# Comparison of Intelligent Computing Techniques for Classification of Clinical EEG Signals

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## Abstract

**Objective:** The objective of this work is to develop efficient classification systems using intelligent computing techniques for classification of normal and abnormal EEG signals.

**Methods:** In this work, EEG recordings were carried out on volunteers (N=170). The features for classification of clinical EEG signals were extracted using wavelet transform and the feature selection was carried out using Principal Component Analysis. Intelligent techniques like Back Propagation Network (BPN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Particle Swarm Optimization Neural network (PSONN) and Radial Basis function Neural network (RBFNN) were trained for diagnosing seizures. Further, the performance of the developed classifiers was compared.

**Results:** Results demonstrate that RBFNN classifies normal and abnormal EEG signals better than the other methods. It appears that the RBFNN is able to detect Generalized Tonic-Clonic Seizure (GTCS) more efficiently than the Complex Partial Seizures (CPS). Positive predictive value was better in PSONN and ANFIS than BPN method.

**Conclusions:** It appears that the combination of Wavelet transform method and PCA derived features along with RBFNN classifier is efficient for automated EEG signal classification.

## Keywords

Epileptic seizure, wavelet transform, intelligent classification systems

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## 1 Introduction

Infections are important cause of epilepsy in developing countries, the frequency of which may differ widely in different locations. Viral, bacterial, fungal and parasitic infections can result in epilepsy [1, 2]. For example, the cytomegalovirus produces typical encephalitis with fever, headache and seizures. Cytomegalovirus can cause seizures in 4% to 11% of HIV patients. Herpes simplex virus is a DNA virus that causes the most common form of sporadic fatal encephalitis in children older than six months and adults worldwide [1]. A seizure complication of infection can consist of a single seizure or can go on to become chronic epilepsy. Epilepsy is a neurological disorder characterised by recurring seizures. Like many other neurological disorders epilepsy can be assessed by electro encephalograms (EEG) [3]. EEG signals are difficult to characterise since they are non-stationary and highly nonlinear. Since seizures occur irregularly and unpredictably, automatic seizure detection in EEG recordings is highly required [4].

Significant diagnostic information can be obtained from the frequency distribution of epileptic EEG. A method such as the wavelet transforms (WT) is powerful for extraction of diagnostic information from clinical EEG signals [5]. WT is also appropriate for analysis of non-stationary signals, and hence it is suitable for locating transient events. The features extracted using WT can be used to analyze various transient events in biological signals. Recently, work on time-frequency analysis of EEG signals for detecting seizures using WT has been reported [5, 6, 7, 8, 9]. Principal component analysis, or PCA, is a technique that is widely used for applications such as dimensionality reduction, lossy data compression, feature extraction, and data visualization. PCA is a statistical method used to transform the input space into a new lower dimensional space. PCA technique has been investigated before by researchers for signal and image processing [10].

Neural networks are routinely employed in signal classification systems [11, 12, 13]. Fuzzy sets have attracted the growing attention and interest in modern information technology, production technique, decision making, pattern recognition, diagnostics, data analysis, etc. [14, 15]. In recent years, the integration of neural networks and fuzzy logic has given birth to new research into Neuro-fuzzy systems. 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 and data classification [16, 17, 18, 19, 20, 21]. Successful implementations of ANFIS in biomedical engineering have been reported, for classification [10, 16, 18], for modeling and controlling real systems [21] and data analysis [22]. Particle swarm optimization (PSO) is an evolutionary optimization technique motivated by the simulation of social behavior [23].

Radial basis function (RBF) neural networks are good at modeling nonlinear data and can be trained in one stage rather than using an iterative process as in multilayer perceptron and also learn the given application quickly. Enrico [24] surveyed the different interpretations of radial basis function neural networks in order to emphasize their relevant properties and concluded that medical applications usually used radial basis function neural networks. Recently, there is a growing interest in the use of RBFNN for its short training time and being guaranteed to reach the global minimum of error surface during training [25]. There are several reports regarding the use of RBFNN for solving classification problems [26, 27, 28, 29]. Additionally, this network is inherently well suited for classification, because it naturally uses unsupervised learning to cluster the input data [30, 31].

This paper aims to extract features from EEG signals using WT and feature selection is performed using PCA. Further, classification systems for diagnosis of normal and abnormal EEG signals have been developed using ANFIS, PSONN and RBFNN techniques.

# 2 Methodology

This paper will focus on an automatic diagnosis system to classify the normal and epileptic seizure EEG signals. This system consists of two stages. The first stage is the feature extraction from EEG signals and the second stage is the classification of EEG signals based on the computed features. Figure 1 shows the block diagram of the proposed methodology.

In this work, EEG recordings are carried out on volunteers (N=170). This dataset includes 60 subjects diagnosed as normal, 60 subjects diagnosed with generalized tonic clonic seizures and 50 subjects diagnosed with complex partial seizures. The typical normal and abnormal EEG signals are shown in Figures 2, 3 and 4.

## 2.1 Subjects and Data Recording

Subjects within the age group of 21 to 40 were selected for this study. The EEG was 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 was sampled at a rate of 500 Hz after filtering between 1 and 70 Hz. A bipolar electrode montage of 16 channels was used in the analysis. The EEGs were recorded with Ag/AgCl electrodes placed at the $F_4$, $C_4$, $P_4$, $O_2$, $F_3$, $C_3$, $P_3$, $O_1$, $Fp_2$, $F_8$, $T_4$, $T_6$, $Fp_1$, $F_7$, $T_3$, and $T_5$, loci of the 10–20 International System. Impedance was kept below 5 k$\Omega$ to avoid polarization effects. All data were stored for off-line processing. All EEGs with artifact, electrode movement and bursts of alpha waves were discarded.

## 2.2 Visual Inspection and Validation

Two EEG technologists with experience in the clinical seizure EEG signals separately inspected every recording included in this study to score clinical seizure and normal signals. The two experts revised the signals together to solve disagreements and set up the training set for the development of the classification systems. They also examined each recording completely for epileptic seizures. This validated set provided the reference evaluation to estimate the performance of the classifiers.

## 2.3 Wavelet Analysis and Feature Extraction

### 2.3.1 Artifact Removal from EEG Signals

The presence of artifacts in the signals is one of the major difficulties in analysis of EEG signals. This nature of disturbance is a serious obstructing factor that prohibits further processing to identify useful diagnostic features. Artifacts in EEG are commonly handled by discarding the affected segments of EEG. The simplest approach is to discard a fixed length segment, perhaps one second, from

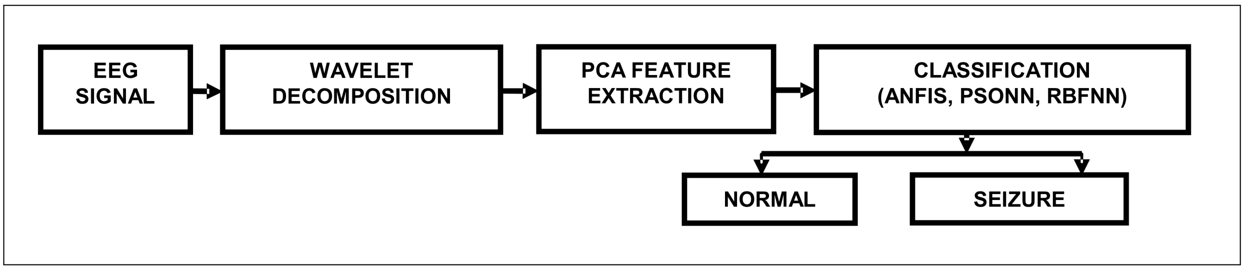


Figure 1: Schematic of the EEG signal classification system.

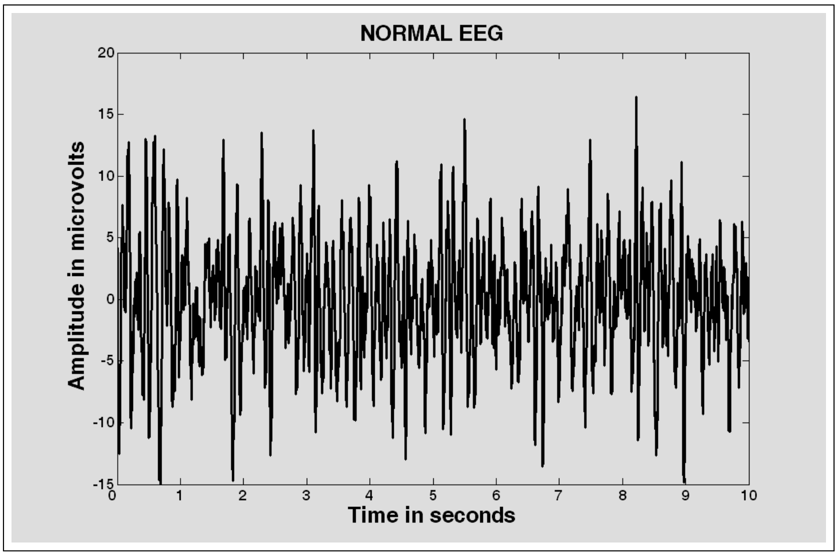


Figure 2: Normal EEG signal.

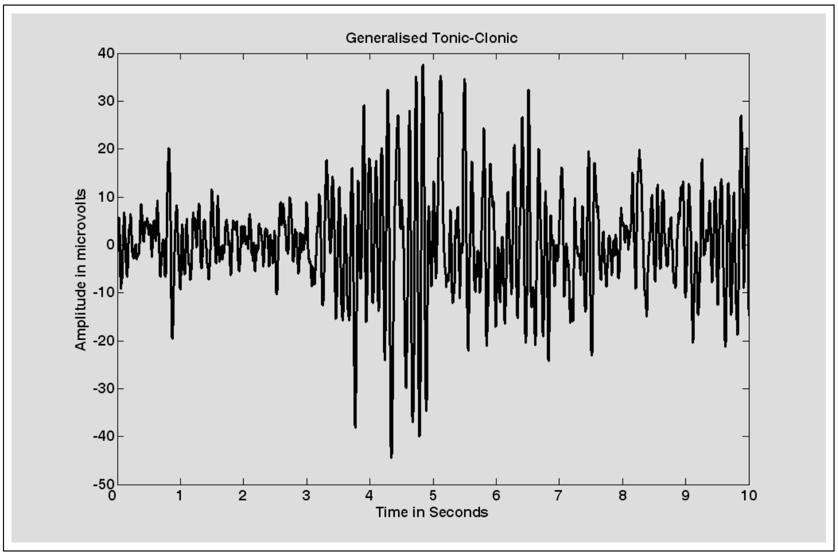


Figure 3: Generalised tonic-clonic seizure EEG signal.

the time an artifact is detected. Discarding segments of EEG data with artifacts can greatly decrease the amount of data available for analysis. Since the frequency bands of these noises may overlap with the seizure signal, conventional method of using filters was not suitable for removal of noise. In this work, DWT based denoising technique, namely wavelet shrinkage denoising was used [31].

#### 2.3.2 Multiresolution Decomposition of EEG Signals

The Discrete Wavelet Transform (DWT) is a versatile signal processing tool that analyzes the signal at different frequency bands, with different resolutions by decomposing the signal into a coarse approximation and detail information [32]. We visually inspect the data first, and if the data is discontinuous, Haar or other sharp wavelet functions are applied [33] 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.

Table 1: Frequencies corresponding to different levels of decomposition.

| 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 |

 

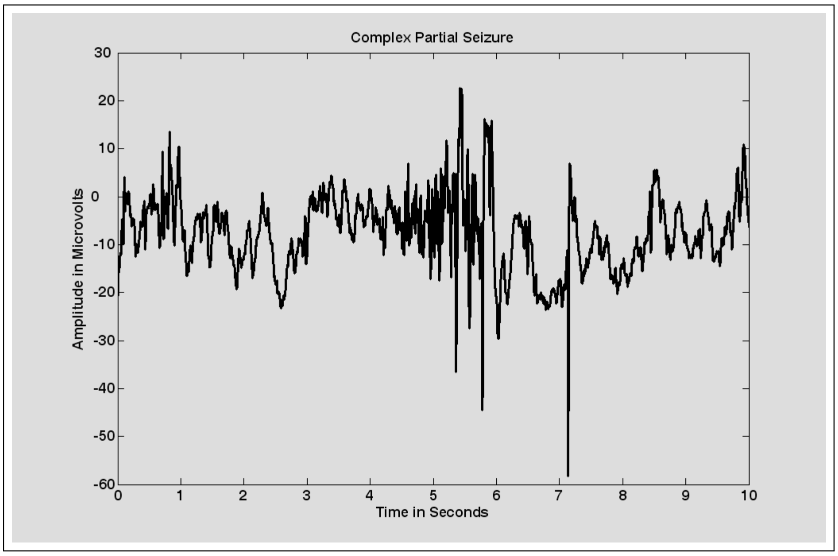


Figure 4: Complex partial seizure EEG signal.

In this study Quadratic spline wavelet is chosen. 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 [27]. The ranges of various frequency bands are shown in Table 1.

### 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 reduce the dimensionality of the extracted feature vectors, Gotman [34] features and some statistical features are used from the wavelet coefficients. These feature vectors, calculated for the frequency bands D4–D8 and A8, is used for classification of the EEG signals.

## 2.4 Intelligent Computing Techniques

### 2.4.1 Adaptive Neuro-Fuzzy Inference system (ANFIS)

ANFIS was first introduced by Jang in 1993 [20]. It is a model that maps inputs through input membership functions (MFs) and associated parameters, and then through output MFs to outputs. We consider one degree of Sugeno's function [18] that 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):

$$\text{Rule 1}: \text{ if } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f = p_1x + q_1y + r_1. \quad (1)$$

$$\text{Rule 2}: \text{ if } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f = p_2x + q_2y + r_2. \quad (2)$$

where $x$ and $y$ are the inputs, $A_i$ and $B_i$ are the fuzzy sets, $f_i$ are the outputs within the fuzzy region specified by the fuzzy rule, $p_i$, $q_i$ and $r_i$ are the design parameters that are determined during the training process.

### 2.4.2 Particle Swarm Optimization Neural Network (PSONN)

The PSO algorithm is a population based search algorithm based on social behavior of birds within a flock. A swarm consists of a set of 'N' particles where each particle represents a potential solution. Particles are then flown through the hyperspace, where the position of each particle is changed according to its own experience and that of its neighbors.

In the original formulation of PSO [23], each particle is defined as a potential solution to the problem in a D-dimensional space and each particle maintains a memory of its previous best position. The particle position with the highest fitness value for the entire run is called the global best.

At each of the iteration the velocity vector ($V_i$) of particle is adjusted based on its best solution and the best solution of its neighbors. The position ($x_i$)of the velocity adjustment made by the particle's previous best position is called the cognition component and the position of the velocity adjustments using the global best is called the social component. The PSO equations described in [21] are

$$\begin{aligned} V_i(t+1) &= wV_id(t) + c_1r_1(\ldots) * (p_id(t) - x_id(t)) + \\ &+ c_2r_2(\ldots) * (pgd(t) - x_id(t)) \quad (3) \\ x_id(t+1) &= x_id(t) + V_id(t) \quad (4) \end{aligned}$$

where $w$ is the inertia weight, $c_1$ and $c_2$ are positive acceleration constants. The velocity vector drives the optimization process and reflects socially exchanged information.

#### 2.4.3 Radial Basis Function Neural Network (RBFNN)

The radial basis function network (RBFN) is a multilayer feed forward neural network, which consists of an input layer of source nodes, a layer of non linear hidden units that operate as kernel nodes and an output layer of linear weights. In response to an input vector, the outputs of the hidden layer are linearly combined to form the network response that is processed with a desired response to the output layer. The weights are trained in a supervised fashion using an appropriate linear method [35]. An activation function for a hidden layer node is a locally radial symmetric function.

### 2.5 Performance Analysis

The performance of the developed classifiers was estimated using False Positive (FP), False Negative (FN), True Positive (TP) and True Negative (TN) values [10]. Classification of a normal data as abnormal is considered as FP and classification of abnormal data as normal is considered FN. TP and TN are the cases where the abnormal is classified as abnormal and normal is classified as normal respectively. The accuracy, sensitivity, specificity, positive predictive value and negative predictive value were estimated using the following relations as shown in equations:

$$\text{Accuracy} = (\mathrm{TP}+\mathrm{TN}) / (\mathrm{TP}+\mathrm{FP}+\mathrm{TN}+\mathrm{FN}) \quad (5)$$

$$\text{Sensitivity} = \mathrm{TP} / (\mathrm{TP}+\mathrm{FN}) \quad (6)$$

$$\text{Specificity} = \mathrm{TN} / (\mathrm{TN}+\mathrm{FP}) \quad (7)$$

$$\text{False Positive Rate} = \mathrm{FP} / (\mathrm{TN}+\mathrm{FP}) \quad (8)$$

$$\text{Positive Predictive Value} = \mathrm{TP} / (\mathrm{TP}+\mathrm{FP}) \quad (9)$$

$$\text{Negative Predictive Value} = \mathrm{TN} / (\mathrm{TN}+\mathrm{FN}) \quad (10)$$

Accuracy is the representation of classifier performance in global sense. Sensitivity and specificity are the proportions of abnormal data classified as abnormal, normal data classified as normal respectively.

## 3 Results and Discussion

The EEG signals were decomposed into details D1–D8 and one final approximation A8 using wavelet transforms. The features like energy, entropy, Hurst exponent, Largest

Table 2: Descriptive statistics of the decomposition level 6.

| Sl. No | D6 Feature | Normal (60) | GTC (60) | CPS (50) | p-value |
|---|---|---|---|---|---|
| | | Mean ± SD | Mean ± SD | Mean ± SD | |
| 1 | Energy | 0.13 ± 0.08 | 0.07 ± 0.001 | 0.06 ± 0.01 | 0.0006 |
| 2 | Max | 0.15 ± 0.06 | 0.17 ± 0.107 | 0.16 ± 0.14 | 0.0001 |
| 3 | Min | 0.50 ± 0.19 | 0.30 ± 0.209 | 0.17 ± 0.16 | 0.0195 |
| 4 | Mean | -0.15 ± 0.001 | 0.03 ± 0.03 | 0.02 ± 0.001 | 0.0032 |
| 5 | Standard deviation | 0.35 ± 0.12 | 0.19 ± 0.11 | 0.17 ± 0.13 | 0.0055 |
| 6 | Variance | 0.14 ± 0.09 | 0.07 ± 0.009 | 0.06 ± 0.009 | 0.0008 |
| 7 | Hurst | 0.94 ± 0.02 | 0.94 ± 0.02 | 0.91 ± 0.03 | 0.0198 |
| 8 | Entropy | 0.13 ± 0.02 | 0.08 ± 0.012 | 0.095 ± 0.014 | 0.0003 |
| 9 | Pyy | 0.24 ± 0.21 | 0.05 ± 0.02 | 0.03 ± 0.004 | 0.0056 |
| 10 | Freq At Pyy | 0.71 ± 0.13 | 0.70 ± 0.11 | 0.70 ± 0.11 | 0.0011 |
| 11 | LLE | 0.93 ± 0.02 | 0.91 ± 0.03 | 0.90 ± 0.04 | 0.0102 |

Table 3: Descriptive statistics of the decomposition level 7.

| Sl. No | D7 Feature | Normal (60) | GTC (60) | CPS (50) | p-value |
|---|---|---|---|---|---|
| | | Mean ± SD | Mean ± SD | Mean ± SD | |
| 1 | Energy | 0.07 ± 0.06 | 0.05 ± 0.01 | 0.05 ± 0.002 | 0.0136 |
| 2 | Max | 0.14 ± 0.07 | 0.16 ± 0.12 | 0.10 ± 0.08 | 0.0171 |
| 3 | Min | 0.43 ± 0.22 | 0.31 ± 0.26 | 0.18 ± 0.17 | 0.0107 |
| 4 | Mean | -0.08 ± 0.03 | 0.01 ± 0.01 | 0.04 ± 0.02 | 0.0013 |
| 5 | Standard deviation | 0.23 ± 0.09 | 0.14 ± 0.09 | 0.14 ± 0.11 | 0.0013 |
| 6 | Variance | 0.07 ± 0.07 | 0.07 ± 0.01 | 0.05 ± 0.004 | 0.0001 |
| 7 | Hurst | 0.95 ± 0.01 | 0.96 ± 0.01 | 0.95 ± 0.02 | 0.0059 |
| 8 | Entropy | -0.04 ± 0.02 | 0.05 ± 0.009 | 0.106 ± 0.015 | 0.0019 |
| 9 | Pyy | 0.10 ± 0.10 | 0.05 ± 0.03 | 0.03 ± 0.001 | 0.0005 |
| 10 | Freq At Pyy | 0.79 ± 0.15 | 0.80 ± 0.16 | 0.81 ± 0.16 | 0.0008 |
| 11 | LLE | 0.89 ± 0.03 | 0.88 ± 0.04 | 0.78 ± 0.04 | 0.0507 |

Lyapunov exponent (LLE), maximum power of the spectrum, frequency at which maximum power exists and statistical features like mean, standard deviation, maximum and minimum of the coefficients and variance were extracted. Totally 55 features were extracted for each subject. The statistical analysis on the extracted features such as mean and standard deviation for level D6 and D7 is shown in Table 2 and Table 3.

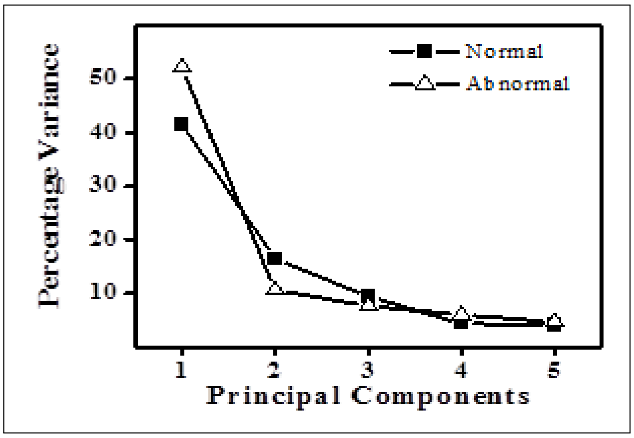


Figure 5: Percentage variance for normal and abnormal subjects for Quadratic Spline Wavelet.

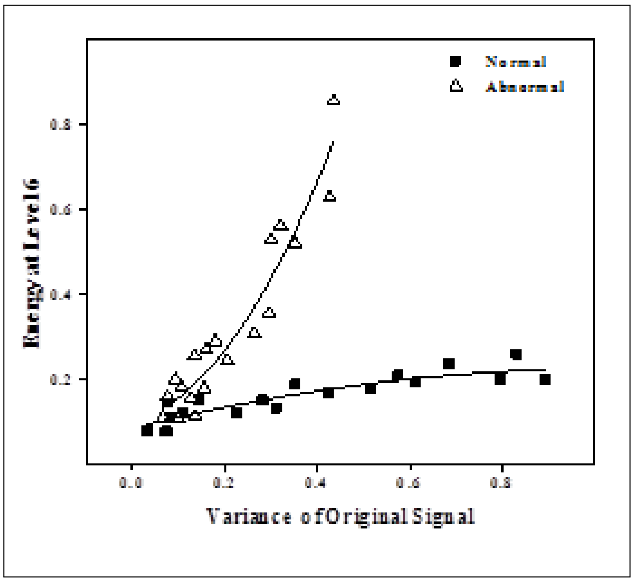


Figure 6: Variation in Energy for both normal and abnormal EEG at D6.

**PCA based choice of wavelets and feature extraction:** PCA was applied for selection of wavelet and feature reduction. The original feature space consists of 55 EEG features which included frequency domain features, the statistical features and the nonlinear features obtained from normal and clinical seizure subjects from the different types of wavelets like Haar, db2, db4, db5 and quadratic spline. Some of the methods like Correlation-based Feature Selection [36], Chi-square Feature Evaluation [36] does not perform feature selection but only feature ranking, and they are usually combined with another method when one needs to find out the appropriate number of attributes. PCA is used to make a classifier system more effective, having less computational complexity, and less time consumption. Hence the dataset obtained from the EEG containing 55 parameters for five types of wavelets were subjected to PCA. The Principal Components obtained from PCA were analyzed for ranking the most significant wavelet and features. When PCA was applied, it was observed that the features derived out of quadratic spline wavelet had the maximum variance than the other wavelets used. The percentage variance of the extracted features of normal and abnormal subjects for the quadratic spline wavelet is plotted in Figure 5. Hence quadratic spline wavelet features were considered for further analysis.

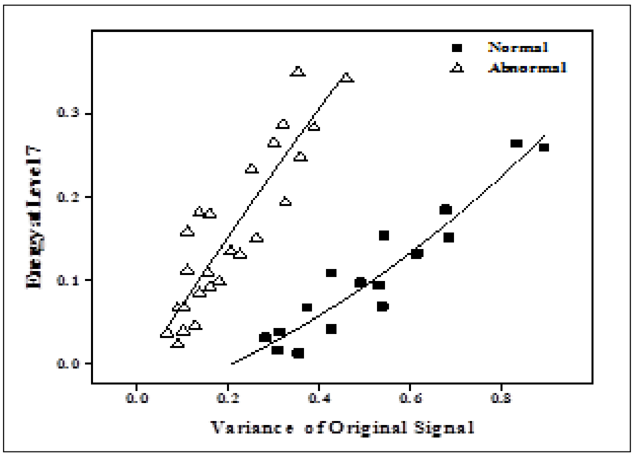


Figure 7: Variation in Energy for both normal and abnormal EEG at D7.

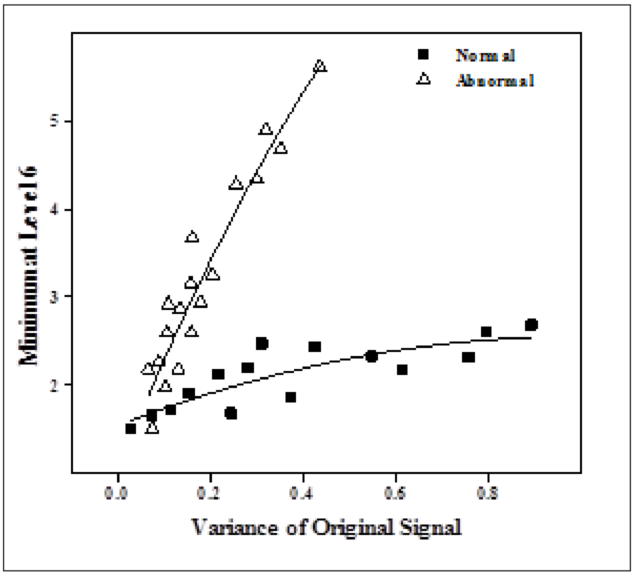


Figure 8: Variation in Minimum for both normal and abnormal EEG at D6.

**Qualitative assessment of features:** One of the simplest linear statistics that may be used for investigating the dynamics underlying the clinical EEG is the variance of the signal calculated in consecutive non overlapping windows. The various features obtained from the wavelet decomposition were correlated with the variance of the original signal. It was observed from Table 4 that at level D4, D5 and at D8, there were poor correlation values for normal and abnormal features. In level D6 and D7 the correlation of certain features with variance was higher than the other levels of decomposition. The Features like energy, minimum, standard deviation and the entropy of DWT coefficients have very high correlation with high significance ($p < 0.001$).

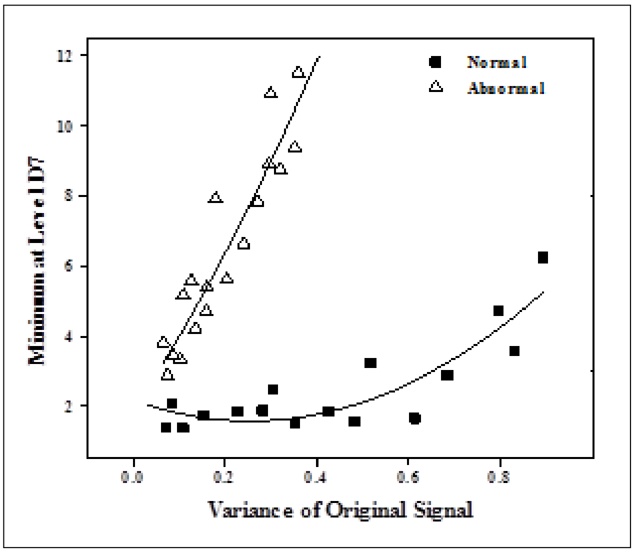


Figure 9: Variation in Minimum for both normal and abnormal EEG at D7.

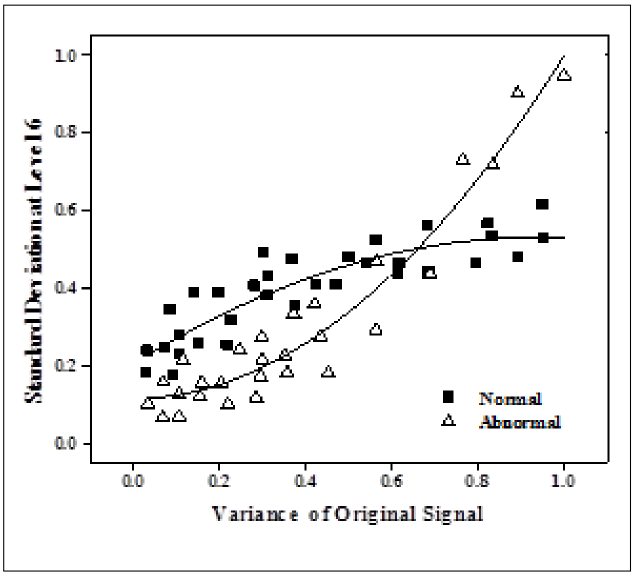


Figure 10: Variation in standard deviation at D6.

Figures 6 and 7 shows the variation in energy with the variance of the original signal for normal and abnormal subjects in levels D6 and D7 respectively. It was observed that the energy correlates well with the variance in level D6 and D7. A high degree of correlation (R=0.95) is found for abnormal subjects in level D6. Figure 8 and 9 show the variation in minimum value with the variance of the original signal for normal and abnormal subjects respectively. A high degree of correlation (R=0.95) was found for abnormal subjects in level D6. It was found that correlation of minimum value with variance was more in abnormal than normals. The variation in measured Standard deviation values of decomposed wavelet coefficient with values of variance for normal and abnormal subjects is shown in Figures 10 and 11 respectively. A high degree of correlation (R=0.97) was found for abnormal subjects in level D7. It was found that correlation of standard deviation value with variance is more in abnormal subjects than normal subjects.

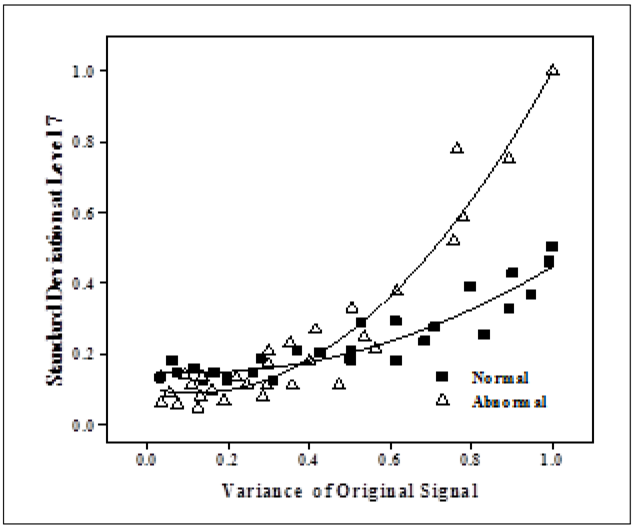


Figure 11: Variation in standard deviation at D7.

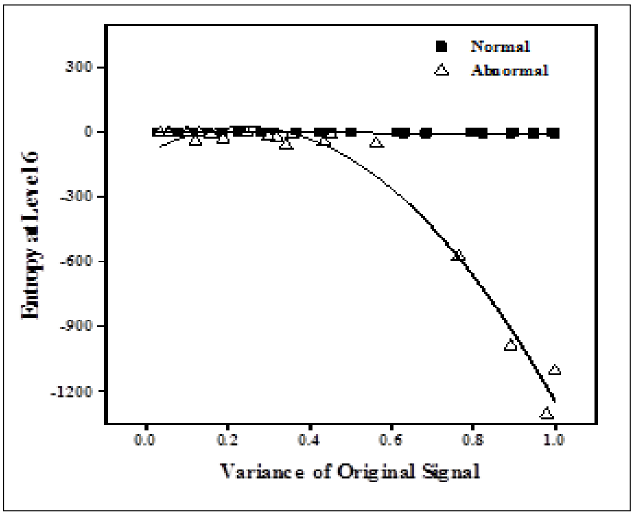


Figure 12: Variation in Entropy for both normal and abnormal EEG at D6.

The variation in Entropy values of wavelet coefficient with values of variance for normal and abnormal subjects is shown in Figures 12 and 13 respectively. Entropy is a measure of the disorder present in a system. The negative value of the entropy of the Abnormal EEG shows that there is a move towards ordered state. From Figures 12 and 13, it is seen that the correlation between entropy and variance for normal subjects is lower (R=0.88, 0.91) stating that the signals are deterministic and for abnormal subjects the correlation values were found to be (R=0.98, 0.96) higher. Among the entire parameters mean, Hurst exponent, frequency at maximum power of the spectrum and largest Lyapunov exponent show poor degrees of correlation. Thus the parameters Energy, minimum, standard deviation and entropy derived from approximated coefficients seems to be useful parameters to differentiate normal and abnormal.

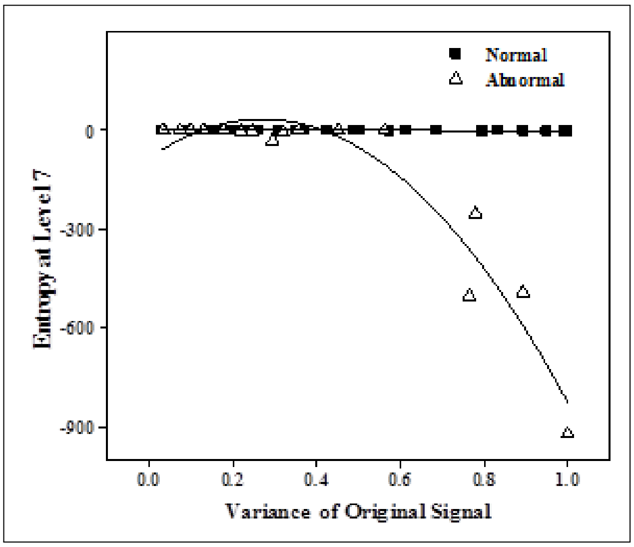


Figure 13: Variation in Entropy for both normal and abnormal EEG at D7.

The percentage variances between the various quadratic spline wavelet features were estimated for the normal and abnormal subjects. The Principal Components that explain the maximum percentage variance were chosen and the corresponding component magnitudes were analyzed. The parameters with highest magnitudes in the loadings of the Principal Components were chosen for further classification and are shown in Table 5.

**Performance of the intelligent computing techniques** Tables 6 and 7 show the performance comparison of all the methods without PCA and with PCA based features. It was found that RBFNN classifies EEG signals better than the other methods for all features and PCA based features. Positive predictive value was better in PSONN and ANFIS than BPN method. It is clearly seen that RBFNN has better accuracy when compared with the other classifiers. These results indicate that the proposed RBFNN model has a potential in clinical seizure detection. Table 8 shows the comparison of classification accuracy with PCA based features for normal EEG and different types of seizure EEG signals.

## 4 Conclusions

In this study, normal and seizure EEG features were extracted using quadratic spline wavelet. The appropriate feature components were delineated and the corresponding statistical parameters were computed. In this work, clinical EEG signals were classified into normal and abnormal, using intelligent computing techniques. The performance of the developed classifiers was assessed and compared using sensitivity, specificity, positive predictive and negative predictive values. The conclusions were drawn after meticulous experimentation on best architecture, number of hidden neurons required and performance goal. It was observed that the RBFNN has better classification accuracy when compared to BPN, ANFIS and PSONN. The value of specificity shows that RBFNN classifies abnormal data more accurately than ANFIS and back propagation network. The positive predictive value suggests that the classification of EEG signals into normal is higher in the RBFNN than that of the other classifiers used in this study. The negative predictive value indicates that the back propagation network diagnoses the abnormal data more correctly than the normal data. It was found that the RBFNN classifies Generalized Tonic Clonic seizure better than the complex partial seizure and normal EEG

Table 4: The correlation coefficient of variance and wavelet derived features for level D4 – D8.

| Features | D4 | | | D5 | | | D6 | | | D7 | | | D8 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N | A | p | N | A | p | N | A | p | N | A | p | N | A | p |
| Energy | 0.84 | 0.85 | 0.0096 | 0.87 | 0.84 | 0.0101 | 0.89 | 0.95 | 0.0039 | 0.85 | 0.89 | 0.0027 | 0.75 | 0.88 | 0.2788 |
| Maximum | 0.89 | 0.84 | 0.0206 | 0.93 | 0.57 | 0.1777 | 0.83 | 0.93 | 0.6657 | 0.93 | 0.94 | 0.5877 | 0.83 | 0.92 | 0.8744 |
| Minimum | 0.96 | 0.84 | 0.0025 | 0.97 | 0.76 | 0.3654 | 0.84 | 0.95 | 0.0011 | 0.88 | 0.93 | 0.0001 | 0.39 | 0.76 | 0.0004 |
| Mean | 0.38 | 0.16 | 0.0091 | 0.21 | 0.38 | 0.4621 | 0.43 | 0.57 | 0.9849 | 0.93 | 0.93 | 0.7396 | 0.92 | 0.65 | 0.2231 |
| Std | 0.83 | 0.96 | 0.0002 | 0.87 | 0.86 | 0.0001 | 0.88 | 0.96 | 0.0021 | 0.93 | 0.97 | 0.0001 | 0.48 | 0.95 | 0.2992 |
| Variance | 0.93 | 0.97 | 0.0046 | 0.90 | 0.85 | 0.0001 | 0.81 | 0.93 | 0.0031 | 0.66 | 0.73 | 0.0008 | 0.61 | 0.65 | 0.0001 |
| Hurst | 0.39 | 0.19 | 0.5256 | 0.85 | 0.43 | 0.5646 | 0.46 | 0.74 | 0.0030 | 0.39 | 0.67 | 0.0001 | 0.93 | 0.86 | 0.3333 |
| Entropy | 0.85 | 0.96 | 0.6977 | 0.82 | 0.87 | 0.0001 | 0.88 | 0.98 | 0.0086 | 0.91 | 0.96 | 0.0167 | 0.87 | 0.73 | 0.0179 |
| Pyy | 0.64 | 0.42 | 0.5088 | 0.89 | 0.69 | 0.1416 | 0.89 | 0.99 | 0.1388 | 0.97 | 0.41 | 0.0046 | 0.91 | 0.28 | 0.0048 |
| Freq at Pyy | 0.30 | 0.04 | 0.0001 | 0.79 | 0.18 | 0.3092 | 0.88 | 0.77 | 0.0249 | 0.28 | 0.42 | 0.7906 | 0.99 | 0.11 | 0.3215 |
| LLE | 0.30 | 0.06 | 0.0239 | 0.64 | 0.19 | 0.9153 | 0.91 | 0.72 | 0.0870 | 0.76 | 0.85 | 0.0081 | 0.76 | 0.33 | 0.0897 |

N=Normal, A=Abnormal, p=pvalue D4 – D8 decomposed levels of wavelet transform

Table 5: Component Magnitudes in PC1 and the corresponding features for Normal and seizure EEG.

| Component | Magnitude | Sub-band | Corresponding features in the dataset |
|---|---|---|---|
| PC(13) | 0.199 | D6,D7 | Minimum of absolute value |
| PC(32) | 0.196 | D6,D7 | Energy |
| PC(18) | 0.195 | D6,D7 | Entropy |
| PC(35) | 0.193 | D6,D7 | Standard deviation |

Table 6: Comparison of Performance of the methods with all features.

| Indices | BPN (%) | ANFIS (%) | PSONN (%) | RBFNN (%) |
|---|---|---|---|---|
| Accuracy | 73 | 79 | 81 | 85 |
| Sensitivity (True positive rate) | 66 | 74 | 80 | 76 |
| Specificity | 83 | 87 | 83 | 100 |
| False positive rate ( 1-specificity) | 17 | 13 | 17 | 0 |
| Positive Predictive Value | 90 | 90 | 89 | 100 |
| Negative Predictive Value | 60 | 67 | 71 | 71 |

Table 7: Comparison of classification performance with PCA based features.

| Indices | BPN (%) | ANFIS (%) | PSONN (%) | RBFNN (%) |
|---|---|---|---|---|
| Accuracy | 89 | 93 | 94 | 99 |
| Sensitivity (True positive rate) | 96 | 90 | 92 | 98 |
| Specificity | 80 | 97 | 97 | 100 |
| False positive rate ( 1-specificity) | 20 | 3 | 3 | 0 |
| Positive Predictive Value | 86 | 98 | 98 | 100 |
| Negative Predictive Value | 93 | 85 | 88 | 97 |

signals. The proposed methodology makes it possible as a real-time detector, which will improve the clinical service of Electroencephalographic recording. Hence the combination of Wavelet transform method and PCA derived features pertaining to normal and seizure EEG along with RBFNN based classification appears to be efficient for automated EEG signal classification.

Table 8: Comparison of classification accuracy with PCA based features for normal EEG and different types of seizure EEG signals.

| Algorithm | NORMAL | GTCS | CPS |
|---|---|---|---|
| BPN | 93.3 | 86.7 | 85 |
| RBFNN | 100 | 96.7 | 100 |
| ANFIS | 96.7 | 90 | 90 |
| PSONN | 96.7 | 93.3 | 90 |

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