Epilepsy Seizure Detection Using EEG signals

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Abstract*—Epilepsy is a neurological disease that is referred to as a disorder of the central nervous system characterized by the loss of consciousness and convulsions. Epileptic patients are subject to epileptic seizures caused by abnormal electrical discharges that lead to uncountable movements, convulsions and the loss of consciousness. Approximately 50 million people around the world are diagnosed with epilepsy, children and adults in the age range of 65-70 years old are effected the most. Although the main cause of this disease is unknown, however, most of the symptoms of the epilepsy seizure can be medically treated. Epileptic patients are subject to seizures that cause uncontrollable movements and loss of consciousness which can lead to serious injuries, and sometimes death. As a result, computerized seizure detection techniques are vital solutions for epileptic patients to protect them from dangers at the time of a seizure. In this paper, we propose an epilepsy seizures detecting method that can be implemented in a hardware device to help epileptic patients. The Electroencephalogram (EEG) is widely recognized for diagnosing and assessing brain activities and disorder. Our study utilized an EEG datasets that is used in various research regarding epilepsy detection. We processed the EEG signal in both time and frequency domains and applied a Chebyschev filter for preprocessing the signal, then, by using Wavelet Analysis, we decomposed the filtered signal into five sub-bands in both time and frequency domain. However, we only used the Delta sub-band for further processing. Discrete Wavelet Transform was used for feature extraction, then thresholding was implemented in order to determine the noisy part of the signal. Moreover, we applied some widely used classifiers for epilepsy seizure detection, and compared our results with other approches.

Keywords—component; formatting; style; styling; insert (key words)

I. Introduction

A. Background

An epilepsy seizure is the result of the transient and unexpected electrical disturbance of the brain. Approximately, 50 million people world-wide, have been diagnosed with epilepsy. Many patients are children and adults within the age range of 65-70 years. Although the main reason of this disease is unknown; most of the activities for an epilepsy seizure can be medically treated. The patient with an epilepsy disease is subject to be in danger whenever a seizure occur as a result of uncontrollable movements, loss of consciousness and convulsions that can lead to serious injuries and sometimes death[1], [2], [3].

EEG is a clinical tool that is used to take images of the human brain while the brain is performing a cognitive task. The EEG is collected by placing electrodes on the scalp of the patient. One can then, record the electro-activity that the brain produce along the scalp.

A Discrete wavelet transform (DWT) is a process in which wavelet transform are individually sampled and captures the features of the signal to detect different signal properties of an image or a signal. It captures all the information about the frequency and location. There are variable techniques such as wavelet series, wavelet transform, and wavelet compression[4].

B. Related Work

Svetlana Bezobrazova and Vladimir Golovko proposed the use of the largest Lyapunov's component for abnormal brain activity detection [2]. They presented an approach based on chaos theory and forecasting ANN. They first removed the artifacts from the EEG signal by using the independent component analysis (ICA). Then they used the following three different forecasting artificial neural networks; Multi-layer perception (MLP), Elman's Recurrent ANN, and Radial Basis Function (RBF) to determine the best forecasting ANN for computing the Lyapunov's exponent. Their results indicated that the MLP network has the highest detection anomaly[5], [6]. Whereas, N. Sivasankari and K. Thanushkodi utilized (ICA) to detect an epilepsy seizure from EEG signals[7]. They further trained the selected EEG signals by using ANN. By applying ICA algorithm they separated the original signal from the mixture of recorded electro migration (EM) signals in order to identify the epileptic seizure. Once they identified the desired signal, the researchers applied the back propagation ANN to train the signal. Furthermore, a system based on neural networks and wavelet analysis was presented by Juarez-Guerra et al. to detect epilepsy seizures with EEG signals [4]. First, they filtered the signals using Finite Impulse Response (FIR) filter, and Infinite Impulse Response (IIR) filter. Then, they decomposed the EEG signal into five sub-bands called delta, theta, alpha, beta, and gamma. However, the work was conducted using only alpha and delta, and feature extraction was performed by using both Discrete Wavelet Transform (DWT) and Maximal Overlap Discrete Wavelet Transform (MODWT) to obtain three features on the delta band and three features on the alpha band that included mean, absolute value, and variance. Feed-Forward Artificial Neural Network classifier was then, trained to distinguish between the normal and the abnormal signals. In their work, they have tested the use of segment which was 93.23% accurate, and sub-segments which was 99.26% accurate when training the FF-ANN classifier.

R. Panda et al, proposed an epilepsy seizure detecting technique by classifying the EEG signal using Wavelet Transform and Support Vector Machine (SVM) [8].. In this technique, they preprocessed the EEG signals, and decomposed the signals into five levels using the (DWT). Then, they extracted from each sub-band of the EEG signals statistical features like energy, entropy and standard deviation. After that, the extracted data was classified using a support vector machine (SVM) linear classifier to detect the epileptic signals, from the normal signals and an accuracy of 91.2% was obtained. Moreover, a novel wavelet-based automatic seizure detection was presented by Yinxa Liu et al. [9]. In this method, a multi-channel intracranial EEG signal was decomposed into five sub-bands using wavelet decomposition. The EEG were collected from 21 patients based on a total of 24-26 hours of non-seizure activity and 2-5 hours of seizure activity totaling 87 seizures. Then, they used (DWT) on three of the sub-bands for feature extractions of relative entropy, relative amplitude, coefficient of variation, and fluctuation index. Following this, they used the Radial Basis Function (RBF) support vector machine for classification. Then, they applied post processing scheme that included smoothing, multi-channel, decision function collar technique on the results of the classification. After using this technique, the achieved 94.46% sensitivity and 95.26% specificity with a false detection rate of .58/h. Another work by M. A. Hadj-Youcef et al, presented a method for detecting epilepsy seizures using SVM [10]. First, a band-pass filter was used on a two sets of EEG signals. Then, a (DWT) was used to extract six features from the EEG signals: statistical features (maximum, minimum, range, and standard deviation) and two non-statistical features (energy and entropy). After that, a data reduction was done by using Principal Component Analysis (PCA). Finally, (SVM) was used to classify the data and present the result which have reached an accuracy of 98%. Md, Mamun et al. proposed a method for epilepsy seizure detection by applying Neural Network classifier to 10 statistical features that were extracted from EEG signals after being decomposed using DWT [11]. Their method achieved an accuracy of (80%, 78%, 80%, and 79%). Furthermore, Vijith V S et al. used an EEG data set that was collected by the Government Medical College Thiruvananthapuram, Kerala to evaluat non-leaner features that were extracted from both normal and epileptic EEG signals [12]. They used SVM to classify features like approximate entropy, sample entropy, and Hurst exponent and the result accuracy was 91%.

C. Contribution and Paper Organization

The main objective of this work is to implement a hardware device for epileptic patients that warns patients of upcoming seizures and enables them to avoid harmful situations. In the preprocessing stage, we applied the Chebyshev Higher Order Filter to the EEG signal so that higher frequency components can be removed. Then, we used Wavelet decomposition technique. We decomposed the EEG signal into different sub-level bands. We then, selected the lowest frequency sub-band to perform feature extraction. To begin the feature extraction stage, the (DWT) and Vector Analysis were utilized. Upon completion, we applied Inverse Discrete Wavelet Transform (IDFT) to transform the signal from the frequency domain to the time domain. Moreover, in order to retrieve better results to detect epilepsy seizures, hence we applied soft and hard thresholding in order to analyze where the artifacts exist in the signal. Furthermore, after applying the ANN and SVM classifiers to differentiate between epileptic and non-epileptic signals, we compared the results.

This paper is organized as follows: Section II describes the methodology and the procedure that includes data acquisition process and data decomposition. Feature extraction is presented in section III. Section IV explains the use of thresholding techniques. Section V explains the widely used classifiers. Section VI shows the results of our work. The conclusion is presented in Section VII.

II. Methodology and Procedure

A. Proposed Method

The overall objective of this paper is to determine whether there is an epileptic seizure or non-seizure from an EEG signal using only one sub-band level of the EEG signal. Figure 1 explains the structure of our proposed work. The system works in a number of stages. For data acquisition, we used a publicly available data set from the University of Bonn, Germany [13]. The dataset contains five sub sets: set A and B have an EEG recording from a healthy patients with their eyes open, and recording of EEG from healthy patients with their eyes closed respectively. C and D sets contain seizure-free EEG signal recordings that have been obtained from seizure free epileptic patients. Set E contain recorded EEG signals from epileptic patients during the occurrence of epileptic seizures. Then to achieve the maximum spectral efficiency, we applied the Chebyshev filter to the IIR filter to eliminate any artifacts from the EEG signal. The next step is decomposing the signal using Wavelet analysis to into different levels. Since the frequency response of signal varies at each level of the decomposition, we used a different wavelet filter at each level based on each frequency response. For feature extraction, we applied a Discrete Wavelet Transform in terms of coefficient vector and in regard of time and frequency analysis using DFT and IDFT process, and the energy of each coefficient was calculated. In the final extraction process, we used soft and hard thresholding as well as overlapping the signal using a rectangular function to determine the noisy part of the signal. In our final stage, we applied Support Vector Machine (SVM) and Artificial Neural Network (ANN) classifiers to identify seizure and non-seizure activities of the EEG signal.

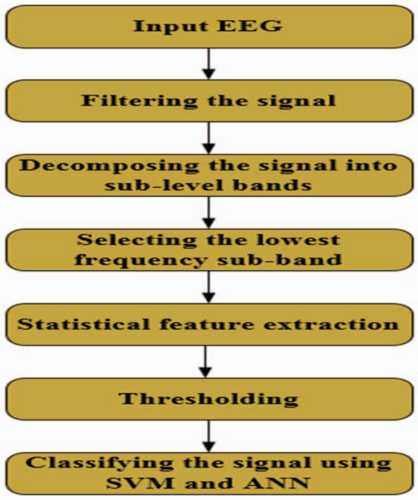

Figure 1. Flow chart of the EEG classification as seizure or non-seizure activity

B. EEG Dataset

As we mentioned before, the online dataset used in this paper is available to the public and contains five sets [13]. Each of the data set consists of EEG signal recordings that have been segmented to 100 segments with a frequency sampling of 173.60Hz and the duration of each segment is 23.6 seconds. However, in our work, we have only used sub-set A and E. Set A contains EEG signals from healthy patients; and set E contains EEG signals from epileptic patients during epilepsy seizures. We have used this data as our inputs in our proposed method.

C. Filtering Figures are related

We applied the Chebyshev filter to the Infinite Impulse Response filter (IIR) to achieve maximum spectrum efficiency. The spectral efficiency is directly proportional to the order of the filter and also on the stop band and band pass coefficients. For this filtering approach, we used the 7th order Chebyschev band pass filter to reduce the frequency spectral noise.

D. Decomposing

Using Wavelet Analysis, the filtered EEG signal was decomposed into five sub-band levels in both time and frequency domain. Although we have decomposed the signal into five different sub-bands, we only used the lowest frequency sub-band for feature extraction and further processing which resulted in a decrease of spectrum usage as well as time complexities reduction.

Many researchers have identified these sub-bands changes during epilepsy seizures. Similarly, the feature extraction of these identified sub-bands will generate vital classification information.

As we can see from Figure 2 the epileptic signal is decomposed in time domain using wavelet analysis, whereas Figure 3 shows the decomposing of the epileptic signal in frequency domain. Figure 4 demonstrate the result of the decomposed normal signal in time domain, and lastly the decomposed normal signal in frequency domain can be seen in Figure 5.

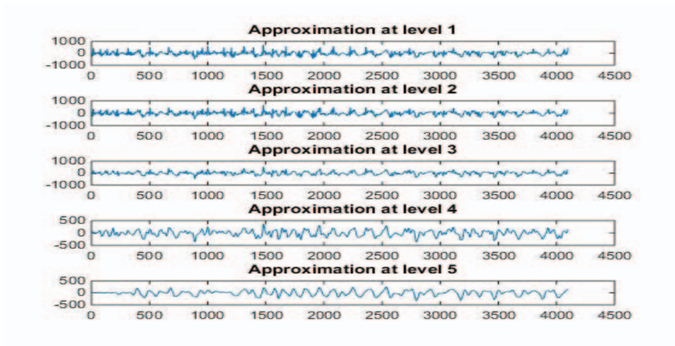

Figure 2. Decomposing the Epileptic signal in time domain

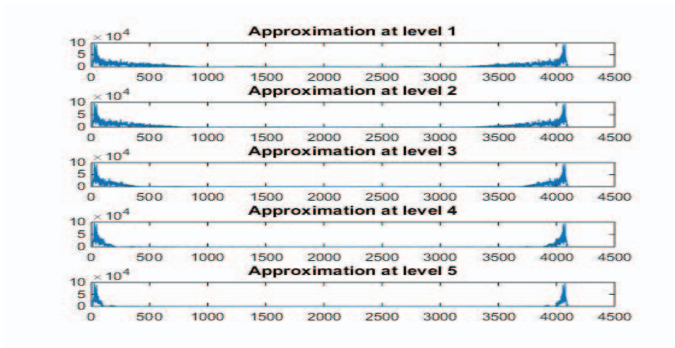

Figure 3. Decomposing the Epileptic signal in frequency domain

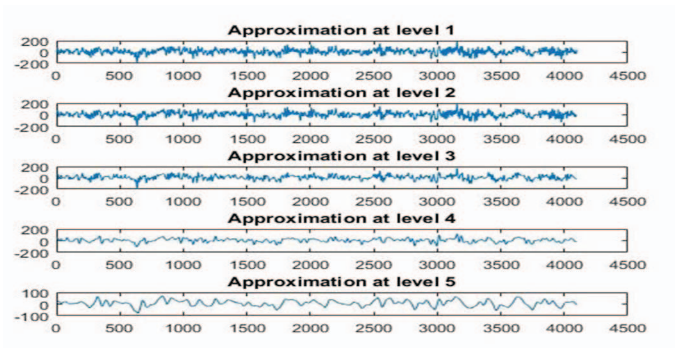

Figure 4. Decomposing the normal signal in time domain

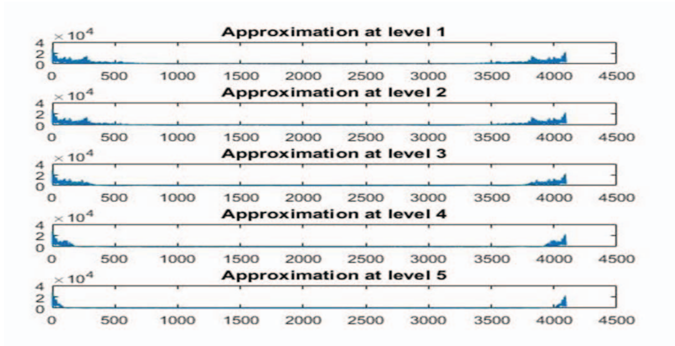

Figure 5. Decomposing the normal signal in frequency domain

III. Feature Extraction

Figure 6 shows feature extraction of the signal where unnecessary components of the signals are removed. Furthermore, Discrete Wavelet Transform was applied for feature extraction in terms of wavelet coefficient vector and in terms of time and frequency analysis using DFT and IDFT process. Hence we have extracted the coefficients at each sub-band level and applied the coefficients to the original signal in both time and frequency domain. Furthermore, we have selected the lowest extracted frequency sub-band for further analysis.

A. Energy

We have used the wavelet coefficients as our features for feature extraction and then we have calculated the energy of each wavelet coefficient.

$$E = \sum_{n=1}^{N} \left| x_i[n] \right|$$

where $1 \leq n \leq 4096$, $1 \leq i \leq 5$. [14].

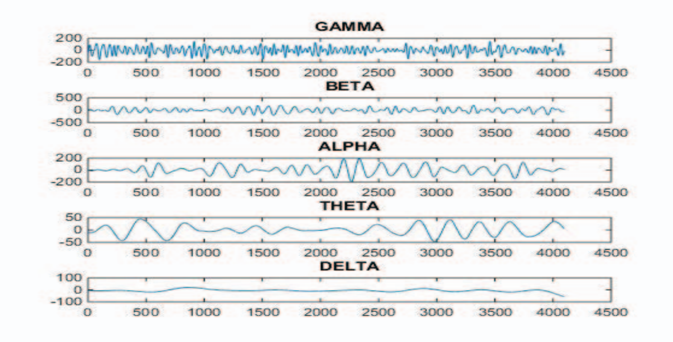

Figure 6. Feature extraction of the Epileptic signal in time domain

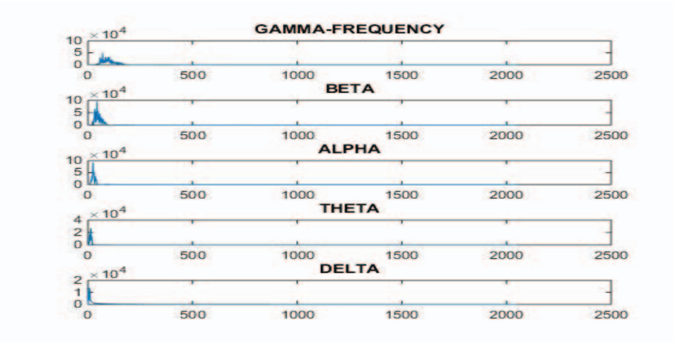

Figure 7. Feature extraction of the Epileptic signal in frequency domain

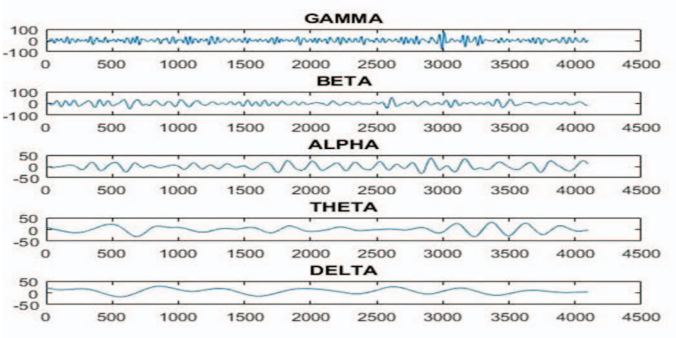

Figure 8. Feature extraction of the normal signal in time domain

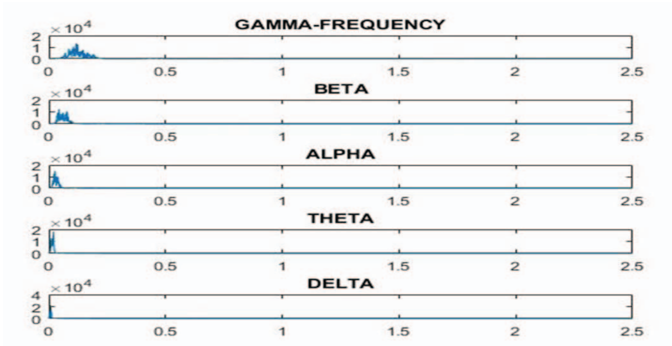

Figure 9. Feature extraction of the normal signal in frequency domain

IV. Thresholding Technique

Filtering and removing the noise of the signal was used for the synthesis of final extraction of the EEG signals by applying Wavelet compression technique. Then both hard and soft Thresholding was applied in order to determine the noisy parts of the signal. However, hard thresholding was unable to detect the noisy part of the signal hence we have overlapped the signal with a rectangular function in order to view the discontinuity due to noise as shown in Figure 10.

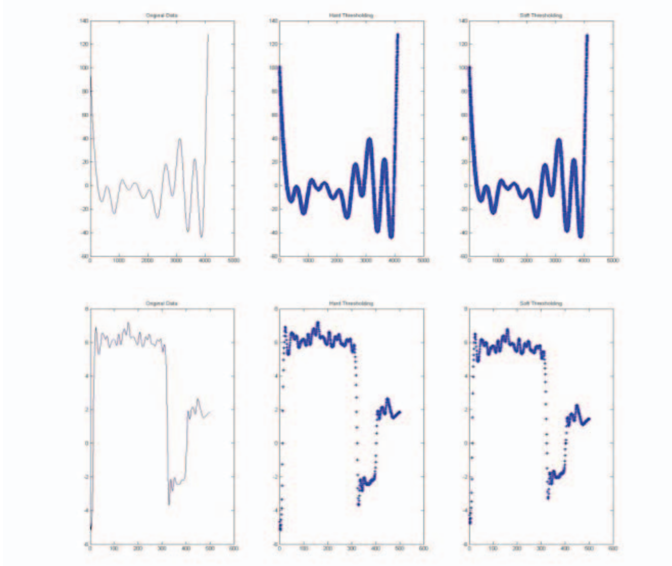

Figure 10. Thresholding of the Epileptic signal after feature extraction

V. Classification

In our work we are using Feed Forward Neural Network which can be used to identify EEG signal types. The FFNN classifier is divided into layers where every layer consists of a number of organized processing neuron units. There is an unequal connection in regards to strength that relates or connects every unit in the layer to each and every unit in the next layer as we can see in Figure 5 [16].

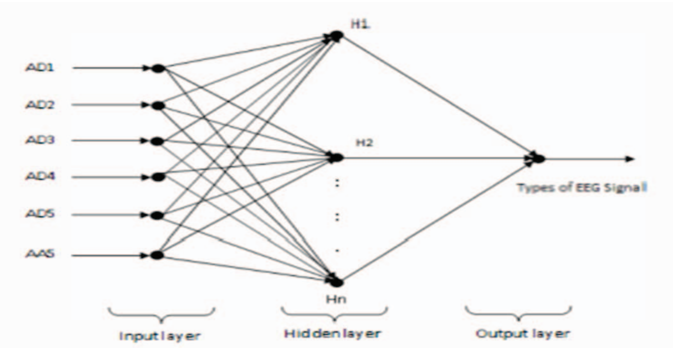

Figure 11. Artificial Neural Network

Support Vector Machine is a binary classifier which is considered as a powerful tool of real data classification [13]. SVM is a discriminative classifier that locates a separating hyperplane between two classes which will identify the largest minimum margin between them shown in Figure 12., We have chosen to use Kernel functions to exploit the data by taking the dot product between the data inputs. When the Kernel function is declared, features of the data can be easily used [16]

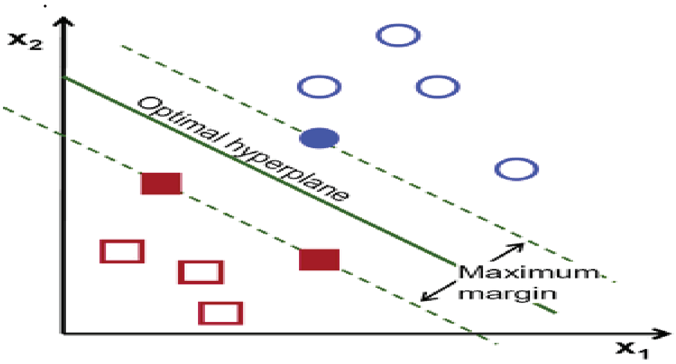

Figure 12. Support Vector Machine

VI. Results

This study was implemented using MATLAB R2014b. the outcome of the developed system was based on using 100 normal EEG signals and 100 Epileptic EEG signals during seizure. The signals were sampled at 173.6 HZ and each signals contains 4097 samples that were evaluated. The EEG signal was decomposed into 5 level sub-bands and then feature extraction was performed on the signal as well as thresholding. Furthermore, features such as the wavelet of the 5th sub-band, the frequency domain of the wavelet and the threshold signal were classified using Artificial Neural Network with feed forward clustering technique (FFANN) as well as Support Vector Machine (SVM). We have calculated the sensitivity (Se) and specificity (Sp) using TP, FP, FN, and TN values in order to evaluate our work performance as shown in table 1.

	Seizure is Present	Seizure is Absent
Correctly detected	True Positive (TP)	False Positive (FP)
Not detected	False Negative (FN)	True Negative (TN)

Table 1. Work Performance

The equation of Se, Sp and Accuracy (Acc) are shown below:

$$Se = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

$$Sp = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}$$

$$Acc = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FN} + \mathrm{TN} + \mathrm{FP}}$$

Table 2 summarizes the overall performance of our work.

Classifier	Se	Sp	ACC
ANN	97.8%	98.6%	98.1%
SVM	96.7	97.5%	96.2%

Table 2. Our Results

VII. Comparison

As we can see from Table 4, we have compared the performance and the results of our proposed method to a number of the existing methods that were carefully studied in the literature review. It is clear from the table that our method has outperformed the existing methods in the literature.

VIII. Conclusion

In this work we have addressed the efficient detection of epilepsy seizure by using EEG processing methods that can be easily implemented in a microcontroller device. The techniques that were used in this paper such as filtering, decomposing, feature extraction, thresholding and classifying are all among the most efficient and informative techniques that are used in analyzing EEG signal and with a high accuracies of 96% using SVM and 98% using ANN. We conclude that our work can be very attractive when implemented on an embedded device for monitoring Epileptic patients.

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Title	Author	Features	Classifier	Results
Automatic Epilepsy Detection Using the Instantaneous Frequency and Sub-Band Energies of the EEG Signals (2011)	Mohammad Fani Ghasem Azemi	Frequency and the energies of the EEG signals in different sub-bands	Artificial Neural Network (ANN)	94%.
Automatic Seizure Detection Using Wavelet Transform and SVM in Long-Term Intracranial EEG (2012)	Yinxia Liu et al.	-Relative Energy - Relative Amplitude - Coefficient of Variation	Support Vector Machine	95.33%
DETECTION OF EPILEPTICS DURING SEIZURE FREE PERIODS (2013)	M.A. Hadj-Youcef et al.	-Maximum -Minimum -Range -STD -Energy -Entropy	Support Vector Machine	99%
Epilepsy seizure detection in EEG signals using wavelet transforms and neural networks (2015)	E. Juarez-Guerra V. Alarcon-Aquino, P. Gomez-Gil	-Mean -absolute -median -variance	Feed-Forward Neural Network	93.23%
Epileptic Seizure Detection Using Non Linear Analysis of EEG (2016)	Vijith V S et al.	-Approximate Entropy -Sample Entropy -Hurst exponent	Support Vector Machine	89% 91%
Epileptic Seizure Classification using Statistical Features of EEG Signal (2017)	Md. Mamun or Rashid Mohiuddin Ahmad	-mean -median -maximum -minimum -range -standard deviation -median absolute deviation -mean absolute deviation -l2 norm -max norm	Neural Network (NN)	80.0% 78.7% 80.0% 79.3%
Proposed Method	Zakareya Lasefr et al	-wavelet coefficient -Energy -Thresholding	ANN SVM	98.1% 96.2%

Table 3. Comparison table

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