

# Electroencephalogram Signal Classification for Automated Epileptic Seizure Detection Using Genetic Algorithm

B. Suguna Nanthini, B. Santhi

ICT, School of Computing, SASTRA University, Thanjavur, Tamil Nadu, India

## Abstract

**Background:** Epilepsy causes when the repeated seizure occurs in the brain. Electroencephalogram (EEG) test provides valuable information about the brain functions and can be useful to detect brain disorder, especially for epilepsy. In this study, application for an automated seizure detection model has been introduced successfully. **Materials and Methods:** The EEG signals are decomposed into sub-bands by discrete wavelet transform using db2 (daubechies) wavelet. The eight statistical features, the four gray level co-occurrence matrix and Renyi entropy estimation with four different degrees of order, are extracted from the raw EEG and its sub-bands. Genetic algorithm (GA) is used to select eight relevant features from the 16 dimension features. The model has been trained and tested using support vector machine (SVM) classifier successfully for EEG signals. The performance of the SVM classifier is evaluated for two different databases. **Results:** The study has been experimented through two different analyses and achieved satisfactory performance for automated seizure detection using relevant features as the input to the SVM classifier. **Conclusion:** Relevant features using GA give better accuracy performance for seizure detection.

**Keywords:** Accuracy, classification, epilepsy, genetic algorithm, seizure, signal

## INTRODUCTION

Human cerebral cortex consists of brain has a tremendous and prosperous spatiotemporal dynamics which is particularly unique to the human. Millions of neurons in the brain communicate each other through chemical and electrical signals (action potentials).<sup>[1]</sup> The abnormal electrical disturbance in the brain is called seizure. Epilepsy causes when the repeated seizures occur in the brain. Careful analysis of electroencephalogram (EEG) provides valuable information about the brain functions and can be useful to detect brain disorder, especially for epilepsy. EEG includes different kinds of waveforms with various frequencies, amplitude, and spatial distribution. The types of EEG waves<sup>[2,3]</sup> are identified according to their frequency range – delta: below 3.5 Hz (0.1–3.5 Hz), theta: 4–7.5 Hz, alpha: 8–13 Hz, beta: 14–40 Hz, and gamma: above 40 Hz. The EEG may show unusual electrical discharge when some abnormality occurs in the brain. The measurement of placing the electrodes in the brain area, namely, frontal pole (Fp), frontal (F), parietal (P), temporal (T), and occipital (O), provides meaningful communication. Even numbers and odd numbers as subscript have been decided to differentiate the brain's hemisphere.

The position of Fp<sub>2</sub>, F<sub>4</sub>, F<sub>8</sub>, C<sub>4</sub>, T<sub>4</sub>, T<sub>6</sub>, P<sub>4</sub>, and O<sub>2</sub> electrodes indicates right hemisphere and Fp<sub>1</sub>, F<sub>3</sub>, F<sub>7</sub>, C<sub>3</sub>, T<sub>3</sub>, T<sub>5</sub>, P<sub>3</sub>, and O<sub>1</sub> electrodes indicates left hemisphere, respectively. The position of F<sub>Z</sub>, C<sub>Z</sub>, and P<sub>Z</sub> electrodes indicates the midline in frontal, central, and parietal regions.<sup>[3]</sup> Providing quality treatment is more important for epileptic patients. Supportive system will be helpful for experts to have better diagnosis. Hence, focusing on automated seizure detection is necessary for the future development. To develop an expert system, the machine has to learn to distinguish the EEG signal features. Machine can learn from data just like human brain acquires knowledge through study and facts. Machine learning carries out a particular task to classify the data in two stages. Training stage is the first stage where the machine trained with the relevant features and the corresponding categorical labels of the data while in testing stage the machine examined with the unknown data of similar features. The classifier has to

**Address for correspondence:** Ms. B. Suguna Nanthini, Research Scholar, School of Computing, SASTRA University, Thanjavur - 613 401, Tamil Nadu, India. E-mail: bs.nanthini@gmail.com

### Access this article online

Quick Response Code:



Website:  
www.jnsbm.org

DOI:  
10.4103/jnsbm.JNSBM\_285\_16

This is an open access article distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike 3.0 License, which allows others to remix, tweak, and build upon the work non-commercially, as long as the author is credited and the new creations are licensed under the identical terms.

**For reprints contact:** reprints@medknow.com

**How to cite this article:** Nanthini BS, Santhi B. Electroencephalogram signal classification for automated epileptic seizure detection using genetic algorithm. J Nat Sc Biol Med 2017;8:159-66.

classify the unknown data to appropriate class. Performance evaluation of the classifier is calculated by the percentage of the test data that are accurately classified by the classifier. Machine learning algorithms are utilized efficiently to build a system that can take decisions based on the inputs.<sup>[4]</sup> Machine learning plays the major role in expert system in such a way to create a system that supports to take a decision by its own. The entire procedure for EEG signal classification or seizure detection can be subdivided into a number of processing modules: preprocessing the EEG signal, extraction of 16 dimension features, selection of 8 relevant features, and classification.

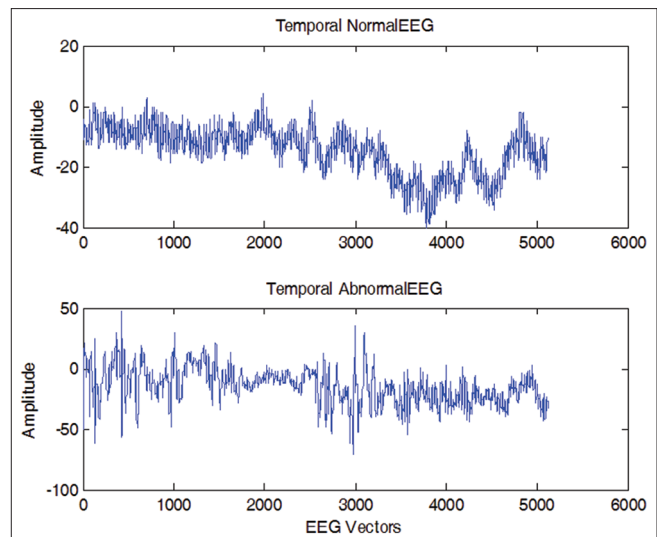
## MATERIALS AND METHODS

### Dataset

Data from two different places are analyzed in this paper. The first database is downloaded from online.<sup>[5]</sup> The five datasets (A-E) each contain EEG segments of 23.6s duration by 100 single channels measured by the standardized electrode placement scheme. These segments were chosen under visual inspection. Set A comprises normal EEG whose relaxation is revealed in the conscious state when eyes open. Set B comprises normal EEG whose relaxation is exposed while awoken state with eyes closed. Set C and D showed the measurement activity in the period of seizure during free intervals. Set E showed merely seizure movement. Using an average common reference with 128-channel amplifier, most of the EEG signals were measured.<sup>[6]</sup> The data measurements were digitized using 12 bit A/D resolution at 173.61 Hz sampling rate.<sup>[7,8]</sup> Datasets A and E are used in this analysis for binary classification. The second database is collected from Sanjeevi EEG diagnostic center, Coimbatore, Tamil Nadu, India. EEG test had taken for 10 normal and 10 abnormal (only seizure) subjects in bipolar longitudinal EEG 16 channels (Fp<sub>2</sub>-F<sub>4</sub>, F<sub>4</sub>-C<sub>4</sub>, C<sub>4</sub>-P<sub>4</sub>, P<sub>4</sub>-O<sub>2</sub>, Fp<sub>2</sub>-F<sub>8</sub>, F<sub>8</sub>-T<sub>4</sub>, T<sub>4</sub>-T<sub>6</sub>, T<sub>6</sub>-O<sub>2</sub>, Fp<sub>1</sub>-F<sub>3</sub>, F<sub>3</sub>-C<sub>3</sub>, C<sub>3</sub>-P<sub>3</sub>, P<sub>3</sub>-O<sub>1</sub>, Fp<sub>1</sub>-F<sub>7</sub>, F<sub>7</sub>-T<sub>3</sub>, T<sub>3</sub>-T<sub>5</sub>, T<sub>5</sub>-O<sub>1</sub>) using 10–20 international electrode placement system with Ag/Agcl disc electrodes. The recorded page on a standard EEG acquisition was digitized with band pass filter settings of 0.1–60 Hz. The sample subjects from this database are shown in Figure 1.

### Wavelet decomposition

The wavelet transform (WT) offers a general technique that can be useful in many tasks of signal processing.<sup>[9,10]</sup> In this analysis, discrete WT (DWT) with the second-order daubechies (db2) wavelet function evaluates the signal at various frequency bands, with different resolutions by decomposing the signal into approximation and detail information. Hence, the design of wavelet analysis has been chosen for investigation and experimentation. As our dataset is in order of 0.53–60 Hz, the raw EEG decomposed at level 4 and its coefficients are cD1 (gamma: 30–60 Hz), cD2 (beta: 15–30 Hz), cD3 (alpha: 8–15 Hz), cD4 (theta: 4–8 Hz), and cA4 (delta: 0.53–4 Hz), respectively. DWT is



**Figure 1:** Sample electroencephalogram signal from normal and seizure subjects

used for preprocessing as well as for decomposing the EEG signals. Using filters, the noise has been removed from the raw EEG. The noise free signals are trained and tested for seizure detection in this paper.

### Feature extraction

To reduce the dimension of raw EEG data, feature extraction is a unique form that has been used in machine learning for classification. Thus, feature extraction acts a significant role in pulling out unique patterns from the original data for consistent classification.<sup>[11]</sup>

#### Statistical features

In this paper, the eight statistical features, namely, mean, median, mode, standard deviation, skewness, kurtosis, maximum, and minimum, are extracted from raw EEG and its sub-bands have been utilized as an input for the SVM classifier.

#### Gray level co-occurrence matrix features

Mostly gray level co-occurrence matrix (GLCM) features are used for texture analysis in image processing. Although it is very much useful in image processing, it is innovative that this analysis has been used GLCM features for EEG signal processing. Here, the signal is considered as an image, and GLCM features such as contrast, correlation, energy, and homogeneity are texture characteristics. Based on the number of intensity pixels in every combination of an image, GLCM is classified to second order statistics. Hence, GLCM is the method of extracting second-order statistical texture features.<sup>[11,12]</sup> The number of gray levels  $G$  in the image of signal is equal to number of rows and columns in GLCM matrix. Therefore, the matrix element in the signal  $S(i, j | \Delta x, \Delta y)$  is the two pixels with the relative frequency separated by a pixel distance  $(\Delta x, \Delta y)$  where  $i$  and  $j$  are intensities occur within a given neighborhood. Consider for the given  $n \times m$  neighborhood of an input image containing  $G$  gray levels from 0 to  $G-1$ . Let  $I(p, q)$  be the intensity at

sample  $m$ , line  $n$  of the neighborhood. Then, the co-occurrence matrix  $C$  is defined over  $n \times m$  and the image  $I$  of EEG signal parameterized by an offset  $(\Delta x, \Delta y)$  as follows:

$$C_{\Delta x, \Delta y}(i, j) = \sum_{p=1}^n \sum_{q=1}^m \begin{cases} 1, & \text{if } I(p, q) = i \text{ and } I(p + \Delta x, q + \Delta y) = j \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Where  $i$  and  $j$  are the image intensity values of the image,  $P$  and  $q$  are the spatial positions in the image  $I$ , and the offset  $(\Delta x, \Delta y)$  a reference pixel and its immediate neighbors depend on the direction used. The GLCM is a two-dimensional array which obtains the specific position of a pixel compared to other pixels. In this study, four GLCM features, namely, contrast; correlation, energy, and homogeneity, are used for classification which is explained as follows.

The GLCM is a two-dimensional array which obtains the specific position of a pixel compared to other pixels. In the measure of contrast, the local intensity varies in  $S(i, j)$  where  $i \neq j$ , therefore this occurs away from the diagonal and defined as:

$$\text{Contrast} = \sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=1}^G \sum_{j=1}^G S(i, j) \right\} \quad (2)$$

Correlation is defined as a measure of gray scale which is linearly dependent between the pixels at the specified positions qualified to each other:

$$\text{Correlation} = \frac{\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{i \times j\} \times S(i, j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y} \quad (3)$$

Energy takes the smallest value when all the entries are equal. It is also called as uniformity and defined as:

$$\text{Energy} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} S(i, j)^2 \quad (4)$$

Angular second moment (ASM) is a measure of homogeneity of an image  $S(i, j)$ . Taking a few gray levels from a homogeneous scene, GLCM gives high values of  $S(i, j)$ . Thus, high values obtained using the following formula:

$$\text{ASM(Homogeneity)} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{S(i, j)\}^2 \quad (5)$$

### Entropy estimation

Shannon is the first entropy concept which has been used in the science of information theory. The Shannon entropy<sup>[13,14]</sup> is defined using the following equation:

$$H(S) = -q \sum_{i=1}^n P_i \log_2 P_i, q = 1 \quad (6)$$

Where the letter  $S$  represents the EEG signal. Although Shannon entropy is applicable for various applications, its capability of extracting information is limited. Renyi entropy<sup>[14]</sup> is the extended version of Shannon by adding  $q$  in the equation. The parameter  $q$  handles the sensitivity of the entropy toward the particular sectors of the probability of the distribution  $P$ . The Renyi entropy inferred from Shannon entropy comprises a gauge of information of order  $q$  and is defined by

$$R_q(S) = \frac{1}{1-q} \log \sum_{i=1}^n P_i^q, q \geq 0, q \neq 1 \quad (7)$$

Shannon entropy is limited to the degree of order ( $q = 1$ ). In this paper, entropy values are estimated from raw EEG as well as from its decomposed signals to evaluate the average amount of information from the EEG signal. The four different values (0.5, 1.5, 2, and 2.5) are given to the parameter  $q$  in the equation 7 are evaluated as features. The estimated values from Renyi entropy and the values from four GLCM features with eight basic statistical features (altogether 16 dimension features) are applied as the input for the SVM classifier. Entropy is used in this paper for not only to extract the maximum amount of information from EEG signals but also to evaluate the performance of Renyi entropy in the range 0.5–2.5.

### Feature selection

Feature Selection is an important step in classification. It is best to feed the selected features to get the optimum result. Redundant features may cause the overload to the system so the optimum result may not occur. Therefore, minimizing the number of features will be helpful to the classifier to learn more robust and to achieve good performance.<sup>[15,16]</sup> Thus, leaving irrelevant features and learning only with appropriate features result in less complexity. The genetic algorithm (GA) technique<sup>[17]</sup> is used in this paper to detect the 8 relevant features from the 16 dimension features.

### Classification in machine learning

Classification is one of the essential techniques in machine learning for data analysis, which classifies the categorical labels. The process can be made into two different stages. The system has been trained with the database tuples and their associated class labels in learning stage. In the second stage, the system is exercised with test data for classification. The performance of the system is evaluated by the percentage of test data that are accurately classified by the classifier.<sup>[18]</sup>

### K-fold cross-validation

To validate the entire input data, partition of data into subsets is necessary. The k-fold cross-validation is the statistical practice which divides the sample data into  $k$  subsets. Out of  $k$  subsets,  $k-1$  subsets are used for training the proposed system and remaining one subset used for testing the performance. This process will be repeated for  $k$  times (folds) until all the subsets used as validation data. The results obtained from the  $k$ -folds can be averaged to determine the accuracy of estimation. The objective of this method is to validate the entire samples.<sup>[16]</sup> In this paper, 10-fold cross-validation method is used for analyses to authenticate the given samples.

### Support vector machine

Support vector machine (SVM) creates hyperplane to classify the normal and abnormal features. SVM classifier can deal with high dimensional data due to its high accuracy.<sup>[19,20]</sup> Kernel is an algorithm which can produce nonlinear decision boundaries.<sup>[21,22]</sup> Basically, SVM is a linear two-class classifier. The features of the two classes are categorized by the labels

“+1” and “-1”.[23] In this paper, the SVM classifier is used for EEG signal classification.

**Performance evaluation**

*Confusion matrix*

For this experimental research, a value “-1” indicates normal EEG pattern and “+1” indicates abnormal EEG types (epileptic seizure). The performance evaluation of the Artificial Neural Network (ANN) classifier and SVM classifier are examined using confusion matrix. In charge of analyzing the output data, sensitivity determines true positive ratio and specificity determines true negative ratio are estimated using confusion matrix. Sensitivity, specificity, and total classification accuracy are determined by the following formula.[19]

$$\text{Sensitivity} = \text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{8}$$

$$\text{Specificity} = \text{TNR} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \tag{9}$$

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})} \times 100\% \tag{10}$$

Where TP, TN, FP, and FN refer true positive, true negative, false positive, and false negative, respectively. The performance of the classifier is compared using the equation 10.

*Analysis of variance*

One-way analysis of variance (ANOVA) is a simple case of the linear model to determine whether the given data are from different groups. It is defined as:

$$Y_{ij} = \alpha_{ij} + \varepsilon_{ij} \tag{11}$$

Where  $Y_{ij}$  is a matrix of observations in which each column represents a different group,  $\alpha_{ij}$  is a matrix whose columns are the group means (constant) and  $\varepsilon_{ij}$  is a matrix of random disturbances.[24] In this paper, ANOVA has been used to determine whether the given datasets (normal and abnormal subjects) are having different characteristics.

**RESULTS**

Two different databases are analyzed in this paper. First, we analyzed the online available data (Andrzejak *et al.*, 2001). Among the five sets in the database, set A and set E are taken for binary classification. The pseudocode for this study is as follows:

- Step 1: Receiving EEG signal from the source after simple preprocessing
- Step 2: The EEG signal is decomposed into sub-bands at level 4
- Step 3: The eight statistical features, four GLCM features and Renyi entropy estimation from four different degrees of orders are extracted from raw EEG signal as well as from its sub-bands
- Step 4: The eight appropriate features are selected from the 16 dimension features using GA method

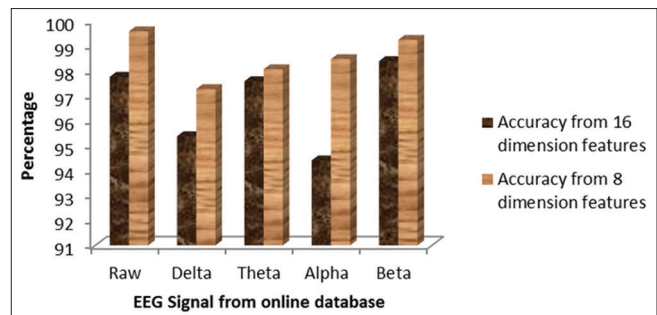
- Step 5: The 16 dimension features and the eight appropriate features are used as the input to the SVM classifier
- Step 6: The performance of the SVM classifier is evaluated for each signal using combined features and appropriate features separately
- Step 7: The accuracy obtained by the SVM classifier is compared
- Step 8: The procedure from step 1 to step 7 is applied for three different analyses
- Step 9: The study declared that the appropriate features can provide better accuracy in the performance of the SVM classifier.

Tables 1-3 show the sample features extracted from the 16 channel raw EEG signal from the second database. In this paper, the study carried out 2 different analyses and their explanations are as follows:

**Analysis 1**

In this analysis, the EEG signals from online database have been examined for binary classification. Among five different sets, set A (normal) and set E (abnormal) are used for seizure detection. The 16 dimension features (extracted) and the eight appropriate features (selected) are given as the input to the SVM classifier. The model has been trained and tested using the 16 dimension features (extracted) and the eight relevant features (selected) separately for raw EEG signal as well as for its sub-bands. The performance of the SVM classifier is evaluated. The 200 samples from set A and E are cross-validated using K-fold cross-validation method. The model is trained and tested for seizure detection. The average of accuracy is taken and compared for EEG signal analysis. Table 4 shows the comparison of accuracy obtained by the SVM classifier. Figure 2 shows the performance analysis of the SVM classifier.

Feature extraction is the process used for reducing the dimension of input vectors. Extracting appropriate features is very important for classification. Training and testing the classifier with these features give better accuracy in the performance of seizure detection. This analysis proved that the relevant features are used for classification can provide better accuracy in the performance of the SVM classifier. The performance shows reliable variation in values when the study is used GA



**Figure 2:** Support vector machine performance analysis for analysis 1

**Table 1: Statistical features from 16 channel raw electroencephalogram signal**

Subjects	Mean	SD	Median	Mode	Skewness	Kurtosis	Maximum	Minimum
NS1	2.8353	43.1483	11.2868	-154.461	-0.5188	3.2744	136.9384	-154.461
NS2	2.4754	46.8310	18.0526	-128.144	-0.9121	3.2155	74.3113	-128.144
NS3	1.5699	43.5731	9.6267	-116.347	-0.6351	2.9783	88.9197	-116.347
AS1	9.1172	28.9742	2.0159	-81.08	-0.5859	3.409	145.1778	-355.224
AS2	5.60315	23.2607	4.4860	-76.034	-0.6164	3.1435	326.8379	-188.489
AS3	4.4985	25.4328	5.7189	-80.082	-0.7644	3.389	220.0801	-159.307

**Table 2: Renyi entropy estimation using equation 3 with different degree of orders**

Subjects	Order			
	q=0.5	q=1.5	q=2	q=2.5
NS1	16.1643	-6.3290	-0.7397	1.1149
NS2	16.076	-6.0204	-0.5250	1.2987
NS3	16.1452	-6.2688	-0.7008	1.1469
AS1	16.7733	-8.1428	-8.1428	0.9799
AS2	16.5582	-7.4862	-6.5635	0.1045
AS3	15.9645	-7.7749	-7.4862	0.4736

**Table 3: Gray level co-occurrence matrix features from 16 channel raw Electroencephalogram signal**

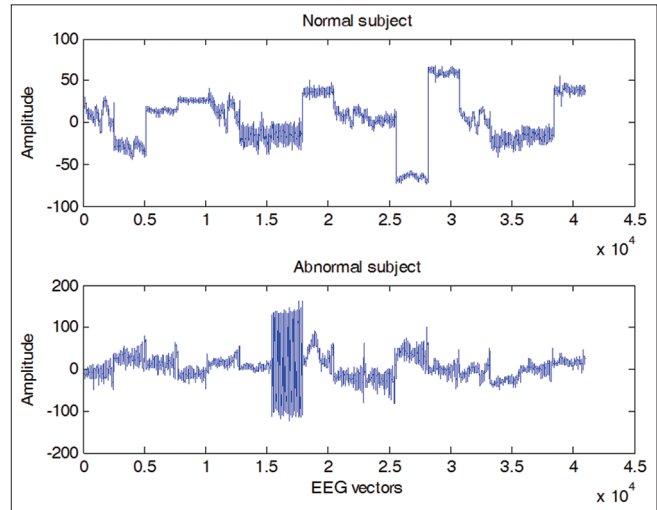
Subjects	Contrast	Correlation	Energy	Homogeneity
NS1	4.0401	0.8262	0.4391	0.9224
NS2	3.1778	0.8641	0.4576	0.9412
NS3	3.9275	0.8323	0.4347	0.9225
AS1	10.8605	0.5423	0.3914	0.7582
AS2	12.9609	0.6606	0.3238	0.7238
AS3	15.0535	0.5554	0.2811	0.7946

**Table 4: Comparison of support vector machine performance from analysis 1**

Signal	Accuracy from 16 dimension features	Accuracy from eight dimension features
Raw	97.75	99.57
Delta	95.37	97.26
Theta	97.57	98.05
Alpha	94.4	98.46
Beta	98.38	99.23

**Analysis 2**

The subjects have taken from 16 channels (Fp<sub>2</sub>-F<sub>4</sub>, F<sub>4</sub>-C<sub>4</sub>, C<sub>4</sub>-P<sub>4</sub>, P<sub>4</sub>-O<sub>2</sub>, Fp<sub>2</sub>-F<sub>8</sub>, F<sub>8</sub>-T<sub>4</sub>, T<sub>4</sub>-T<sub>6</sub>, T<sub>6</sub>-O<sub>2</sub>, Fp<sub>1</sub>-F<sub>3</sub>, F<sub>3</sub>-C<sub>3</sub>, C<sub>3</sub>-P<sub>3</sub>, P<sub>3</sub>-O<sub>1</sub>, Fp<sub>1</sub>-F<sub>7</sub>, F<sub>7</sub>-T<sub>3</sub>, T<sub>3</sub>-T<sub>5</sub> and T<sub>5</sub>-O<sub>1</sub>) bipolar longitudinal EEG signals are digitized to 40960 vectors. The sample of normal and seizure cases from the database is shown in Figure 3. Figure 4 shows the result of the ANOVA test which is examined our database. From the obtained *P* (0.0485) and *F* (4.48) values, the analysis has been concluded that the datasets (normal and seizure) are 95% significantly different in characteristics. The signal consists of 40,960 EEG vectors is decomposed



**Figure 3: Sample normal and seizure subjects from the second database**

into sub-bands, namely, delta (0.53–4 Hz), theta (4–8 Hz), alpha (8–15 Hz), beta (15–30 Hz), and gamma (30–60 Hz). The 16 features as mentioned above in the pseudocode are extracted from raw EEG and its sub-bands. The model is trained by combining 200 samples (set A 100 normal epochs and set E 100 abnormal epochs) from online database and twenty samples (10 normal subjects and ten abnormal subjects) from our database. Thus, the model has been trained with 220 samples and tested with the twenty samples from Indian database. The performance of the SVM classifier is evaluated for seizure detection. Since the obtained solution is heuristic, to achieve the best solution, the method GA is used to select the relevant features from the 16 dimension features. The eight relevant features are selected from raw EEG and its sub-bands for analysis. Again the model has been trained using relevant features for 220 samples and tested with twenty samples. Now, the performance of the SVM classifier is evaluated, and the accuracies are compared [Table 5]. Figure 5 represents the performance analysis of the study. The analysis states that the accuracy obtained from the appropriate features is better for seizure detection.

**DISCUSSIONS**

In this paper, the raw EEG and its sub-bands are analyzed individually. The 16 dimension features are inserted into the SVM classifier in the following order: mean, Standard deviation, median, mode, skewness, kurtosis, maximum, minimum, Renyi

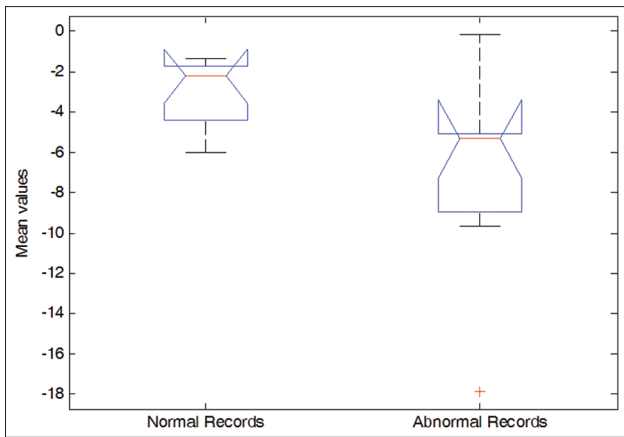


Figure 4: Analysis of variance test for normal and abnormal datasets

Table 5: Comparison of support vector machine performance from analysis 2

Signal	Accuracy from 16 dimension features	Accuracy from eight dimension features
Raw	85	90
Delta	75	85
Theta	95	95
Alpha	95	95
Beta	95	100

entropy with degree of order 0.5, 1.5, 2, 2.5, contrast, correlation, energy, and homogeneity. To select half of the relevant features from 16 dimension features, genetic technique is used for feature selection. The system is trained and tested for EEG signal classification using these relevant features. Table 6 shows the eight dimension features which are selected by GA for analysis 1. Table 7 shows the eight dimension features which are selected by GA for analysis 2.

From Tables 6 and 7, the study shows that the genetic technique selected mostly statistical features. When dealing with entropy, the technique selected the higher degree of order from Renyi entropy.

**Comparison with previous work**

Many authors had worked on automated epileptic seizure detection system. This work differs from other author’s work while combining entropy estimations with GLCM and statistical features. These features are used as the input to the SVM classifier. Related works is given in Table 8. Even though many authors had worked on SVM with different features and their system achieved some accuracy, this work explains the EEG signal classification with unique combination of features.

Nanthini and Santhi, 2014<sup>[19]</sup> had analyzed raw EEG signals with only GLCM features. The study compared the performance of the Classifiers such as ANN and SVM. The result obtained that the SVM classifier had better accuracy. To overcome the limitation, Nanthini and Santhi, 2015,<sup>[11]</sup> made their work by decomposing the EEG signals using

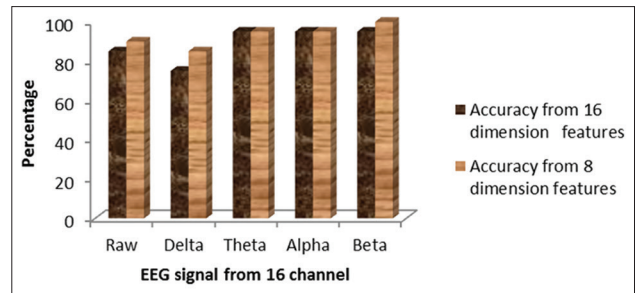


Figure 5: Support vector machine performance analysis for analysis 2

DWT. The study compared different wavelets such as db1, db2, and Haar for decomposing the EEG signals. Further, the study analyzed the performance of the classifiers (ANN and SVM) for the raw EEG signal and its sub-bands using GLCM, statistical, and hybrid features. The study concluded that SVM using db2 wavelet with hybrid features are the best outcome for seizure detection. Nanthini and Santhi, 2014<sup>[30]</sup> explained brief review of the authors work. To strengthen the analysis, the proposed system included feature selection process for 16 dimension (GLCM, Statistical and Renyi entropy) features. This system concluded that the appropriate features for EEG signal classification give high-performance accuracy. Maszczyk and Duch evaluated the usefulness of Shannon, Renyi, and Tsallis entropy measures in decision trees for classifying the datasets.

In our previous work, we compared Shannon, Renyi, and Tsallis performance for automated epileptic seizure detection using EEG signals. The results were consistent in accuracy for different *q* values (0.5, 1, 1.5, 2, and 2.5). In that analysis, the accuracy rate using Renyi entropy was higher and successful. Thus, Renyi entropy is selected for this analysis.

Victor Sucic *et al.*<sup>[31]</sup> used short-term Renyi entropy for detecting the number of components that are presented in short time interval of the signal. They analyzed the nonstationary signals from natural sonar system using bat sound in time-frequency distribution and concluded that short-term Renyi entropy can be an effective tool for estimating the number of components in the signals.

Lerga *et al.*<sup>[32]</sup> applied short-term Renyi entropy and analyzed EEG analysis in time-frequency domain. They proposed a method using short-term Renyi entropy and tested on both noisy and noisy-free EEG signal. Using filters, the noise has been removed from the raw EEG signals in this paper. Moreover, this paper used different values for the order of Renyi entropy and tested the noise free EEG signal. The drawback of this paper is that it concentrates only on frequency distribution. In the near future, the work will be extended by analyzing the EEG signals in time-frequency domain.

**CONCLUSION**

Careful analysis of EEG provides valuable information about the brain functions and can be useful to detect brain disorder,

**Table 6: The eight dimension features for analysis 1**

EEG signal	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Feature 7	Feature 8
Raw	SD	Median	Skewness	Kurtosis	Renyi entropy order 2	Renyi entropy order 2.5	Correlation	Energy
Delta	SD	Median	Skewness	Kurtosis	Renyi entropy order 2	Renyi entropy order 2.5	Correlation	Energy
Theta	Mean	Median	Skewness	Kurtosis	Renyi entropy order 1.5	Renyi entropy order 2	Contrast	Energy
Alpha	Mean	SD	Median	Skewness	Kurtosis	Renyi entropy order 2	Correlation	Energy
Beta	Mean	Median	Skewness	Renyi entropy order 2	Contrast	Correlation	Energy	Homogeneity

SD: Standard deviation, ECG: Electroencephalogram

**Table 7: The eight dimension features for analysis 2**

EEG signal	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Feature 7	Feature 8
Raw	Mean	SD	Mode	Skewness	Kurtosis	Renyi entropy order 2	Renyi entropy order 2.5	Contrast
Delta	Mean	SD	Mode	Skewness	Kurtosis	Renyi entropy order 2	Renyi entropy order 2.5	Correlation
Theta	Mean	SD	Median	Kurtosis	Maximum	Minimum	Contrast	Correlation
Alpha	Mean	SD	Median	Kurtosis	Maximum	Renyi entropy order 2	Energy	Homogeneity
Beta	Mean	SD	Median	Skewness	Renyi entropy order 2	Contrast	Correlation	Energy

SD: Standard deviation, ECG: Electroencephalogram

**Table 8: Related works**

Author(s)/year	Feature extraction
Gular and Ubeyli (2007) <sup>[21]</sup>	Wavelet transform and Lyapunov exponents
Derya Ubeyli (2008) <sup>[25]</sup>	Eigenvector methods
Chandaka <i>et al.</i> (2009) <sup>[26]</sup>	Cross-correlation
Liang <i>et al.</i> (2010) <sup>[27]</sup>	Time-frequency analysis and approximate entropy
Subasi and Gursoy (2010) <sup>[6]</sup>	Wavelet transform and principal component analysis and Independent component analysis and linear discriminate analysis
Lima <i>et al.</i> (2010) <sup>[28]</sup>	Wavelet transform
Iskan <i>et al.</i> (2011) <sup>[29]</sup>	Cross-correlation and power spectral density
This study	GLCM and statistical and Renyi entropy

GLCM: Gray level co-occurrence matrix

especially for epilepsy. Providing quality treatment is more important for epileptic patients. Supportive system will be helpful for experts to have better diagnosis. In this paper, an automated seizure detection model had been introduced successfully. The EEG signals were decomposed into sub-bands by DWT using db2 wavelet at level 4. The eight statistical features, the four GLCM and Renyi entropy estimation with four different degrees of order, are extracted from the raw EEG and its sub-bands. The 16 dimension features were extracted from the raw signal and its five subgroups (delta as approximation coefficient and theta, alpha, beta and gamma as detail coefficients). GA was used to select eight relevant features

from the 16 dimension combined features. The model had been trained and tested using SVM classifier successfully for raw EEG and its sub-bands signals. The performance of the SVM is evaluated for two different databases. The study had been experimented through three different analyses and achieved satisfactory performance for automated seizure detection using appropriate features as the input to the SVM classifier. In the near future, this work will be extended by collecting more subjects from the EEG diagnostic center for testing this automated seizure detection model.

### Financial support and sponsorship

Nil.

### Conflicts of interest

There are no conflicts of interest.

### REFERENCES

1. Subasi A. Automatic recognition of alertness level from EEG by using neural network and wavelet coefficients. *Expert Syst Appl* 2005;28:701-11.
2. Orhan U, Hekim M, Ozer M. EEG signals classification using the k-means clustering and a multilayer perceptron neural network model. *Expert Syst Appl* 2011;38:13475-81.
3. Misra UK, Kalita J. *Clinical Electroencephalography*. Noida, UP India: Elsevier a Division of Reed Elsevier India Private Limited; 2005.
4. Dastidar SG. *Models of EEG Data Mining and Classification in Temporal Lobe Epilepsy; Wavelet-chaos-neural Network Methodology and Spiking Neural Network*. Dissertation-School of the Ohio State University; 2007.
5. Andrzejak RG, Lehnertz K, Mormann F, Rieke C, David P, Elger CE. Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording

- region and brain state. *Phys Rev E Stat Nonlin Soft Matter Phys* 2001;64(6 Pt 1):061907.
6. Subasi A, Gursoy IM. EEG signal classification using PCA, ICA, LDA and support vector machines. *Expert Syst Appl* 2010;37:8659-66.
  7. Siuly, Li Y, Wen PP. Clustering technique-based least square support vector machine for EEG signal classification. *Comput Methods Programs Biomed* 2011;104:358-72.
  8. Ocak H. Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy. *Expert Syst Appl* 2009;36:2027-36.
  9. Gandhi T, Panigrahi BK, Anand S. A Comparative study of wavelet families for EEG signal classification. *Neurocomputing* 2011;74:3051-7.
  10. Hasan O. Optimal classification of epileptic seizures in EEG using wavelet analysis and genetic algorithm. *Signal Processing* 2008;88:1858-67.
  11. Nanthini BS, Santhi B. Different approaches of analyzing EEG signals for seizure detection. *Int J Signal Imaging Syst Eng* 2015;8:28-38.
  12. Albrechtsen F. *Statistical Texture Measures Computed from Gray Level Co-occurrence Matrices*. Image Processing Laboratory, Department of Informatics, University of Oslo; 2008.
  13. Kannathal N, Choo ML, Acharya UR, Sadasivan PK. Entropies for detection of epilepsy in EEG. *Comput Methods Programs Biomed* 2005;80:187-94.
  14. Maszczyk T, Duch W. Comparison of Shannon, Renyi and Tsallis Entropy used in decision trees. *Lect Notes Comput Sci* 2008;5067:643-57.
  15. Subasi A. Automatic detection of epileptic seizure using dynamic fuzzy neural networks. *Expert Syst Appl* 2006;31:320-8.
  16. Gandhi TP, Chakraborty P, Roy GG, Panigrahi BK. Discrete harmony search based expert model for epileptic seizure detection in electroencephalography. *Expert Syst Appl* 2012;39:4055-62.
  17. Guo L, Rivero D, Pazos A. Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks. *J Neurosci Methods* 2010;193:156-63.
  18. Ubeyli ED. Combined neural network model employing wavelet co-efficients for EEG signals classification. *Digital Signal Process* 2009;19:297-308.
  19. Nanthini BS, Santhi B. Seizure detection using SVM classifier on EEG signal. *J Appl Sci* 2014;14:1658-61.
  20. Burges CJ. A tutorial on support vector machines for pattern recognition. *Data Min Knowl Discov* 1998;2:121-67.
  21. Gular I, Ubeyli ED. Multiclass support vector machines for EEG-signals classification. *IEEE Trans Inf Technol Biomed* 2007;11:117-26.
  22. Nicolaou N, Georgiou J. Detection of epileptic electroencephalogram based on permutation entropy and support vector machines. *Expert Syst Appl* 2012;39:202-9.
  23. Li Z, Zhou M, Lin H, Pu H. A two stage sparse SVM training. *Int J Mach Learn Cybern* 2014;5:425-34.
  24. Armstrong RA, Eperjesi F, Gilmartin B. The application of analysis of variance (ANOVA) to different experimental designs in optometry. *Ophthalmic Physiol Opt* 2002;22:248-56.
  25. Derya Ubeyli E. Analysis of EEG signals by combining eigenvector methods and multiclass support vector machines. *Comput Biol Med* 2008;38:14-22.
  26. Chandaka S, Chatterjee A, Munshi S. Cross-correlation aided support vector machine classifier for classification of EEG signals. *Expert Syst Appl* 2009;36:1329-36.
  27. Liang SF, Wang HC, Chang WL. Combination of EEG complexity and spectral analysis for epilepsy diagnosis and seizure detection. *EURASIP J Adv Signal Process* 2010;2010:853434.
  28. Lima CA, Coelho AL, Eisencraft M. Tackling EEG signal classification with least squares support vector machines: A sensitivity analysis study. *Comput Biol Med* 2010;40:705-14.
  29. Iscan Z, Dokur Z, Tamer D. Classification of electroencephalogram signals with combined time and frequency features. *Expert Syst Appl* 2011;38:10499-505.
  30. Nanthini BS, Santhi B. EEG signal analysis for epileptic seizure detection using soft computing techniques. *World Appl Sci J* 2014b; 29:65-9.
  31. Sucic V, Saulig N, Boashash B. Estimating the number of components of a multi component non stationary signal using the short-term time-frequency Renyi entropy. *EURASIP J Adv Signal Process* 2011;2011:125.
  32. Lerga J, Saulig N, Mozetic V. Algorithm based on the short-term Rényi entropy and IF estimation for noisy EEG signals analysis. *Comput Biol Med* 2016;80:1-13.