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EEG signal classification for Epilepsy Seizure Detection using Improved Approximate Entropy

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ABSTRACT

Epilepsy is a common chronic neurological disorder. Epilepsy seizures are the result of the transient and unexpected electrical disturbance of the brain. About 50 million people worldwide have epilepsy, and nearly two out of every three new cases are discovered in developing countries. Epilepsy is more likely to occur in young children or people over the age of 65 years; however, it can occur at any age. The detection of epilepsy is possible by analyzing EEG signals. This paper, presents a hybrid technique to classification EEG signals for identification of epilepsy seizure. Proposed system is combination of multi-wavelet transform and artificial neural network. Approximate Entropy algorithm is enhanced (called as Improved Approximate Entropy: *I*ApE) to measure irregularities present in the EEG signals. The proposed technique is implemented, tested and compared with existing method, based on performance indices such as sensitivity, specificity, accuracy parameters. EEG signals are classified as normal and epilepsy seizures with an accuracy of ~90%.

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1. INTRODUCTION

EEG measures the electrical activity of the brain and represents a summation of post-synaptic potentials from a large number of neurons. EEG has several advantages over the other methods: its temporal resolution is higher and it directly measures the electrical activity of the brain. EEG has been a very useful clinical tool, especially in the field of epileptology, but also in other areas of neurology and psychiatry [1-5].

Despite the fact that EEG is an important clinical tool for diagnosing, monitoring and managing neurological disorders, distinct difficulties associated with EEG analysis and interpretation, which hindered its wide-spread acceptance. Traditional method of analysis of the EEG is based on visually analyzing the EEG activity using strip charts. This is laborious and time consuming task which requires skilled interpreters, who by the nature of the task are prone to subjective judgment and error. Furthermore, manual analysis of the temporal EEG trace often fails to detect and uncover subtle features within the EEG which may contain significant information, Hence many researchers are working to develop an automated tool which easily analysis the EEG signal and revel important information present in the signal. Many research contribution already exist in the literatures that make use of epilepsy detection in EEG signal using different methods like template matching, Fourier Transfer, NN based approaches [5-20].

This paper proposes a hybrid technique to classification of EEG signal for identification epilepsy seizure by combining MWT and ANN; also existing approximate entropy method (ApE) [23] which is uses fixed window length for calculating irregularity present in the EEG signal is less accurate, to overcome fixed window length problem in ApE, the paper implemented an *Improved Approximate Entropy (I*ApE*)*.

The rest of the paper is organized as follows: Section 2 makes a brief review over the related literary works, Section 3 describes the proposed methodology, Section 4 discusses about the implementation results and Section 5 concludes the paper.

2. RECENT RESEARCH WORKS: A REVIEW

Numerous research works already exist in the literatures that make use of epilepsy detection in EEG signal. Important papers are reviewed below, for detailed review refer [20].

A wavelet-chaos-neural network methodology for classification of electroencephalograms (EEGs) into healthy, ictal, and interictal EEGs has been offered by Samanwoy Ghosh-Dastidar et al. [6]. In order to decompose the EEG into delta, theta, alpha, beta, and gamma sub-bands the wavelet analysis is utilized. Three parameters are used for EEG representation: standard deviation (quantifying the signal variance), correlation dimension, and largest Lyapunov exponent (quantifying the non-linear chaotic dynamics of the signal). The classification accuracies of the following techniques are compared: 1) unsupervised - means clustering; 2) linear and quadratic discriminant analysis; 3) radial basis function neural network; 4) Levenberg–Marquardt back propagation neural network (LMBPNN). The research was carried out in two phases with the intention of minimizing the computing time and output analysis, band-specific analysis and mixed-band analysis. In the second phase, over 500 different combinations of mixed-band feature spaces comprising of promising parameters from phase one of the research were examined. It is decided that all the three key components the wavelet-chaos-neural network methodology are significant for enhancing the EEG classification accuracy. Judicious combinations of parameters and classifiers are required to perfectly discriminate between the three types of EEGs. The outcome of the methodology clearly let know that a specific mixed-band feature space comprising of nine parameters and LMBPNN result in the highest classification accuracy, a high value of 96.7%.

Gabor and Seyal [6] introduce a neural network algorithm that relies primarily on the spike field distribution. MLP networks with the number of input and hidden nodes equal to the number of channels in the record and a single output node are used. Five bipolar 8 channel records from the EMU with durations ranging from 7.1 to 23.3 min are used for training and testing. Two networks are trained on only the slopes of the spike's half-waves, and there is no notion of background context. The first uses the slope of the half-wave before the spike's apex for all 8 channels as inputs, and the second uses the slope after the apex. The output of the algorithm is a weighted combination of the two network outputs with a value near 1.0 indicating a spike has been found. The duration (not specified) of the spike half waves is fixed so that no waveform decomposition is required. The algorithm slides along the data one sample at a time and identifies a spike when the output is greater than a threshold (e.g. 0.9). The method requires a distinct network for each patient and spike foci, so 7 networks were trained because two of the patients had independent foci. The training required 4–6 example spikes and the non spikes were generated by statistical variation resulting in 4 times more non-spikes. Although this method does not seem to be well suited for general detection, it might be a promising method for finding 'similar' events.

For the detection of seizure and epilepsy Hojjat Adeli et al. [7] have offered a wavelet chaos methodology for analysis of EEGs and delta, theta, alpha, beta, and gamma sub-bands of EEGs. In the form of the correlation dimension (CD, representing system complexity) and the largest Lyapunov exponent (LLE, representing system chaoticity) the nonlinear dynamics of the original EEGs are quantified. The new wavelet-based methodology isolated the changes in CD and LLE in specific sub-bands of the EEG. The methodology was applied to three diverse groups of EEG signals i.e. healthy subjects, epileptic subjects during a seizure-free interval (interictal EEG), and epileptic subjects during a seizure (ictal EEG).The effectiveness of CD and LLE in distinguishing between the three groups is examined based on statistical importance of the variations. It has been noted that in the values of the parameters acquired from the original EEG there may not be noteworthy differences, differences may be recognized when the parameters were employed in conjunction with particular EEG sub-bands and concluded that for the higher frequency beta and gamma sub-bands, the CD distinguished between the three groups, in disagreement to that the lower frequency alpha sub-band, the LLE distinguished between the three groups.

Subasi [10] deals with a novel method of analysis of EEG signals using discrete wavelet transform, and classification using ANN. In this work the signal decomposed in 5 levels using DB4 wavelet filter .The energy of details and approximation were used as the input features.

M.Akin, M.A.Arserim, M.K.Kiymik, I.Turkoglu [11] have tried to find a new solution for diagnosing the epilepsy. For this aim, the Wavelet Transform of the EEG signals have taken, and the δ, θ, α, and β sub frequencies are extracted. Depending on these sub frequencies an artificial neural network has been developed and trained. The accuracy of the neural network outputs is too high (97% for epileptic case, 98% for healthy case, and 93% for pathologic case that have been tested). This means that this neural network

identifies the health conditions of the patients approximately as 90 of 100. From this point we can say that an application of this theoretical study will be helpful for the neurologists when they diagnose the epilepsy.
Xiaoli Li [35] proposed an approach based on multi –resolution analysis to automatically indicate the epileptic seizures or other abnormal events in EEG. The energy of EEG signals at the different frequency bands is calculated for detecting the behaviors of brain during epileptic seizures. The energy change of each frequency band is indicated as a feature by calculating the Euclidean distance between a reference segment and the segments extracted in real time. The selection of wavelet functions, scale parameters, width of wavelet function, and sample sizes (segment length) are emphasized. Then, the features go through a recursive in-place growing FIR-median hybrid (RIPG-FMH) filter. The results suggest that wavelet transform is a useful tool to analyze the EEG signals with the epileptic seizures.

Ganesan.M, Sumesh.E.P, Vidhyalavanya.R [12] proposed a technique for the automatic detection of the spikes in long term 18 channel human electroencephalograms (EEG) with less number of data set. The scheme for detecting epileptic and non-epileptic spikes in EEG is based on a multi resolution, multi-level analysis and Artificial Neural Network (ANN) approach. The signal on each EEG channel is decomposed into six sub bands using a non-decimated WT. Each sub band is analyzed by using a non-linear energy operator, in order to detect spikes. A parameter extraction stage extracts the parameters of the detected spikes that can be given as the input to ANN classifier. The system is evaluated on testing data from 81 patients, totaling more than 800 hours of recordings.90.0% of the epileptic events were correctly detected and the detection rate of non-epileptic events was 98.0%.

3. PROPOSED METHODOLOGY FOR EPILEPSY DETECTION

The proposed method uses MWT and ANN to classify the EEG signal for epilepsy seizure detection. The below block diagram shows flow of proposed methodology.

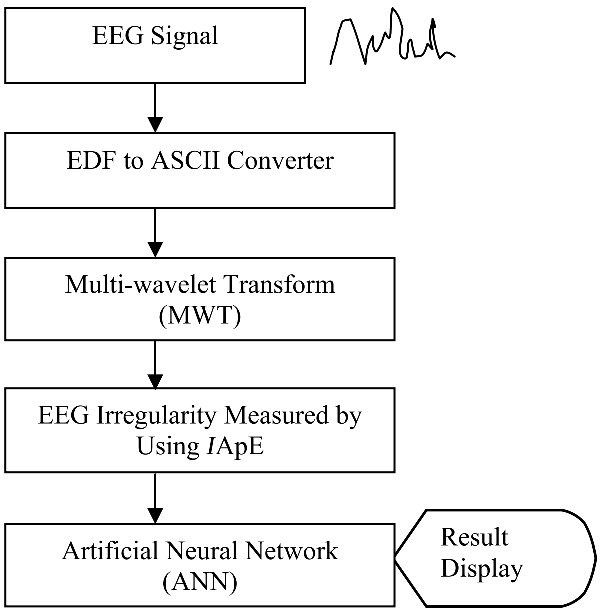

Figure 1.Block diagram of proposed Methodology.

The standard database [16, 17] EEG signals are in EDF (European Data Format) format. The EEG signal is converted in to ASCII format and stored in the temp.txt file using EDF to ASCII converter. The output of the converter is given as an input to MWT, the brain signal is decomposed and the irregularities of the signal are determined by using the *I*ApE process. Then the *I*ApE output is trained by using Feed Forward Neural Network (FFNN) and result is displayed.

3.1 Multi Wave Transform for EEG Feature Extraction

The multi-wavelet idea originates from the generalization of scalar wavelets. Instead of one scaling function and one wavelet, multiple scaling functions and wavelets are used. This leads to more degree of freedom in constructing wavelets. Therefore opposed to scalar wavelets, properties such as compact support, orthogonally, symmetry, vanishing moments, short support can be gathered simultaneously in multi-wavelets

[19]. In this paper, MWT is used to extract the features of EEG signal. The MWT uses multiple scaling functions and multiple wavelet functions. The scaling function is denoted as and the wavelet function is denoted as . The vector notation of scaling function and wavelet function is as follows.

$$\Phi(x) = [\Phi_1(x), \Phi_2(x), \ldots\ldots\ldots\ldots\ldots \Phi_n(x)]^T \tag{1}$$

$$\Psi(x) = [\Psi_1(x), \Psi_2(x), \ldots\ldots\ldots\ldots\ldots \Psi_n(x)]^T \tag{2}$$

Where, T is denoted as the vector response and $n > 1$ is an integer. The wavelet relation of low pass filter and high pass filter is as follows.

$$\Phi(x) = \sqrt{2} \sum_{k \in Z} H_k \Phi(2x - k) \tag{3}$$

$$\Psi(x) = \sqrt{2} \sum_{k \in Z} G_k \Psi(2x - k) \tag{4}$$

Where, H_k is the low pass filter coefficient and G_k is the high pass filter coefficient. The initial basis condition of scaling function and wavelet function is given below.

$$\Phi(x) = \begin{cases} 1 & x = 0 \\ 0 & otherwise \end{cases} \tag{5}$$

$$\Psi(x) = \begin{cases} 1 & x = 1/2 \\ 0 & otherwise \end{cases} \tag{6}$$

These are the initial basis condition of scaling and wavelet function of MWT.

3.2 Multi-Wavelet Transform Decomposition

In this MWT decomposition, the input signal is denoted as $x(n)$. The decomposed low pass filter outputs are denoted as A_1, A_2, A_3, A_4 *and* A_5, and the decomposed high pass filter outputs are denoted as D_1, D_2, D_3, D_4 *and* D_5. The Fig.2 shows the decomposition structure of MWT. Using this structure, the decomposition stage of EEG signal is calculated.

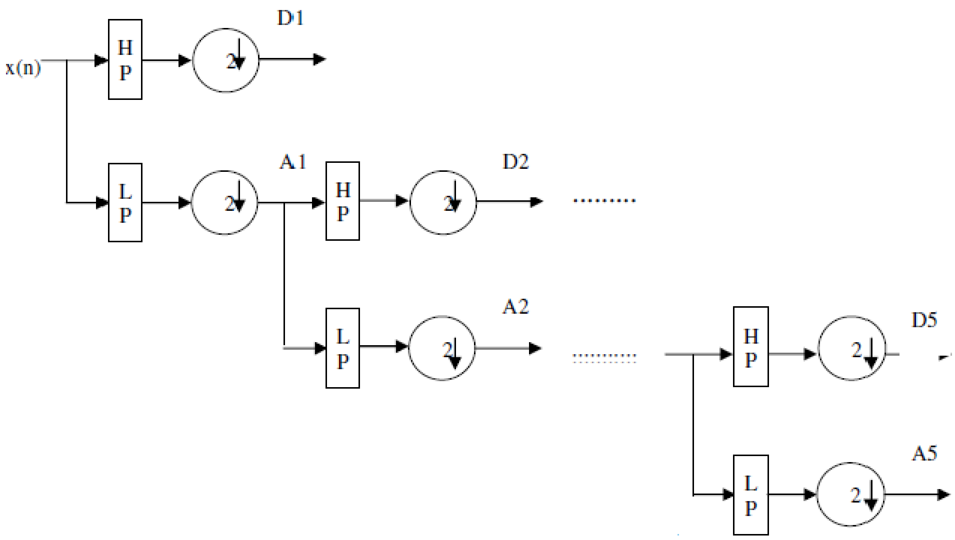

Figure 2. Decomposition of MWT

The decomposition of MWT is calculated by using the following formulas. The decomposition of low frequency component is calculated as,

$$A_{i-1} = \sum_{k} H_k \; A_{i,2k+n} \tag{7}$$

The decomposition of high frequency component is calculated as,

$$D_{i-1} = \sum_{k} G_k \; D_{i,2k+n} \tag{8}$$

Using the above two formulas, the decomposition of MWT is calculated.

3.3 Improved Approximate Entropy (*I*ApE) Method

In existing work, the irregularity of EEG signal is measured by using ApE method [23]. In the ApE method, the accuracy is less due to fixed window length, so the quality of EEG signal is loosed. To overcome this problem, in this paper proposes Improve Approximate Entropy (*I*ApE) method for measure the irregularities present in the decomposed EEG signal. The output of *I*ApE is denoted as $AD_1, AD_2, AD_3, AD_4, AD_5$ *and* AA_5. Steps for calculating the *I*ApE is given below.

Step 1: Calculate *N* data points from the signal i.e. $n = [n_{(1)}, n_{(2)}, ... n_{(N)}]$

Step 2: Select the window length i.e. $m = [m_{(1)}, m_{(2)}, ... m_{(N-1)}]$

Step 3: Then select the tolerance (*rr*) value, If the values signal length *n= 1: N*, then, *m=n*. otherwise select, *n=n (1), m=m (1).* Calculate distance *(D) = (m (1)-n (1)).*

Step 4: Then, increment *n=n+1* and *m=m+1*, Calculate *D* and select $D_{max} = D$;

Step 5: If value window length *m= 1:* D_{max}, Then, check $D_{\max} \geq Tolerance\,(rr)$ and Calculate *I*ApE.

Step 6: Then the *I*ApE is calculated by using the below formula.

$$Improved\ Approximate\ Entropy\ (I\text{ApE}) = \frac{Total\ window\ length}{Total\ window\ size}$$

The irregularities of signal depend on the *I*ApE value. These *I*ApE value is then applied as input to the neural network and the training dataset is generated.

3.4 Neural Network Structure For Proposed Method

Feed Forward Neural Network (FFNN) is an artificial intelligence technique that is used to generate training data set for the applied input data. In this paper, a feed-forward neural network is used for identifying the types of EEG signal. A feed-forward neural network is a biologically inspired classification algorithm. It consists of a (possibly large) number of simple neuron-like processing units, organized in layers. Every unit in a layer is connected with all the units in the previous layer. These connections are not all equal; each connection may have a different strength or weight. The weights on these connections encode the knowledge of a network. Often the units in a neural network are also called node.

The input layers of FFNN are $AD_1, AD_2, AD_3, AD_4, AD_5$ *and* AA_5. The n numbers of hidden layers of neural network are $H_1, H_2, ... H_n$ and the neural network process takes place in this hidden layer. The training of the neural network is performed by back propagation algorithm. The output of neural network is used to determine the types of EEG signal. Using the neural network output, epilepsy affected brain signal is detected.

Fig.3. shows the neural network, the multi-wavelet output is trained and the training dataset is generated for epilepsy detection. The weight between input and hidden layer is denoted as W_1, the weight between hidden and output layer is denoted as W_2. The weight adjustment depends on the output requirement. The formula for weight adjustment between the layers is $W_{ji}\,(n+1) = W_{ji}\,(n) + \Delta W_{ji}\,(n)$.

The neural network output is calculated by using the formula $\sum_{j=i=1}^{n} W_{ji}\, AD$. Once the training process is completed, then, the network is trained well for classifying the EEG signal. After the training process, the next process of neural network is testing. In this testing phase, an input signal is applied and then the types of EEG signal are calculated. From these types of EEG signal, the epilepsy can be detected.

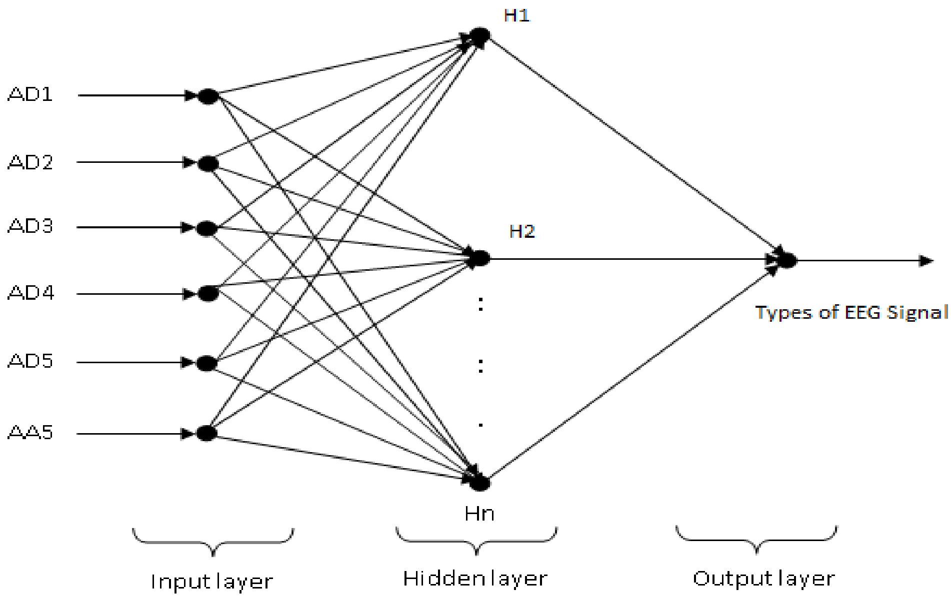

Figure 3. Proposed Neural Network Training Structure

4. RESULTS AND DISCUSSION

The proposed epilepsy detection technique is implemented using MATLAB 7.11 on windows 7 PC with Intel i3 processor. Here, the wavelet level was chosen as 5 for extracting the feature of the signal and for *I*ApE calculation value of *rr* = 1 to 5 is considered. The hidden layer neuron was set as 20. For testing the performance of proposed method, the dataset is used [15, 16]. The EEG signals are, grouped into 23 cases, were collected from 22 subjects (5 males, ages 3- 22; and 17 females, ages 1.5-19). All signals were sampled at 256 samples per second with 16-bit resolution. Most files contain 23 EEG signals (24 or 26 in a few cases). The International 10-20 system of EEG electrode positions and nomenclature was used for these recordings.

The proposed *I*ApE method is compared with existing ApE method [23]. The true positive, true negative, false positive and false negative values are calculated; these parameters further used in calculating performance indices such as sensitivity, specificity, precision and accuracy using below equations. Results are shown in Table 1 for various tolerance values.

Specificity: Number of correctly detected negative patterns/total number of actual negative patterns.
A negative pattern indicates a detected normal/non-seizure.

$$Specificity = \frac{TN}{(FP + TN)} \tag{13}$$

Sensitivity: Number of correctly detected positive patterns/total number of actual positive patterns.
A positive pattern indicates a detected seizure.

$$Sensitivity = \frac{TP}{(TP + FN)} \tag{14}$$

Accuracy: Number of correctly classified patterns/total number of patterns. Then the determined values are tabulated and it is shown in the below table.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (15)$$

$$\Pr ecision = \frac{TP}{(TP + FP)} \quad (16)$$

Table 1. Performance Evaluation Table

Parameter	Tolerance	Proposed Method	Existing Method
Sensitivity	1	0.78	0.75
	2	0.54	0.5
	3	0.59	0.5
	4	0.73	0.24
	5	0.78	0.42
Specificity	1	0.88	0.55
	2	0.7	0.5
	3	0.56	0.5
	4	0.72	0.45
	5	0.88	0.44
Accuracy	1	0.83	0.58
	2	0.56	0.51
	3	0.57	0.5
	4	0.73	0.42
	5	0.83	0.43
Precision	1	0.9	0.24
	2	0.9	0.03
	3	0.46	0.25
	4	0.72	0.08
	5	0.9	0.36

The comparison of sensitivity, specificity, accuracy, precision of proposed *I*ApE method and existing ApE method are shown in the following graphs.

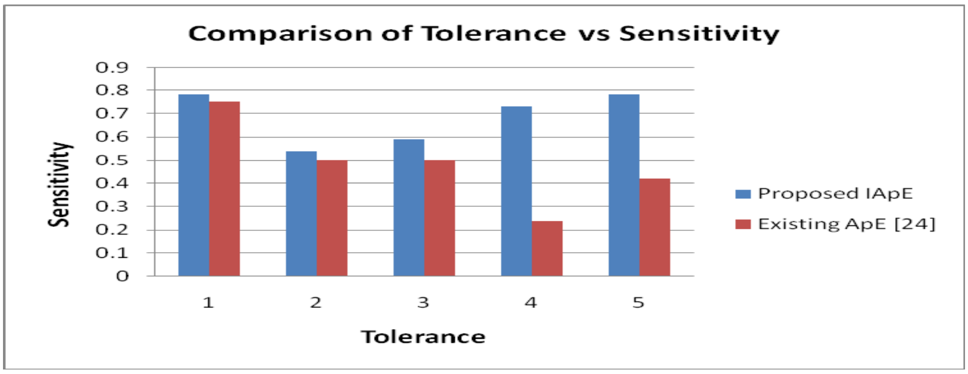

Figure 4. Comparison of Proposed and Existing Methods Sensitivity

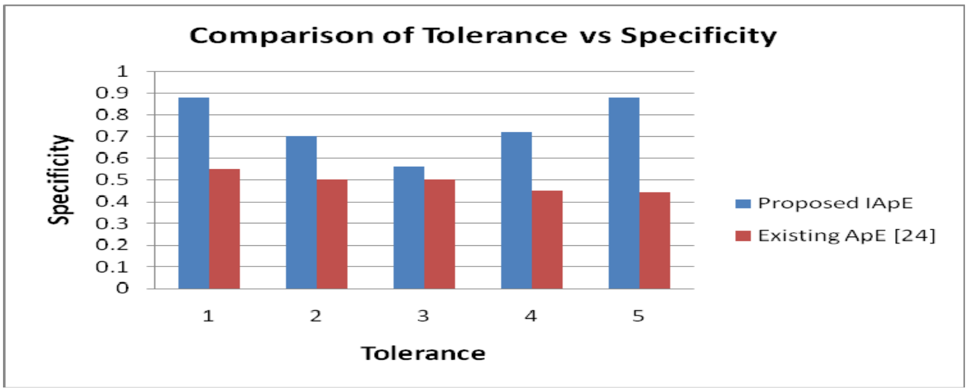

Figure 5. Comparison of Proposed and Existing Methods Specificity

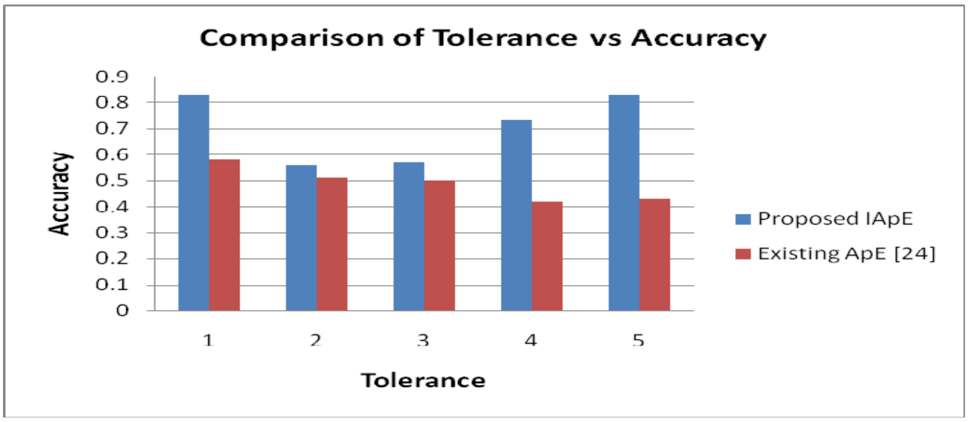

Figure 6. Comparison of Proposed and Existing Methods Accuracy

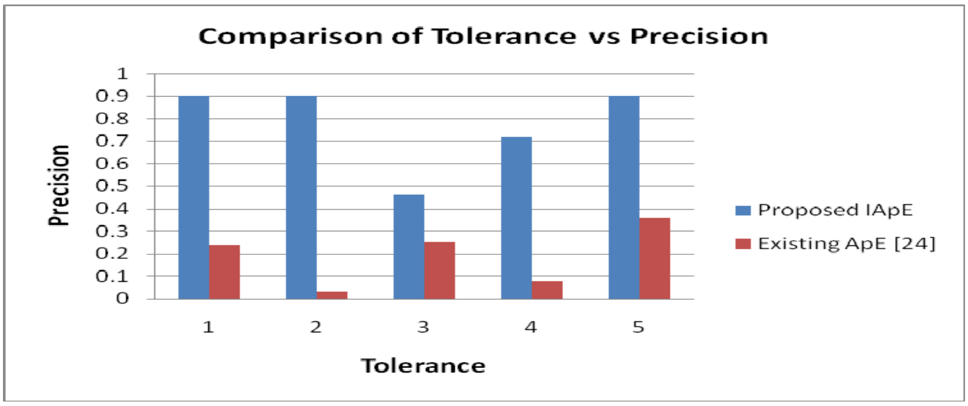

Figure 7. Comparison of Proposed and Existing Method Precision

The above bar chart reveals that sensitivity, specificity, accuracy and precision of *I*ApE are higher than conventional ApE. Fig.8 shows the GUI of the proposed system.

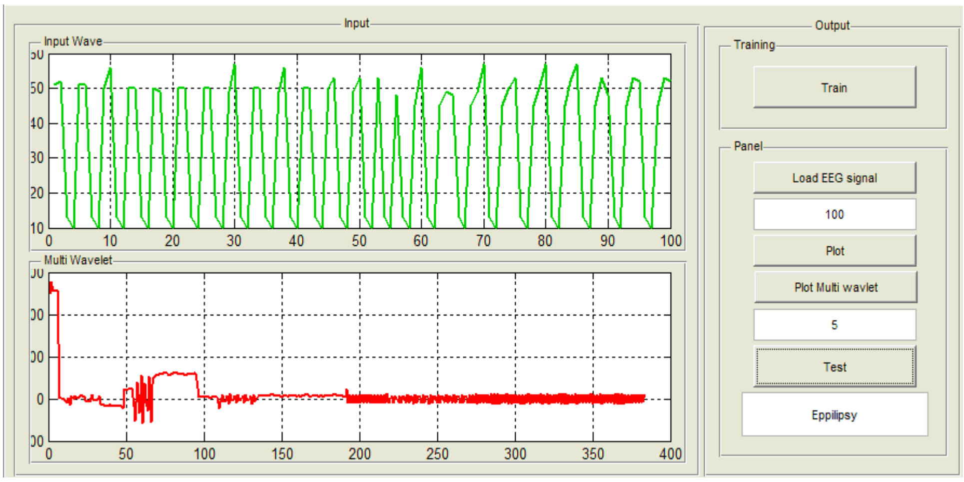

Figure 8 GUI of proposed method system

5. CONCLUSION

This paper, proposes a hybrid technique to classification EEG signal for epilepsy seizure detection, which is combination of multi-wavelet transform and artificial neural network. Irregularity in the EEG signals is measured by using the Improved Approximate Entropy.

Using multi-wavelet transform, the EEG signal is decomposed into low frequency and high frequency components. Then the decomposed signal is applied to Improved Approximate Entropy (*I*ApE) process. In the improved approximate entropy process, the disturbance and irregularity of the EEG signal is calculated. Then the output of *I*ApE is applied to the input FFNN. FFNN is one of the artificial intelligence techniques, which is used for generating training dataset. From the generated dataset, the types of EEG signal classified as normal and epilepsy seizures signal.

The proposed technique is implemented and tested on standard EEG signals, the performance of *I*ApE and existing ApE method compared based on performance indices such as sensitivity, specificity, accuracy parameters, and results shows that accuracy of proposed method is better than existing method for identification epilepsy seizure. The work is in progress extended the same method for identification of brain tumor.

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BIOGRAPHY OF AUTHORS

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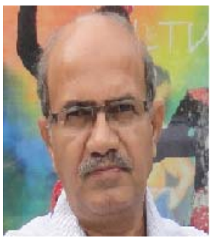

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