Detection and Classification of Epileptic Seizures using Wavelet feature extraction and Adaptive Neuro-Fuzzy Inference System

Dr. D. Najumnissa'* Dr. T . R. Rangaswamy
B S Abdur Rahman University, Chennai, India
*Corresponding author

Abstract - Epilepsy, a neurological disorder in which patients suffer from recurring seizures, affects approximately 1% of the world population. In this work, an attempt has been made to enhance the diagnostic importance of EEG using Adaptive neuro fuzzy inference system (ANFIS) and Wavelet transform coefficients. For this study, EEG for 20 normal and 30 seizure subjects under standard recording procedure is used. A method based on wavelet transform and ANFIS is used to detect the epileptic seizures. Further, BPN algorithm is used to study and compare the datasets. Average specificity of 99% and sensitivity of 97% are obtained. Results show that the ANFIS is able to detect seizure. It appears that this method of detection makes it possible as a real-time detector, which will improve the clinical service of Electroencephalographic recording.

Keywords - ANFIS, ANN, BPN, Discrete Wavelet Transform, Epileptic seizure.

1. INTRODUCTION

Surveys report that about 1% of the people in the world suffer from epilepsy and about 30% of epileptics are not helped by medication [1]. It is characterized by recurrent, paroxysmal (short-term) electrical discharges of the cerebral cortex that result in intermittent disturbances of brain function as reported by Neidermeyer [2]. Electro-encephalography (EEG) is an inexpensive and an important clinical tool for the evaluation and treatment of neurophysiologic disorders [3].

The only reliable and quantitative method of assessment of epileptiform discharges occurring in the EEG between seizures is an important component in the diagnosis of epilepsy is by digital recording with subsequent analysis [4, 5]. This paper will concentrate in building a computer aided diagnosis system to classify the normal signals and epileptic seizure signals by analyzing the EEG. This system consists of two stages. The first stage is the feature extraction from EEG signals and the second stage is the classification of these features, as shown in figure 1.

Significant diagnostic information can be obtained from the frequency distribution of epileptic EEG. However, selecting the signal processing technique is very important. Many efforts have been reported in literature on the classification of epileptic seizures using frequency analysis [6–10]. One popular approach as shown by Sharma et al.[6] is to use the Fast Fourier Transform (FFT) for the first stage and using FFT calculate the features from the FFT such as relative power in various frequency bands. But Fast Fourier Transform (FFT) suffers from large noise and sensitivity. The second stage then uses an Artificial Neural Network (ANN) to generate a single number that indicates the degree to which the event is a seizure. A few workers like Pritchard et al [7] , Anderer et al [8] have compared ANNs to some of the statistical methods on the same EEG data when looking for changes in the background EEG and have generally found that the ANNs perform better;. that is they more closely model human performance in observing differences between normal and abnormal subjects.

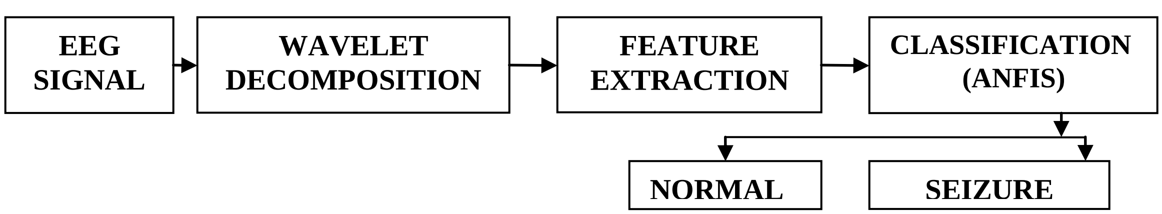

Fig.1. Schematic of the Classification method

Comparing techniques of seizure detection developed by diverse groups is filled with problems because of no objective definition of the appearance of a seizure in the EEG. It has been shown by Gotman et al [9], that there are significant differences among EEG readers regarding which individual events to mark, even when there is overall agreement on the elucidation of an EEG record. A powerful method to perform time-scale analysis of signals is the wavelet transforms (WT). This technique provides a consistent framework for different techniques that have been developed for various applications [4, 10 -12]. It should also be emphasized that the WT is appropriate for analysis of non-stationary signals, and this represents a major advantage over spectral analysis. Hence the WT is suitable for locating transient events. Such transient events as spikes can occur during epileptic seizures. Wavelet is an effective time–frequency analysis tool for analyzing transient signals. Its properties and feature extraction can be used to analyze various transient events in biological signals as reported by Adeli et al. [4] gave an overview of the DWT developed to be renowned with and quantifying spikes, sharp waves and spike-waves. They used wavelet transform to analyze and characterize epileptiform discharges in the form of 3-Hz spike and wave complex in patients with absence seizure. Through wavelet decomposition of the EEG records, transient features are accurately captured and localized in both time and frequency context. The capability of this mathematical microscope to analyze different scales of neural rhythms is a powerful tool for investigating small-scale oscillations of the brain signals. An understanding of the dynamics of the human brain through EEG analysis can be obtained through further analysis of such EEG records. Recently, a work on time-frequency analysis of EEG signals for detecting seizures using WT has been reported [13 - 17].

Neural networks are routinely employed in signal classification algorithms including automatic seizure detection. Gotman, Ives and P Gloor., [18] used template matching for the detection of epileptic seizures. Cheng-wen et al [19] employed an Artificial Neural Network (ANN) for identifying seizures using radial basis function. [20 – 22] used wavelet coefficients as an input to a feed forward neural network for the detection of epileptogenic transient waveforms. As EEG signals are non-stationary, Proakis and Manolakis,[23] apply the conventional method of visual analysis but is not highly successful in diagnostic classification. Temporal patterns are processed by the approach of using recurrent neural networks (RNNs) which have memory to encode past history [24,25] extracted features and used back propagation algorithm to classify normal and abnormal EEG.

Fuzzy set theory plays a vital role in dealing with uncertainty when making decisions in biomedical applications. Introduced by Zadeh [26], fuzzy logic and fuzzy set theory are employed to describe human thinking and reasoning in a mathematical framework. Fuzzy-rule based modeling is a qualitative modeling scheme where the system behavior is described using a natural language [27]. Fuzzy sets have attracted the growing attention and interest in modern information technology, production technique, decision making, pattern recognition, diagnostics, data analysis, etc. [28, 29]. These intelligent computational methods offer real advantages over conventional modeling, especially when the underlying physical relationships are not fully understood.

In recent years, the integration of neural networks and fuzzy logic has given birth to new research into neuro-fuzzy systems. Neuro-fuzzy systems have the potential to capture the benefits of both these fields in a single framework. Neuro-fuzzy systems eliminate the basic problem in fuzzy system design (obtaining a set of fuzzy if–then rules) by effectively using the learning capability of an ANN for automatic fuzzy if–then rule generation and parameter optimization. As a result, those systems can utilize linguistic information from the human expert as well as measured data during modeling. Such applications have been developed for signal processing, automatic control, information retrieval, database management, computer vision and data classification [30–34].

A specific approach in neuro-fuzzy development is the adaptive neuro-fuzzy inference system (ANFIS), which has shown significant results in modeling nonlinear functions. In ANFIS, the membership function parameters are extracted from a data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion [34]. Successful implementations of ANFIS in biomedical engineering have been reported, for classification [30–33, 35–39], for modeling and controlling real systems [40] and data analysis [41].

In this study, a simple approach based on ANFIS is implemented to classify the EEG signal to one of the categories: epileptic or normal. The aim of this study is to develop a simple algorithm for the detection of epileptic seizure which could also be applied to real-time. This paper aims to extract features using WT and to detect and classify seizure using ANFIS and neural network techniques. The choice of the network is based on the fact that it is the most popular type of ANNs and the most powerful networks commonly used in solving classification / discrimination problems. The accuracy of the classifiers will be assessed and compared. Finally, some conclusions is drawn concerning the superiority of the ANFIS over the ANNs and impacts of features on the detection of epileptic seizure through analysis of the ANFIS.

2. MATERIALS AND METHOD

2.1. Subjects and data recording

Subjects within the age group from 21 to 40 were selected for this study. The EEG is collected using Nihon Kohden digital EEG system comprising of a data acquisition system, signal processor and a personal computer from Sri Ramachandra Medical University and Research Institute, Chennai. The 10 second scalp EEG data used in this study is sampled at a rate of 500 Hz after filtering between 1 and 70 Hz. A bipolar electrode montage of 16 channels is used in the analysis. The EEGs were recorded with Ag/AgCl electrodes placed at the F_4, C_4, P_4, O_2, F_3, C_3, P_3, O_1, Fp_2, F_8, T_4, T_6, Fp_1, F_7, T_3, & T_5, loci of the 10–20 International System. Impedance is kept below 5 kΩ to avoid polarization effects. All data are stored for off-line processing. All EEGs with artifact, electrode movement and bursts of alpha waves is discarded. In order to assess the performance of the classifier, we selected 900 EEG segments containing spike and wave complex, artifacts, and background normal EEG.

2.2. Visual inspection and validation

Two EEG technologists with experience in the clinical analysis of EEG signals separately inspected every recording included in this study to score ictal and normal signals. The two experts jointly revised the signals to solve disagreements and set up the training set for the program for the epileptic seizure detection. The agreement between the two experts was evaluated for the testing set. A further step was then performed with the aim of checking the disagreements and setting up a 'gold standard' reference set as done by Subasi, [14]. When revising this unified event set, the human experts, by mutual consent, marked each state as ictal or normal. They also examined each recording completely for epileptic seizures. This validated set provided the reference evaluation to estimate the sensitivity and specificity of computer scorings.

2.3. Wavelet analysis and feature extraction

2.3.1. Denoising the EEG signals

One of the major difficulties in analysis of EEG signal is the presence of artifacts in the signals. This nature of disturbance is a serious obstructing factor that prohibits further processing to identify useful diagnostic features. Hence denoising of the signals is a must for effective utilization for diagnosis. Since the frequency bands of these noises may overlap with the seizure signal, conventional method of using filters is not suitable for removal of noise. In this work, DWT based denoising technique, namely wavelet shrinkage denoising, as reported by Kandaswamy et al [42] is used.

2.3.2. Multiresolution decomposition of EEG signals

The Discrete Wavelet Transform (DWT) is a versatile signal processing tool that finds many engineering and scientific applications.. DWT analyzes the signal at different frequency bands, with different resolutions by decomposing the signal into a coarse approximation and detail information [10 - 13]. DWT employs two sets of functions called scaling functions and wavelet functions, which are associated with low-pass and high-pass filters, respectively. The decomposition of the signal into the different frequency bands is simply obtained by successive high-pass and low-pass filtering of the time domain signal. Selection of wavelet that is suitable and the number of levels of decomposition is very vital in analysis of signals using DWT. We visually inspect the data first, and if the data are discontinuous, Haar or other sharp wavelet functions are applied [44] or else a smoother wavelet can be employed. Usually, tests are performed with different types of wavelets and the one which gives maximum efficiency is selected for the particular application. In this study db4 is chosen [4,5]. The levels are chosen such that those parts of the signal that correlate well with the frequencies required for classification of the signal are retained in the wavelet coefficients. Since the EEG signals do not have any useful frequency components above 30 Hz, the number of levels was chosen to be 8. Thus the signal is decomposed into the details D1–D8 and one final approximation, A8 [5, 42]. The ranges of various frequency bands are shown in Table 1.

Table 1: Frequencies corresponding to different levels of decomposition for Daubechies 4 filter wavelet with a sampling frequency of 500 Hz

Decomposed signal	Frequency range (Hz)
D1	125 – 250
D2	62.5 – 125
D3	31.25 – 62.5
D4	15.625 - 31.25
D5	7.8125 - 15.625
D6	3.9063 - 7.8125
D7	1.9531 - 3.9063
D8	0.9766 - 1.9531
A8	0 - 0.9766

2.3.3. Feature extraction

The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the signal in time and frequency. It is anticipated that the coefficients of the seizure frequency spectrum ranges from 0.5 to 30 Hz. So the coefficients corresponding to the frequency bands, D1- D3 were discarded, thus reducing the number of feature vectors representing the signal. In order to further lessen the dimensionality of the extracted feature vectors, Gotman [9] features are used from the wavelet coefficients. These feature vectors, calculated for the frequency bands A8 and D4–D8, is used for classification of the EEG signals.

2.4. Adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS first introduced by Jang in 1993 [34]. It is a model that maps inputs through input membership functions (MFs) and associated parameters, and then through output MFs to outputs. The initial membership functions and rules for the fuzzy inference system can be designed by employing human expertise about the target system to be modeled. ANFIS can then purify the fuzzy if–then rules and membership functions to describe the input–output behavior of a complex system. Jang showed that even if human expertise is not available it is possible to intuitively set up practical membership functions and employs the neural training process to generate a set of fuzzy if–then rules that approximate a desired data set [30–33,35].

Five layers are used to create this inference system. Each layer involves several nodes described by node function. The output signals from nodes in the previous layers will be accepted as the input signals in the present layer. After manipulation by the node function in the present layer will be served as input signals for the next layer. Here square nodes, named adaptive nodes, are adopted to represent that the parameter sets in these nodes are adjustable. Whereas, circle nodes, named fixed nodes, are adopted to represent that the parameter sets are fixed in the system. For simplicity to explain the procedure of the ANFIS, we consider two inputs *x*, *y* and one output *f* in the fuzzy inference system. And one degree of Sugeno's function [34] is adopted to depict the fuzzy rule. Hence, the rule base will contain two fuzzy *if–then* rules as shown in equations (1) and (2):

Rule 1: if x is $A1$ and y is $B1$ then $f = p1x + q1y + r1$. (1)

Rule 2: if x is $A2$ and y is $B2$ then $f = p2x + q2y + r2$. (2)

For detailed literature refer [34].

3. Results and discussion

In this study, the potential of neuro-fuzzy computing techniques for epileptic seizure detection is investigated by using an ANFIS -Takagi Sugeno Model. Since an ANFIS model is essentially a fuzzy model with learning capabilities; we consider the various methods that are involved in the design of a fuzzy model. To construct a fuzzy model we need to perform knowledge acquisition, which takes a human operators knowledge about how to control the system and generates a set of fuzzy if-then rules as the backbone for a fuzzy model that behaves like the original human operator [34].

The design method for the proposed neurofuzzy model makes use of the numerical information method to create a fuzzy inference system that learns the input-output data pairs presented to it. The inputs to the ANFIS network are the extracted features, obtained from the WT at various levels. In this study, training and test sets were formed by 900 feature vectors. The 700 feature vectors (from 20 epileptic and 15 normal subjects) were used for training and the 200 feature vectors (from 10 epileptic and 5 normal subjects) were used for testing. The type distribution of the samples in the training and validation data set is summarized in Table 2. In order to improve the generalization capability of the ANFIS, the training and the test sets were formed by data obtained from different subjects. The training data set was used to train the ANFIS, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for the detection of epileptic seizure in patients with generalized tonic-clonic (GTC) seizures.

Table 2 Type distribution of the samples in the training and test data sets

Type	Training set	Test set	Total
Epileptic	450	120	570
Normal	250	80	330

3.1 Design of ANFIS model

The input output data set is features extracted from the wavelet coefficients. The first step involved in the training of an ANFIS is the creation of the initial Sugeno type FIS based on the input output data set. This was accomplished by using the *genfis1* function in MATLAB. This function partitions the fuzzy space into various regions based on the number of membership functions given for each input. Three membership functions (Low, Medium, and High) were used for each input variable.

The three membership functions correspond to low, medium, high respectively. Here the fuzzy space which is a plane with input features as the rectangular co-ordinates is divided into 243 regions; each corresponding to a rule and an output membership function which is linear in nature. The Sugeno FIS thus created was trained by invoking the *ANFIS editor* GUI.

Input membership function:

$$\mu_{Ai}(x) = \frac{1}{1+\{((x-c_i)/a_i)^2\}bi}, \qquad (3)$$

Output membership function: Z = px+qy+r (4)

Where a, b, c are the antecedent parameters and p, q, r are the consequent parameters. Training proceeds in two phases; in first phase the premise parameters a, b, c of the model is fixed and the consequent parameter is estimated by the method of Recursive Least Squares (RLSE). In the second phase the consequent parameters is fixed and the premise parameters is tuned by the back propagation algorithm. This is done until the specified numbers of epochs are reached or the error between the input and the target patterns is lesser than the tolerance value specified [34]. At the end of training the parameters i.e. a, b, c & p, q, r obtained, represents the optimum parameters of the ANFIS network. Figures 2 - 7 show the changes in the shape of the membership functions before and after training for the input features. Figures 8-9 show the rule outputs before training and after training.

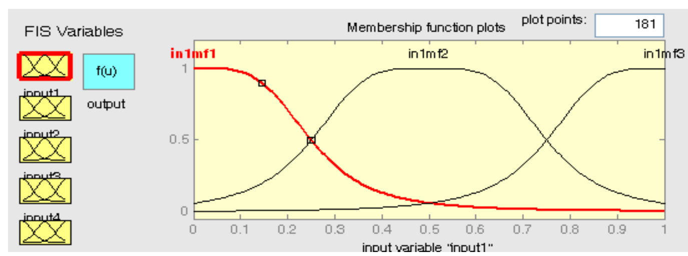

Fig 2. Membership functions before training

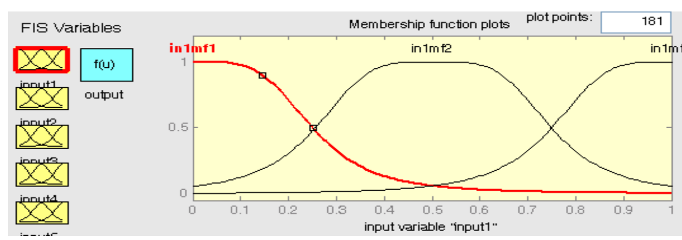

Fig 3. Membership input1 functions after training

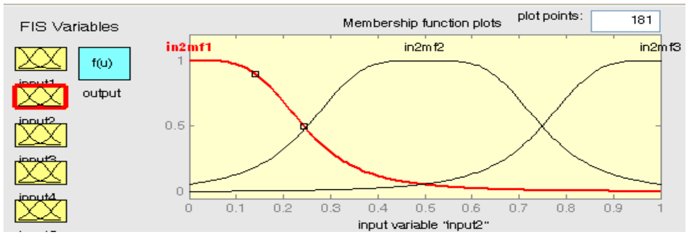

Fig 4. Membership input2 functions after training

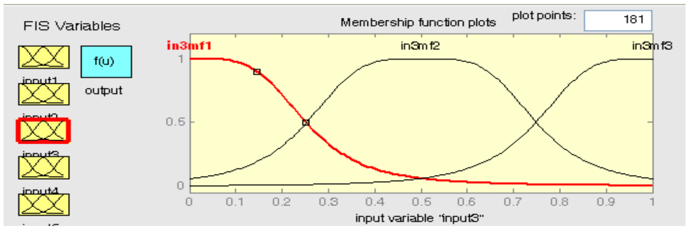

Fig 5. Membership input3 functions after training

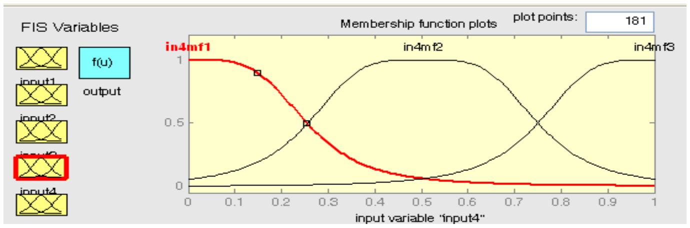

Fig 6. Membership input4 functions after training

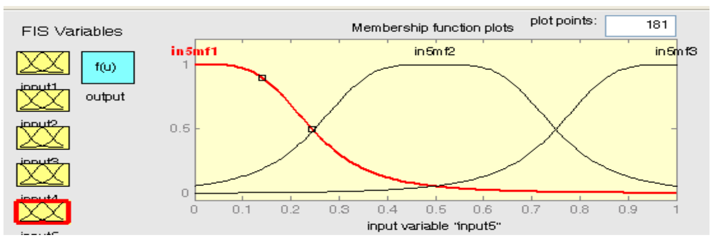

Fig 7. Membership input5 functions after training

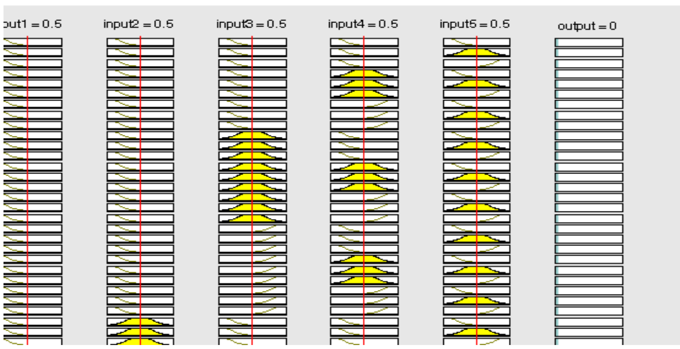

Fig 9. Rule outputs before training

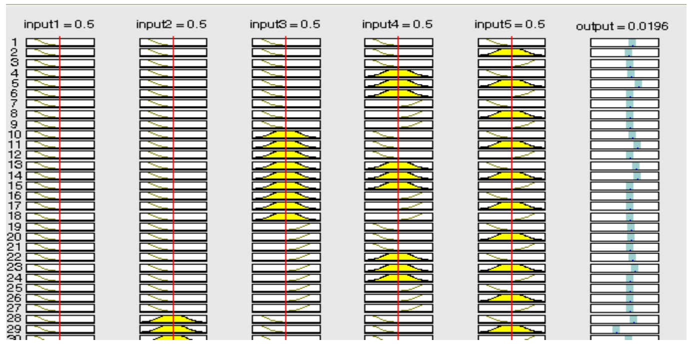

Fig 10. Rule outputs after training

3.2 Performance analysis

The test performance of the ANFIS model was determined by the computation of the statistical parameters such as sensitivity, specificity and total classification accuracy. The sensitivity, specificity and total classification accuracy are defined as follows:

Sensitivity: The ratio of the number of true positives to the sum of true positives and false negatives.
Specificity: The ratio of the number of true negatives to the sum of true negatives and false positives
Accuracy: It is the number of patterns detected by the total number of patterns.

Out of 120 feature vectors of seizure 117 patterns were detected (TP) and 3 were not detected (FN). Out of 80 non-seizures feature vectors 78 were detected (TN). The performance of the classifier for normal and seizure conditions are shown in Table 3 and success rate in Table 4.

Table 3. The performance of the classifier for normal and seizure conditions

Type of seizure	Total feature	Correctly detected	Incorrectly detected
Normal	80	78	2
Tonic-Clonic	120	117	3

Table 4. The accuracy of the network

Test outcome	Total feature	Correctly detected	Accuracy (%)
Specificity	80	79	98.75
Sensitivity	120	116	96.7
Accuracy	200	195	98

Table 5 Comparison of BPN and ANFIS models for EEG signal classification

Classifier type	Correctly classified (%)	Specificity (%)	Sensitivity (%)
BPN	95	95.7	94.3
ANFIS	98	98.5	96.7

As it is seen from Table 5, the ANFIS model classified normal subjects and epileptic subjects with the accuracy of 98.75.7% and 96.7%, respectively. The correct classification rates of the neural network (BPN) were 95.7% for normal subjects and 94.3% for epileptic patients. The total classification accuracy of the stand-alone neural network was 95%. Thus, the accuracy rates of the ANFIS model presented for this application were found to be higher (98%) than that of the stand-alone neural network model. These results indicate that the proposed ANFIS model has some prospective in epileptic seizure detection

4. CONCLUSION

Diagnosing epilepsy is a difficult task requiring observation of the patient, an EEG, and gathering of additional clinical information. In this work, a simple and new technique of an automatic diagnostic classification system is designed and executed. Conventional method of classification of EEG signals using mutually exclusive time and frequency domain representations does not give efficient results. The epileptic seizure signals were decomposed into time-frequency representations using wavelet transform and statistical features were calculated to describe their distribution. An ANFIS-based system was implemented for the classification of epileptic seizure using the statistical features as inputs. The proposed technique involved training the ANFIS classifier to detect epileptic seizure in EEG when the statistical features extracted from the wavelet sub-bands of EEG signals were used as inputs. The presented ANFIS classifier combined the neural network adaptive capabilities and the fuzzy logic qualitative approach. Some conclusions relating to the impacts of features on the epileptic seizure detection were obtained through analysis of the ANFIS. The classification results and statistical measures were used for evaluating the ANFIS. The classification of normal subjects and epileptic patients were done with the accuracy of 99% and 97%, respectively.

Acknowledgements

We would like to thank the EEG experts and the team of technicians for their technical support especially for the data acquisition and handling, from the department of Neurology, Sri Ramachandra University, Chennai.

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