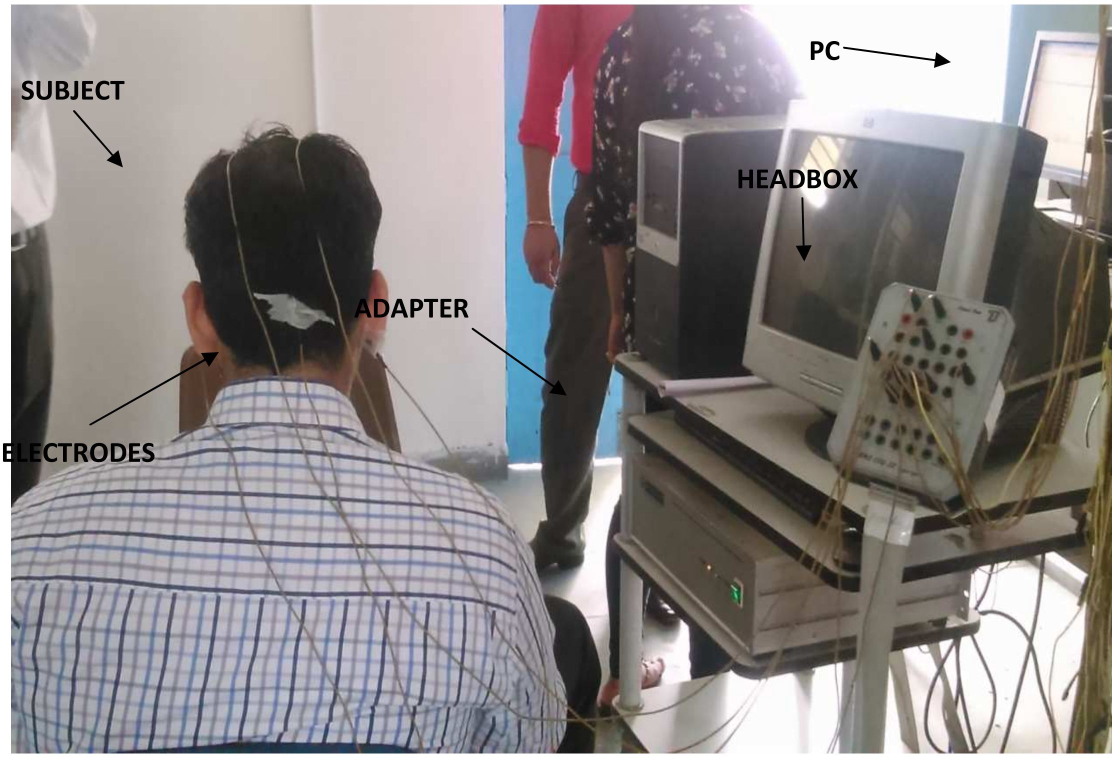

Figure 5: Experimental Setup for EEG Acquisition

RESULTS AND DISCUSSION

Wavelet transform uses a mother wavelet to derive its different sets of wavelet functions. This system used db5. Figure 6 shows the decomposition of EEG signals of normal patients whereas figure 7 shows decomposition of epileptic EEG signal. In this figure detail coefficients are represented as D1, D2, D3, D4, D5 and the approximated coefficient is represented as A5.

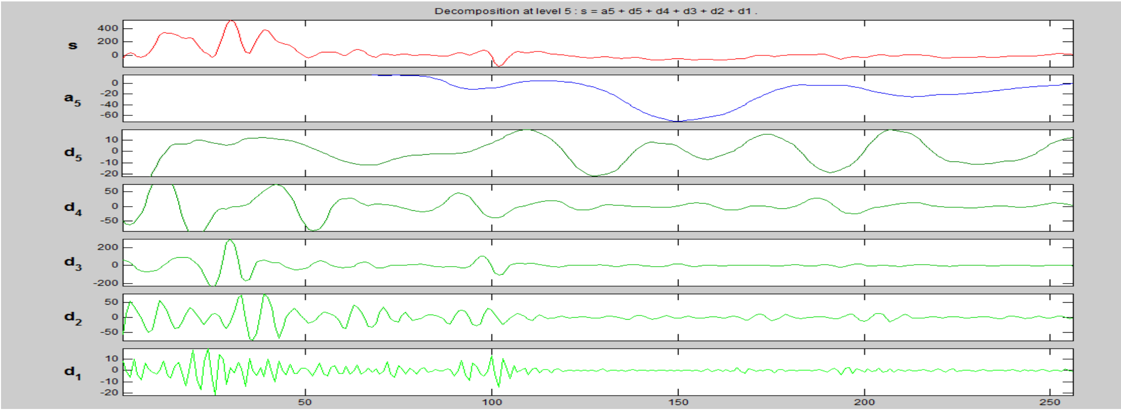

Figure 6: Decomposition of EEG Signals of Normal Patients

The energy distribution for each set of input signals i.e. for epilepsy patients and for healthy subjects are shown in figure 8 and figure 9 respectively. It can easily be recognized that the energy distribution of normal/healthy subjects in D3 and D4 (beta, alpha) are approximately equal and its total value is around 30% and that of epilepsy patients is approximately 50%. The energy distribution of D5 (theta) of normal patients is approximately 20% and that of epilepsy patients is above 40%. It can also be seen that A5 (delta) energy distribution of epilepsy patients is less as compared to that of normal patients. Table 3 shows the average values of detailed energy coefficients and approximated energy coefficients for both healthy as well as epilepsy subjects.

Table 3: Average Energy Distribution of Decomposed and Approximated Coefficients

Average Energy Distribution of Normal Subjects		Average Energy Distribution of Epilepsy Subjects	
EA5	47.68686	EA5	63.84576
ED1	0.11135	ED1	0.166008
ED2	4.025968	ED2	1.484796
ED3	17.19991	ED3	9.093766
ED4	20.48524	ED4	11.16387
ED5	10.49068	ED5	8.854353

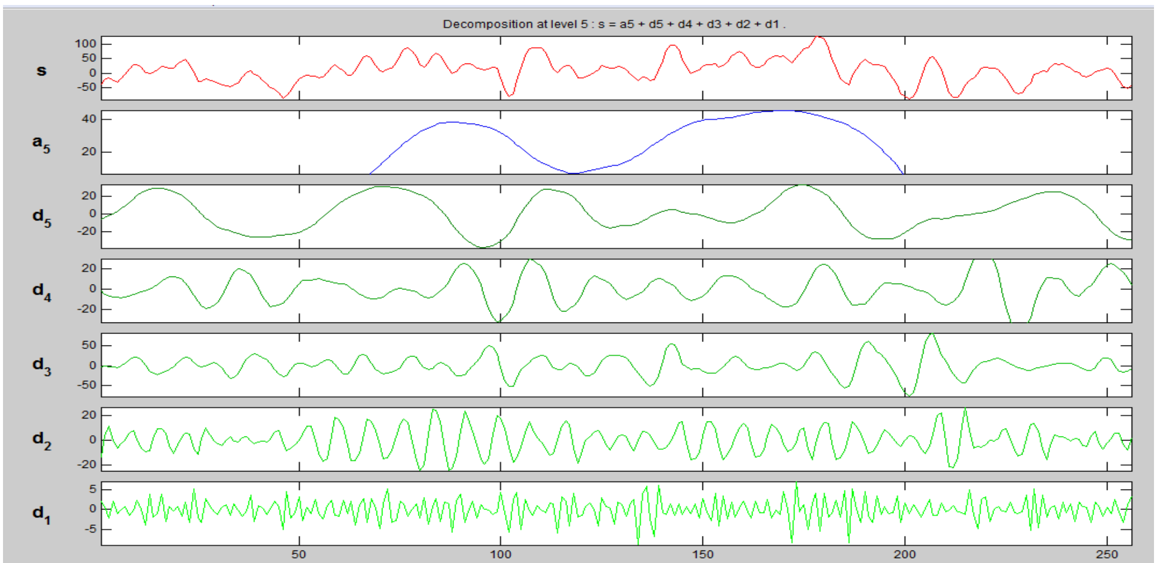

Figure 7: Decomposition of EEG Signals of Epileptic Patients

These energy distribution percentages can easily be used as classifier inputs for classification of these EEG signals. Six dimensional feature sets for training and testing data were constructed based on these energy distribution percentages.

The total size of training or that of testing data is 6 X 300. These vector inputs are applied to the neural network as input vectors. We used different training algorithms to test our neural networks such as Levenberg-Marquardt Algorithm, Bayesian Regularization Algorithm and One Step Secant Algorithm.

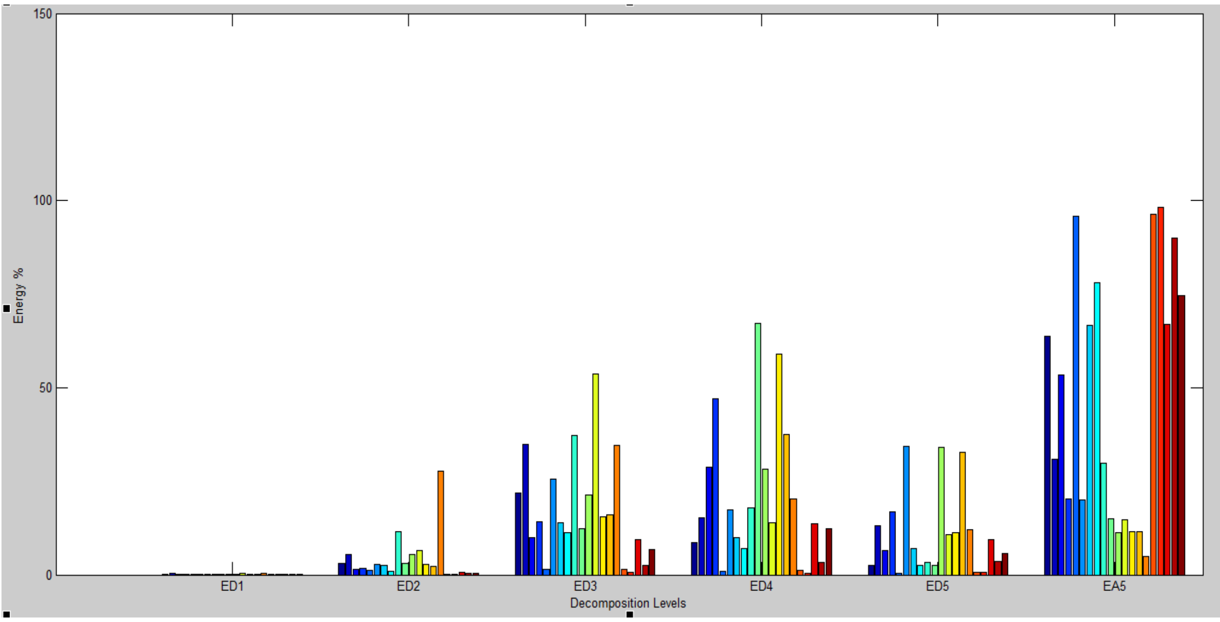

Figure 8: Energy Distribution of Decomposed Signals for Epilepsy Patients

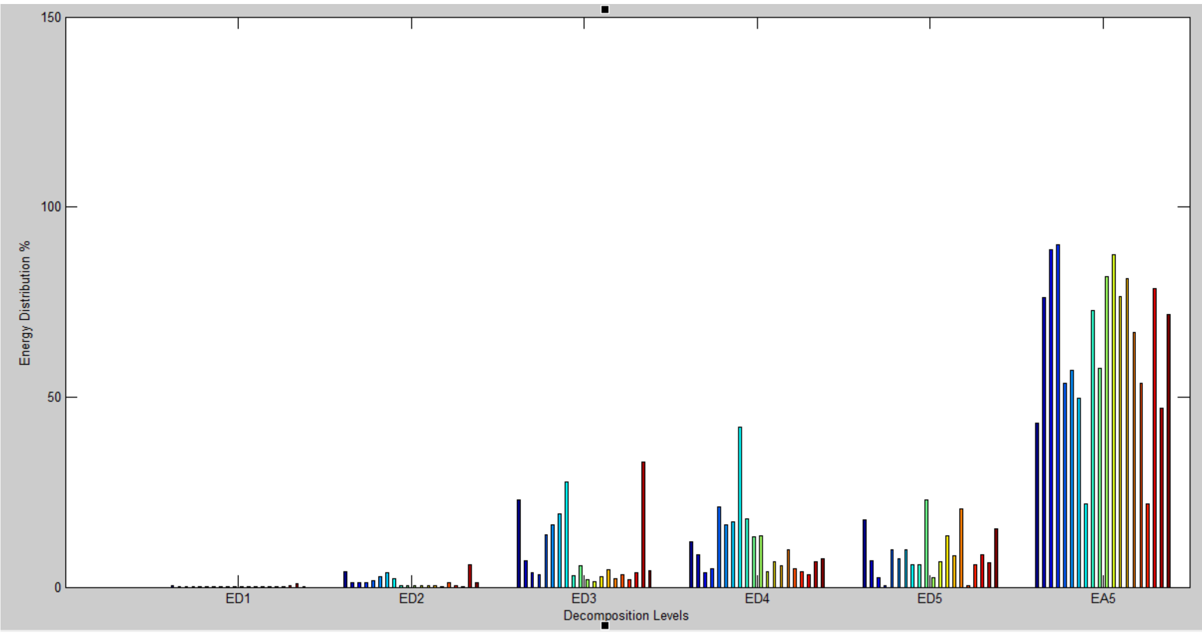

Figure 9: Energy Distribution of Decomposed Signals for Healthy Subjects

Results with Different Training Algorithms

One Step Secant Algorithm is used to minimize the gap between the conjugate gradient algorithms. This algorithm does not require any storage space. The parameters used to train the network are given in table IV. The overall accuracy obtained by this algorithm is shown in figure 10 along with testing and training accuracy. The regression accuracy of the system is 82%.

Table 4: Training Parameters of One Step Secant Algorithm

Architecture	Parameters
Number of Layers	3
Number of Neurons on layers	INPUT: 6, HIDDEN: 5, OUTPUT: 1
Initial Weights and Biases	Random
Learning Rule	One Step Secant Algorithm
Mean-Squared Error	$1e^{-01}$

The input vectors are now tested with different training algorithm i.e. with Bayesian Regularization Algorithm. Bayesian algorithm minimizes the weights and biases and finds out the final product which generalizes the network efficiently. Table V gives the description of the training parameters used to train the network and figure 11 shows the regression, training and validation plots of the system. The overall accuracy of the system using Bayesian regularization algorithm comes out to be 91% and the training accuracy is 96% as shown in figure.

Table 5: Training Parameters of Bayesian Regularization Algorithm

Architecture	Parameters
Number of Layers	3
Number of Neurons on layers	INPUT: 6, HIDDEN: 5, OUTPUT: 1
Initial Weights and Biases	Random
Learning Rule	Bayesian regularization Algorithm
Mean-Squared Error	$1e^{-01}$

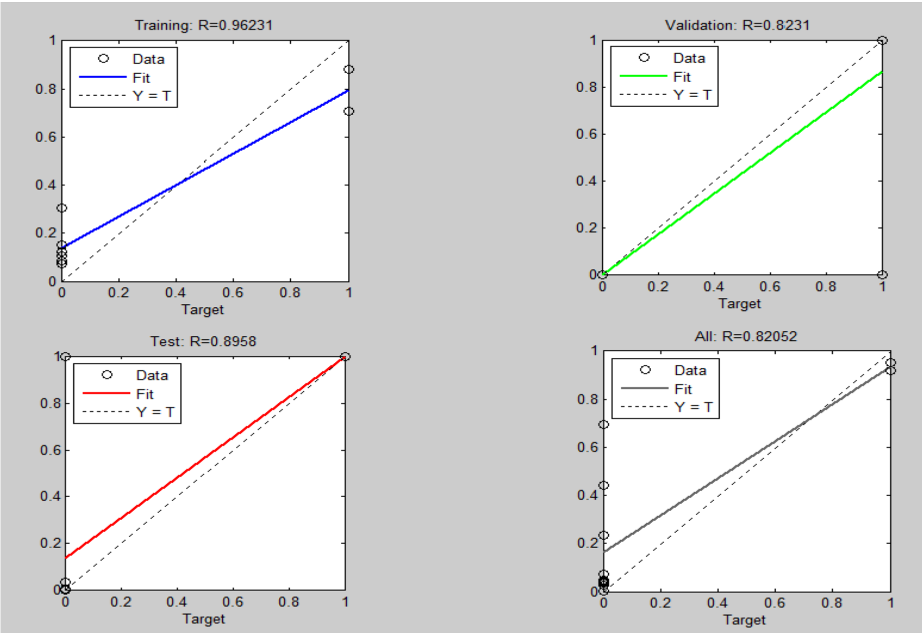

Figure 10: Regression Plot of the System Using One Step Secant Algorithm

The system design and parameters used while testing input vectors with Levenberg-Marquardt Algorithmare given in Table 6. The overall regression or accuracy of the system when feed forward algorithm used is 93.9%. The training, testing and the overall regression is shown in figure 12.

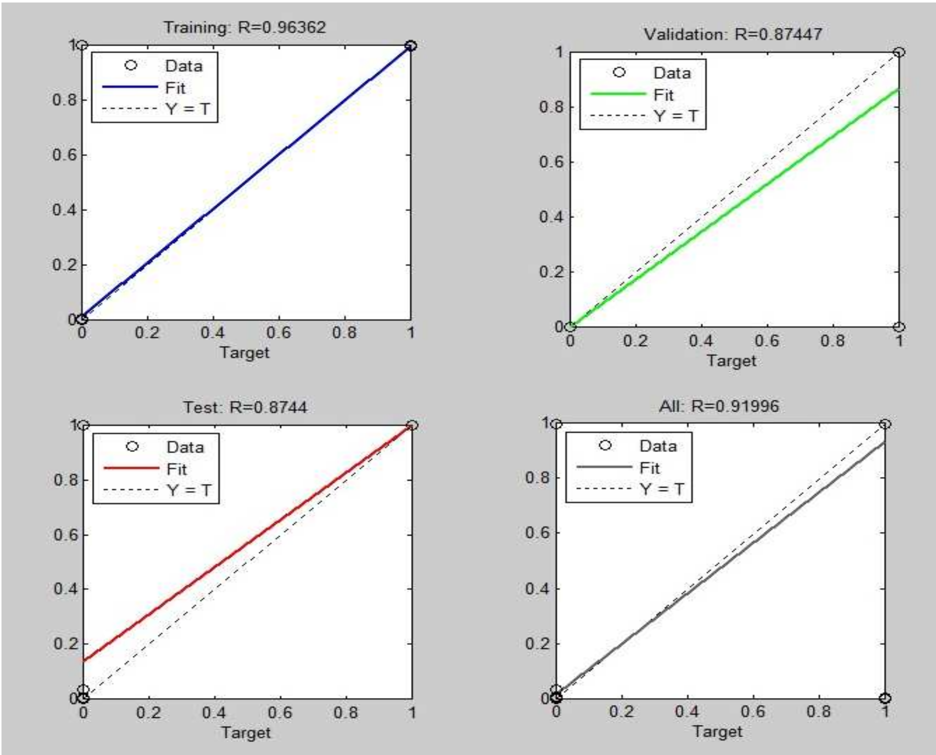

Figure 11: Regression Plot of the System Using Bayesian Regularization Algorithm

Table 6: Training Parameters of Feed Forward Back Propagation Algorithm

Architecture	Parameters
Number of Layers	3
Number of Neurons on layers	INPUT: 6, HIDDEN: 5, OUTPUT: 1
Initial Weights and Biases	Random
Learning Rule	Levenberg-Marquardt Algorithm
Mean-Squared Error	$1e^{-01}$

Table 7 gives brief evaluation of results of three training algorithms. The overall regression accuracy for these algorithms is 82.05%, 91.99% and 93.95% respectively and it can easily be seen that the accuracy of the system when Levenberg-Marquardt algorithm is used is high.

Table 7: Comparison of Different Training Algorithms

Training Algorithm	Training Accuracy	Validation Accuracy	Testing Accuracy	Regression Accuracy
One Step Secant	96.23%	82.31%	89.58%	82.05%
Bayesian Regularization	96.36%	87.47%	87.44%	91.99%
Levenberg-Marquardt	92.22%	93.54%	87.50%	93.95%

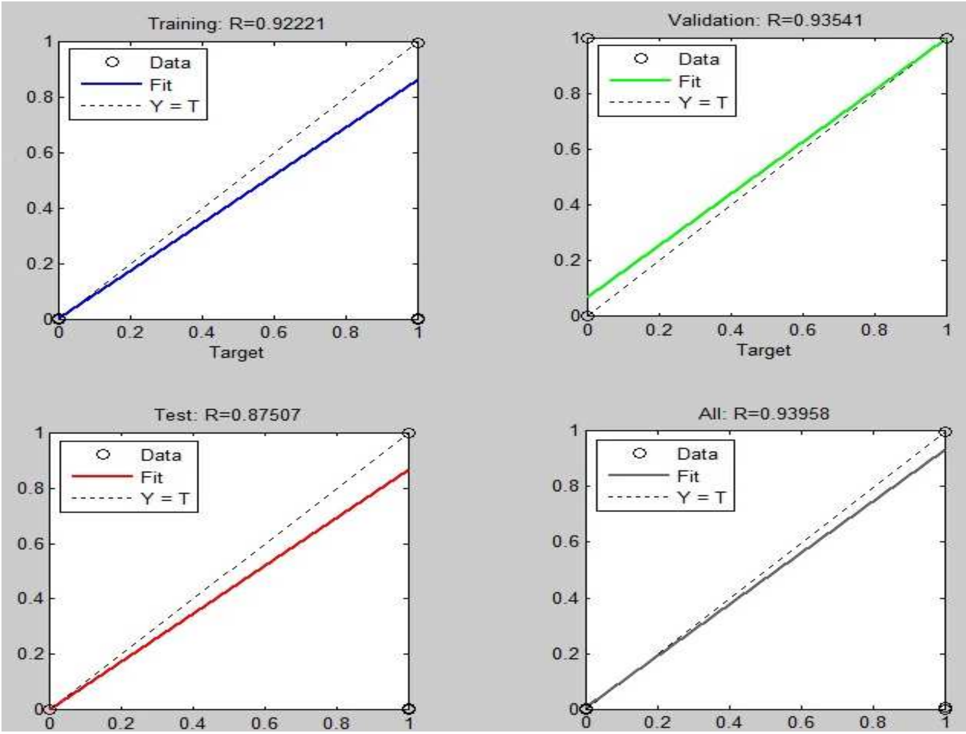

Figure 12: Regression Plot of the System Using Levenberg-Marquardt Algorithm

CONCLUSIONS

Epilepsy is a perilous neurological disease covering about 4-5% of total population of the world. Its main characteristics are seizures which occur due to certain disturbance in brain function. EEG is the technique used in this paper to acquire the brain signals of both epileptic and healthy persons. As EEG signals are non-stationary signals so wavelet decomposition technique is preferred to decompose these signals and the energy distribution of decomposed signals are considered for the classification of EEG signals. For classification, the neural network system was tested with different training algorithms such as Levenberg-Marquardt Algorithm, Bayesian Regularization Algorithm and One Step Secant Algorithm. The results showed that when Levenberg-Marquardt training algorithm was used the accuracy comes out to be 93.9% which is better than other training algorithms.

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