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Research paper

Epileptic Seizure Detection from Eeg Signals by Adaptive Wavelets and Support Vector Machine

T. Venkateshkanna[1], Punithavathy K[2], Vallikannu R[3]

Research scholar[1], Assistant Professor [2], Associate Professor[3]
Hindustan Institute of Technology and Science
**Corresponding author E-mail:Venkateshkanna2@gmail.com*

Abstract

Recent advances in computer technologies help to diagnose various disorders of the brain using Electroencephalogram (EEG) signals. The importance of a diagnostic application is to reduce the False Positive (FP) cases. To achieve this, an efficient approach for epileptic seizure classification is proposed using adaptive wavelets called Empirical Wavelet Transform (EWT). The different modes of EEG signals are extracted using EWT and then features from the different modes are extracted. Then, classification is done by a typical machine learning technique, Support Vector Machine (SVM). The performance of EWT-SVM system is evaluated using confusion matrix. From the confusion matrix, sensitivity and specificity are computed. In this paper, an efficient approach for the diagnosis of epileptic seizure using EEG signals is designed. At first, the given EEG signal is decomposed using EWT to extract the information of all components. The EWT energy features are extracted from the EEG signals which are used for training the SVM classifier. Results show that EWT-SVM system reduces the FP cases with 100% of accuracy, sensitivity and specificity which indicates that no misclassification occurs.

Keywords: *Brain disorder, EEG signal classification, epileptic seizure, adaptive wavelets, EWT, SVM*

1. Introduction

An invasive approach to diagnose brain disorder is the analysis of EEG signals. The epileptic seizure, a brain disorder can be identified with the help of pattern recognition approaches using EEG signals. Correlation based feature selection approach is used for EEG signal classification [1]. It consists of three steps; segmentation of EEG signals into five bands, feature selection and classification by five different techniques such as Radial Basis Function (RBF) network, SVM, logistic model trees, Multi-Layer Perceptron (MLP), and Random Forest (RF) classifier schemes.
Multiclass SVM is used for the epileptic and epilepsy seizure detection in [2] using EEG signals. It uses 3-level Discrete Wavelet Transform for feature extraction with an optimization technique called modified sequential minimal optimization. Finally, one verses one multiclass SVM is used. An approach for signal modelling and classification of seizure EEG signals is discussed in [3]. At first, EEG signal is segmented into its brain rhythms. The rhythms; delta, beta, theta, gamma and alpha are modelled by a Gaussian random process to classify EEG signals by the use of SVM classifier.
Epileptic seizure classification by learning approaches and fuzzy system is discussed in [4]. The shortage of training data and data description discrepancy are tackled by semi-supervised and transfer learning approaches respectively. Then, the fuzzy system is used as a classifier. EEG classification by Mel-frequency cepstral coefficients is discussed in [5]. From the detected **QRS** complex wave, the above mentioned frequency components are extracted and then trained by Artificial Neural Network (ANN).
Local Mean Decomposition (LMD) based automatic seizure detection of EEG Signals is discussed in [6]. From the LMD decomposed signals, non-linear and temporal statistical features are extracted. Then, the classification task uses K-Nearest Neighbour (KNN) and different format of SVM classifier. Complex network features from the EEG signal is used for epileptic seizure detection with weighted visibility graph method in [7]. Two major statistical properties like the average weighted degree and the modularity features from the complex network are extracted. KNN and different SVM kernels are used for EEG classification.
A combination of the power spectrum and an Intrinsic Mode Function (IMF) is used for EEG signal classification in [8]. It uses Empirical Mode Decomposition (EMD) to get the EEG signals IMF and the power spectrum as features. Then, ANN scheme is used for classification. EMD based temporal and spectral features are discussed in [9]. From the IMF, spectral skew, coefficient of variation and spectral centroid are extracted and then SVM scheme is used as a classifier.
Multiple filters approach for epilepsy seizure detection is discussed in [10]. Features are computed from the multiple filtered outputs of EEG signals and then three classifiers; KNN, ANN and SVM are used. Discrete short time Fourier transform for EEG classification is discussed in [11]. Features are computed from the Fourier transform and then MLP classifies the seizure epochs from seizure-free epochs. A fuzzy clustering approach for EEG signal classification is discussed in [12]. EMD decomposes the EEG signal for feature extraction and then modified fuzzy clustering algorithm classifies the EEG into normal or abnormal.
In this paper, epileptic seizure detection from EEG signal based on EWT and SVM is presented. The organization of the paper is as follows: The preliminaries of the techniques used for the successful EEG classification approach is discussed in section 2. Section 3 explains the system design of the EEG classification by EWT and SVM techniques. Results of the EWT-SVM based EEG

classification system is given in Section 4 and the last section presents the conclusions based on performance of the EWT-SVM system.

2. Preliminaries

The detection of brain disorder (epileptic seizure) from EEG signals generally requires raw signals obtained from the brain to extract features and then classification stage. Figure 1 shows a computer vision system for disease diagnosis and its various components.

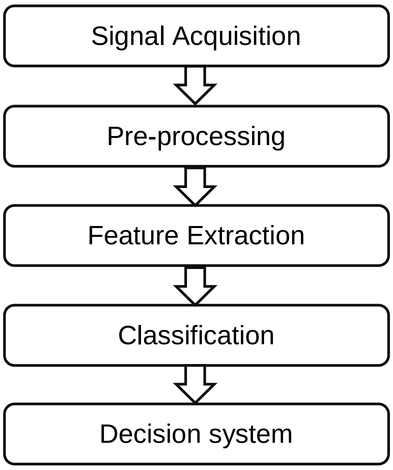


Figure 1 Components of Computer vision system

First, the required input signals or images are acquired by using medical instruments. In the pre-processing stage, the acquired signal is de-noised and or enhanced if required. The next stages are feature extraction and classification. The following sub-sections focus the extraction of EEG signal features using EWT and then classification by SVM classifier.

2.1. Empirical Wavelet Transform

Distinguishing EEG signals to identify epileptic seizure can be achieved by extracting features that are differentially expressed between normal and epileptic seizure. Adaptive wavelet named EWT is designed by Gilles [13]. In contrast to wavelets, the basis of adaptive wavelets depends on the contents of the given signal.
Let us consider, the Fourier support [0 π] is partitioned into continuous N segments with limits w_n between the segments. Each segment is given by $\left[w_{n-1}, w_n\right]$ such that $\square_{n=1}^{N} = [0,\pi]$. On each segment, empirical wavelets are defined. The construction of empirical wavelets follows the Meyer's and Littlewood-Paley in [14]. More information about the scaling function in eqn. 1 and empirical wavelets in eqn.2 can be obtained from [14].

$$\hat{\phi}_n(\omega)=\begin{cases}1 & \text{if } |\omega| \le \omega_n - \tau_n \\ \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\tau_n}\left(|\omega|-\omega_n+\tau_n\right)\right)\right] & \text{if } \omega_n - \tau_n \le |\omega| \le \omega_n + \tau_n \\ 0 & \text{Otherwise}\end{cases} \tag{1}$$

$$\hat{\varphi}_n(\omega)=\begin{cases}1 & \text{if } |\omega| \le \omega_n - \tau_n \\ \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\tau_{n+1}}\left(|\omega|-\omega_{n+1}+\tau_{n+1}\right)\right)\right] & \text{if } \omega_{n+1} - \tau_{n+1} \le |\omega| \le \omega_{n+1} + \tau_{n+1} \\ \sin\left[\frac{\pi}{2}\beta\left(\frac{1}{2\tau_n}\left(|\omega|-\omega_n+\tau_n\right)\right)\right] & \text{if } \omega_n - \tau_n \le |\omega| \le \omega_n + \tau_n \\ 0 & \text{Otherwise}\end{cases} \tag{2}$$

2.2. SVM Classifier

In general, SVM creates high dimension space by plotting the training samples feature vectors of all samples. Then a hyperplane is constructed between the references and different classes in such a way that the distance between them is at maximum. In classification, the unknown features are compared with stored feature database to classify the input into normal and abnormal. Let us consider the input training sample set

$$(\mathrm{x_i}, \mathrm{y_i}), \mathrm{i} = 1....\mathrm{n}, \mathrm{x} \in \mathrm{R}^{\mathrm{n}}, \mathrm{y} \in \{-1,+1\} \tag{3}$$

Where the input training samples and their corresponding target are x_i and $\mathbf{y_i}\mathbf{y_i}$ y_i respectively. Then the hyperplane that separates the training sample set has the form

$$(\omega.x) + b = 0 \tag{4}$$

Many linear classifiers are available to separate the hyperplane. However, the best one can be chosen based on the margin. To maximize the margin, the problem of optimal hyper plane selection is transformed into quadratic programming problem which is given as.

$$\begin{aligned}&\min \Phi(\omega) = \frac{1}{2}(\omega, \omega)\\ &s.t. y_i((\omega.x) + b \ge 1, i = 1,2....l\end{aligned} \tag{5}$$

After the introduction of Lagrange multiplier, the dual problem is given by,

$$\begin{aligned}&\max Q(\alpha) = \sum_{i=1}\alpha_i - \frac{1}{2}\sum_{i=1}\sum_{i=1} y_i y_j \alpha_i \alpha_j K(x_i.x_j)\\ &s.t \sum_{i=1}^{n} y_i \alpha_i = 0, \alpha_i \ge 0, i = 1,2,....,n\end{aligned} \tag{6}$$

The optimal solution must satisfy the condition in eqn. 7 according to Kuhn-Tucker rules,

$$\alpha_i(y_i((w.x_i) + b) - 1 = 0, i = 1,2,...n \tag{7}$$

and if the optimal solution to the above problem,

$$\alpha^* = (\alpha_1^*, \alpha_2^*,...., \alpha_i^*)^T, i = 1,2,...n \tag{8}$$

Then

$$w^* = \sum_{i=1}^{n} \alpha_i^* y_i x_i$$

$$b^* = y_i - \sum_{i=1}^{n} y_i \alpha_i^* (x_i . x_j), j \in \{j \mid \alpha_i^* \rangle 0\} \tag{9}$$

A Lagrange multiplier is available for each sample points $\mathrm{x_i x_i}$ x_i in the training dataset. The contribution to solve the classification problem depends on $\alpha_i = 0\alpha_i = 0 \alpha_i$. Only the sample points which correspond to $\alpha_i > 0\alpha_i > 0 \alpha_i \square 0$ form the optimal hyper plane are called as SVs. The following eqn. 10 gives the optimal hyperplane equation,

$$\sum_{x, \in SV} \alpha_i y_i (x_i . x_j) + b = 0 \tag{10}$$

Then, the hard classifier is given by

$$y = \mathrm{sgn}\left[\sum_{x, \in SV} \alpha_i y_i (x_i . x_j) + b \right] \tag{11}$$

By introducing kernel function $\mathrm{K(x.y)} = \emptyset(\mathrm{x}).\emptyset(\mathrm{y})$, $\mathrm{K(x.y)} = \emptyset(\mathrm{x}).\emptyset(\mathrm{y})$, an optimal separating hyperplane is constructed by SVM for non linear situation. Then, the nonlinear SVM is specified by $K(x.y) = \phi(x).\phi(y)$ the eqn. 11

$$\min \Phi(\omega) = \frac{1}{2}(\omega, \omega)$$

$$s.t. y_i((\omega.\phi(x_i)) + b) \geq 1, i = 1,2,\ldots l \tag{12}$$

And its dual problem is,

$$\max L(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{i=1}^{l} y_i y_j \alpha_i \alpha_j K(x_i . x_j)$$

$$s.t. \sum_{i=1}^{n} y_i \alpha_i = 0, 0 \leq \alpha_i \leq C . i = 1,2,\ldots,l \tag{13}$$

The solution to the above eqn. 13 is optimal hyperplane that separates the given training set with maximum accuracy. The constructed hyperplane by SVM separates the features optimally into two categories. It treats the two class problem as a quadratic problem. The reasons to choose SVM as a classifier are its fast convergence rate and superior generality in high dimensional data.

3. Ewt-Svm Based Eeg Classification System

The EWT-SVM based EEG classification system discussed in this section is considered as a pattern recognition system.

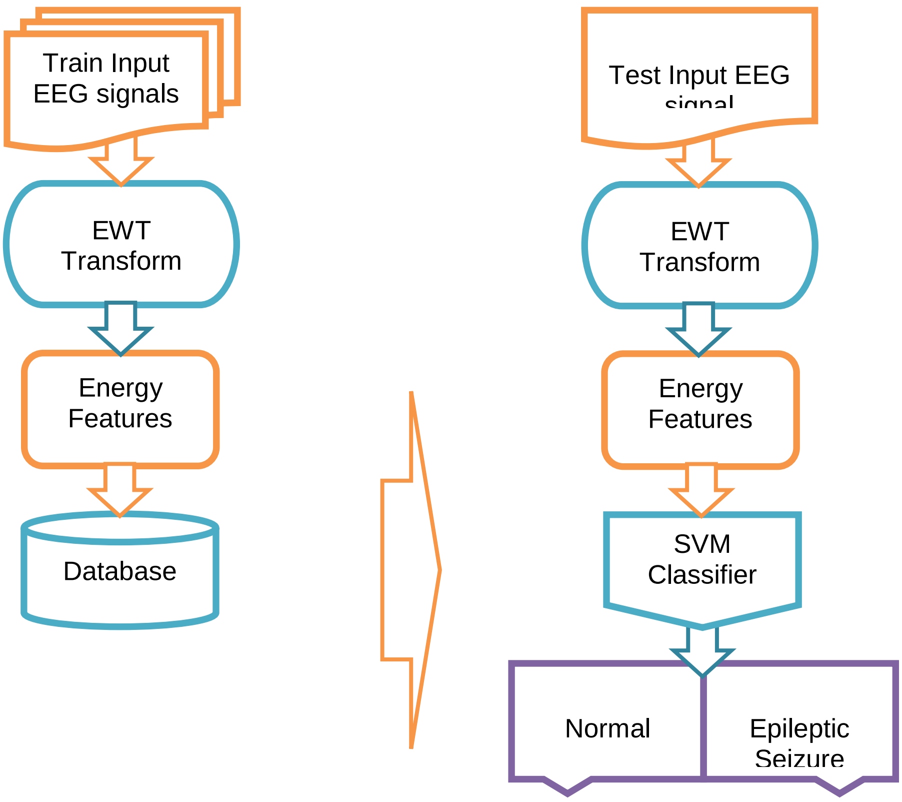


Figure 2 EWT-SVM Based EEG Classification System

Feature extraction and classification are the two main stages in many pattern recognition systems. The discriminant features are extracted in the former stage and then in the later stage the given EEG signals are classified. Figure 2 shows the flow of EWT-SVM based EEG classification system.The efficacy of EWT-SVM based EEG classification system mainly depends on the discriminative nature of the features/attributes used for the representation of normal and abnormal signals. In this study, adaptive wavelets are used for the representation of EEG. Figure 3 shows the sample EEG signals from the database; Normal (Top Row) and Seizure (Bottom Row) and its representation using EWT are shown in Figure 4.

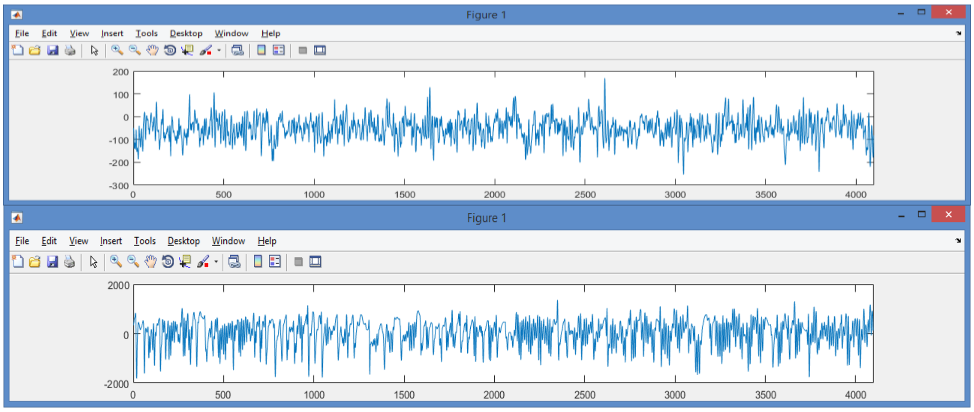


Figure 3 Sample EEG Signals; Normal (Top Row) and Seizure (Bottom Row)

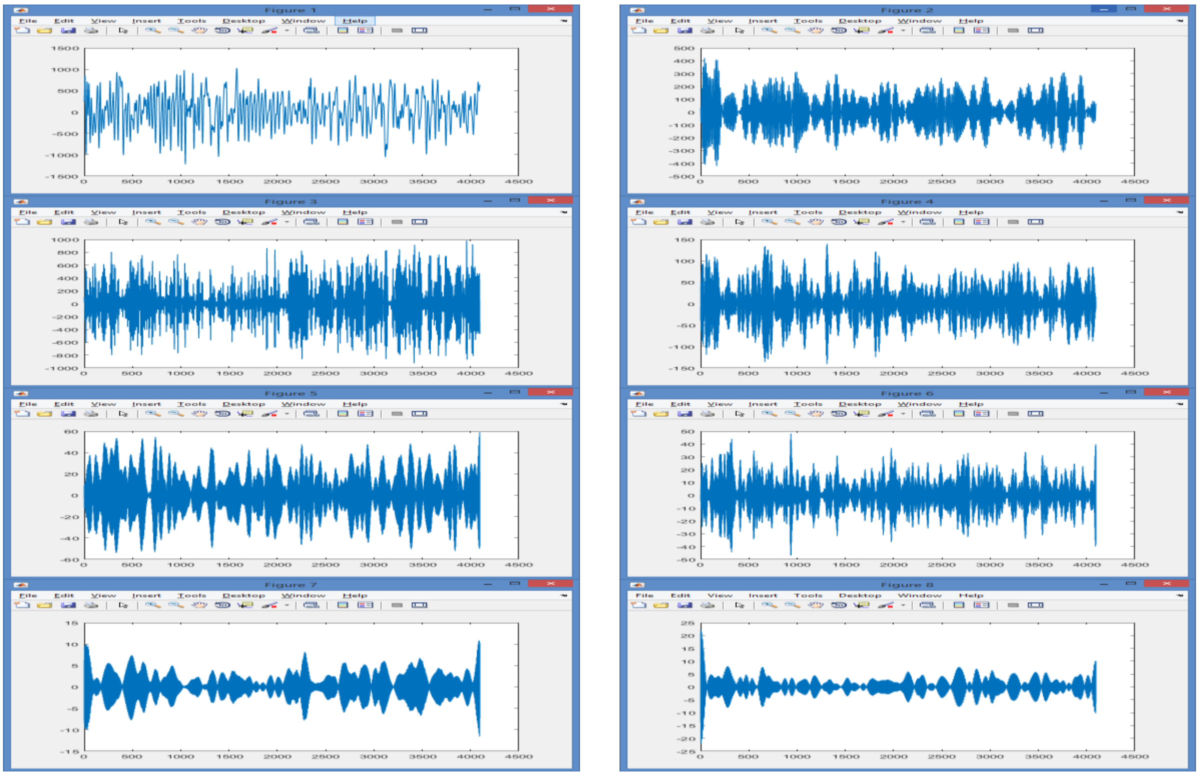


Figure 4 EWT components obtained for EEG epileptic seizure signal shown in the Figure 3(b)

Feature extraction process reduces the dimensionality and detains the uniqueness of input pattern. Also, the extracted features preserve the class separability very effectively. Hence, the extracted features with high discriminative nature will assist the classification system effectively while the lack of discrimination reduces the accuracy of the classification system. To characterize the features of EEG signals, energy from EWT components are extracted. All EWT components from the EWT decomposition are considered for the extraction. The mean of the magnitude of the EWT components is computed and used as its energy.

Before classification, SVM classifier is trained by the use of features extracted from the training signals. Thus, the EWT energy features are extracted from the EEG signals which are used for training the SVM classifier. Finally, the trained SVM classifier is used to test the EEG signal with the help of features extracted from the EWT components of the unknown EEG signals. On successful classification, SVM predicts the given EEG signal into normal/seizure.

4. Results and Discussion

The performance of EWT-SVM system for EEG classification is analyzed using normal and epileptic seizures of 100 signals each. These signals are freely available in [15] and given by Andrzejak *et al*. [16]. The length of each signal is 23.6 seconds and 4097 samples are available as they are digitized at 173.61 Hz for the analysis. The performance of EWT-SVM system is evaluated using confusion matrix. From the confusion matrix, sensitivity and specificity are computed. Also, the Receiver Operating Characteristics (ROC) curves are drawn which gives the diagnostic ability of the system. Table 1 illustrates the components of a confusion matrix; class A (abnormal EEG) and class 2 (normal EEG). It is constructed using the actual class with the test outcome.

Sensitivity (S_n) guarantees the ability of the classifier while testing it. It considers only the positive cases and is defined by eqn. 14. Specificity (S_p) deals with only negative cases and is defined by eqn. 15. Another important performance analysis used is ROC. From the ROC, the area below the curve called Az value is computed. A higher Az value indicates the better performance of the classifier.

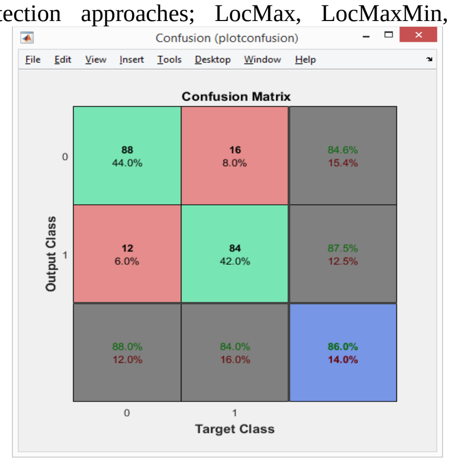
$$Sensitivity = \frac{TP}{(TP + FN)} \tag{14}$$

$$Specificity = \frac{TN}{(FP + TN)} \tag{15}$$

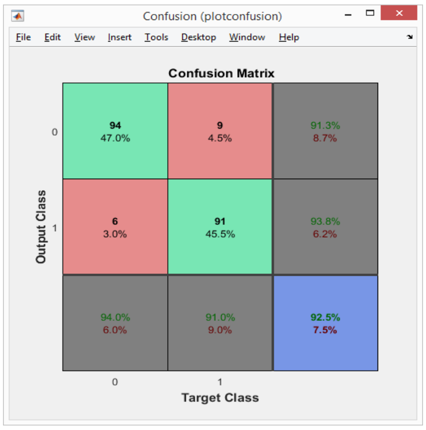
Table 1 Confusion matrix

Test outcome	Actual Class	
	Class A (abnormal EEG signals)	Class B (normal EEG signals)
Class A (abnormal EEG signals)	True Positive (TP) - abnormal EEG signals image is correctly classified as abnormal)	False Positive (FP)- abnormal EEG signals image is correctly classified as abnormal
Class B (normal EEG signals)	False Negative (FN) - abnormal EEG signals image is incorrectly classified as normal	True Negative (TN) - normal EEG signals image is correctly classified as normal

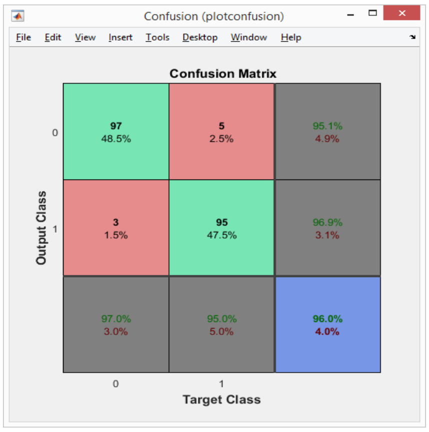
In a testing scenario, the aforementioned measures are computed. Also, the validation of SVM classifier is done using *k*-fold (*k*=10) approach. The performance of EWT-SVM system is analyzed by varying the boundary detection approach in EWT. The following five boundary detection approaches; LocMax, LocMaxMin, adaptive, adaptiveReg, and scale-space are used to extract the EWT components. These components are then classified using SVM to detect the seizure. Figure 5 shows the confusion matrices obtained by EWT-SVM and also the ROCs.



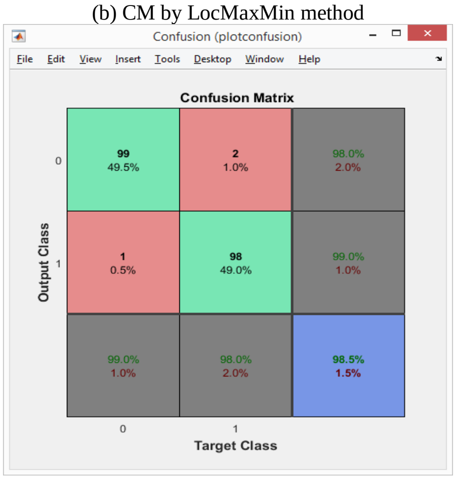
(a) CM by LocMax method



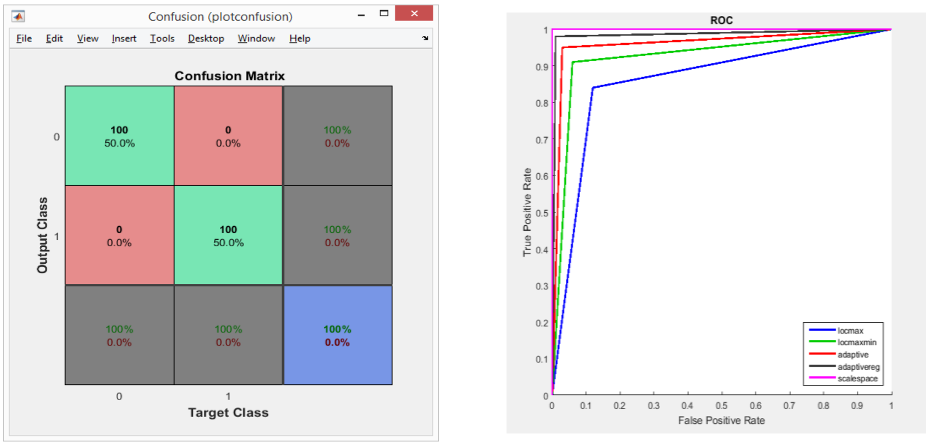
(b) CM by LocMaxMin method



(c) CM by adaptive method



(d) CM by adaptive regularization method



(d) CM by scale-space method (f) ROC curves

Figure 5 Performance of EWT components for epileptic seizure classification

It is observed from the Figure 5 that the maximum S_n and S_p of EWT-SVM system is 100% which is obtained by the boundaries detected by scale-space approach. Similarly, S_n of 88% and S_p of 84% which is the lowest performance by EWT-SVM system for signal classification while using Loc Max method for detecting the boundaries. It is clearly observed from the Figure 5 (f) that the EWT components obtained by the use of scale-space approach outperform others by the use of Az which is 1. In order to visualize the performance of EWT-SVM system in terms of S_n and S_p, Figure 6 is drawn.

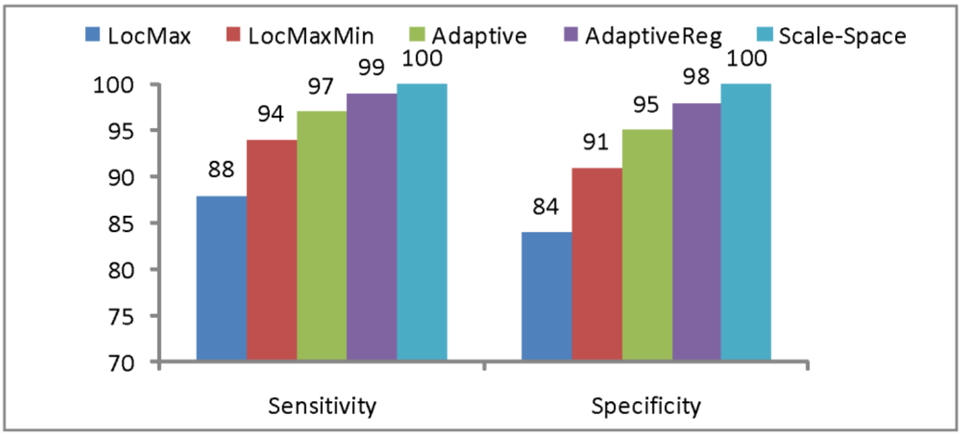


Figure 6 S_n and S_p of EWT-SVM system for EEG classification

5. Conclusion

In this paper, an efficient approach for the diagnosis of epileptic seizure is designed using EEG signals. At first, the given EEG signal is decomposed using EWT to extract the information of all components. The boundaries of the spectrum are detected using five different approaches. Then, a signal classification system is designed using SVM to classify the given EEG signals into normal/seizure. The results show the effectiveness of EWT-SVM system for EEG classification. The EWT-SVM system provides promising results in terms of sensitivity and specificity with 100% accuracy.

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