

# Epileptic Seizures Classification from EEG Signals using Neural Networks

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**Abstract.** Computer assisted automated detection is highly inevitable for recognizing neurological disorders, as it involves continuous monitoring of Electroencephalogram (EEG) signal. Being a non stationary signal, suitable analysis is essential for EEG to differentiate the normal EEG and epileptic seizures.. This paper proposes classification system for epilepsy based on neural networks A wavelet based feature extraction technique has been adopted to extract features Energy, Covariance Inter-quartile range (IQR) and Median Absolute Deviation (MAD) These features has been applied to Neural Networks for classification The results gave an classification accuracy of 98%. This method makes it possible as a real-time Classifier, which will improve the clinical service of Electroencephalographic recording.

**Keywords:** electroencephalogram (EEG) signals, epileptic seizures, discrete wavelet transform (DWT), artificial neural network (ANN).

## 1. Introduction

Epilepsy is one of the most common neurological disorders with a prevalence of 0.6–0.8% of the world's population. Two-thirds of the patients achieve sufficient seizure control from anticonvulsive medication, and another 8–10% could benefit from respective surgery. For the remaining 25% of patients, no sufficient treatment is currently available. The epilepsy is characterized by a sudden and recurrent malfunction of the brain, which is termed “seizure.” Epileptic seizures reflect the clinical signs of an excessive and hyper synchronous activity of neurons in the brain. The detection of epilepsy, which includes visual scanning of EEG recordings for the spikes and seizures, is very time consuming, especially in the case of long recordings. In addition, bio-signals are highly subjective so disagreement on the same record is possible. These EEG signal parameters extracted and analyzed using computers, are highly useful in diagnostics. The EEG signals, like most biological signals, are inherently difficult to quantify. These signals can be characterizes as non stationary. The EEG signals, like most biological signals, are inherently difficult to quantify. These signals can be characterized as non stationary.

There are number of researches present in literature and still going on regarding automated detection of seizures. The work proposed by Abdulhamit Subasi [1] in 2005 decomposition of EEG signal and applied to neural networks and the work proposed by D. Najumnessa[2], "classification of epileptic seizures". The features used in this work are needs to elaborate. Farooq [3] in 2011 proposed wavelet based technique is adopted to extract features such as IQR and MAD. These fetures are considered and modified these feature extraction techniques in our work. Two types of neural networks are used for classification of these features.

## 2. Materials and Methods

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## 2.1. Experimental data

EEG data, acquired from university of Bonn, contains three different cases: 1) healthy, 2) epileptic subjects during seizure-free interval (interictal), 3) epileptic subjects during seizure interval (ictal) [4]. Each case has five datasets named: O, Z, F, N, and S. Sets O and Z are obtained from healthy subjects under condition of eyes open and closed; respectively by external surface electrodes. Sets F and N are attained from interictal subjects. Set F taken from epileptogenic zone of the brain shows focal interictal activity; set N obtained from hippocampal formation of the opposite hemisphere of the brain indicates non-focal interictal activity, and set S is got from an ictal subject. Each set contains 100 single channel EEG segments of 23.6 sec duration. Sampling frequency is 173.61 Hz, so each segment contains  $N = 4096$  samples [4]. All these EEG segments are recorded with the same 128- channel amplifier that converts by 12 A/D convertor with bit rate of 12, and then were sampled on 173.61 Hz [4].

## 2.2. Discrete Wavelet Transform

Wavelet transform is a spectral estimation technique in which any general function can be expressed as an infinite series of wavelets. The basic idea underlying wavelet analysis consists of expressing a signal as a linear combination of a particular set of functions (wavelet transform, WT), obtained by shifting and dilating one single function called a mother wavelet. The decomposition of the signal leads to a set of coefficients called wavelet coefficients. Therefore the signal can be reconstructed as a linear combination of the wavelet functions weighted by the wavelet coefficients. In order to obtain an exact reconstruction of the signal, adequate number of coefficients must be computed. The key feature of wavelets is the time-frequency localization. All wavelet transforms can be specified in terms of a low-pass filter  $g$ , which satisfies the standard quadrature mirror filter condition

$$G(z)G(z^{-1}) + G(-z)G(-z^{-1}) = 1 \quad (1)$$

Where  $G(z)$  denotes the  $z$ -transform of the filter  $g$ . Its complementary high-pass filter can be defined as

$$H(z) = zG(-z^{-1}) \quad (2)$$

A sequence of filters with increasing length (indexed by  $i$ ) Can be obtained

$$\begin{aligned} G_{i+1}(z) &= G(z^{2^i})G_i(z), \\ H_{i+1}(z) &= H(z^{2^i})G_i(z), i = 0, 1, 2, \dots, I-1 \dots \end{aligned} \quad (3)$$

with the initial condition  $G_0(z) = 1$ . It is expressed as a two-scale relation in time domain

$$\begin{aligned} g_{i+1}(k) &= [g]_{\uparrow 2^i} g_i(k), \\ h_{i+1}(k) &= [h]_{\uparrow 2^i} g_i(k) \end{aligned} \quad (4)$$

Where the subscript  $[.]_{\uparrow m}$  indicates the up-sampling by a factor of  $m$  and  $k$  is the equally sampled discrete time. One area in which the DWT has been particularly successful is the epileptic seizure detection because it captures transient features and localizes them in both time and frequency content accurately.

In the present work, since the EEG signals do not have any useful frequency components above 30 Hz, the number of decomposition levels was chosen to be 4. Thus, the EEG signals were decomposed into details D1–D4 and one final Approximation, A4. Usually, tests are performed with different types of wavelets and the one, which gives maximum efficiency, is selected for the particular application. The wavelet coefficients were computed using the db4 in the present work.. The proposed method was applied on both data set of EEG data Fig. 1 shows approximation (A4) and details (D1–D4) of an epileptic EEG signal.

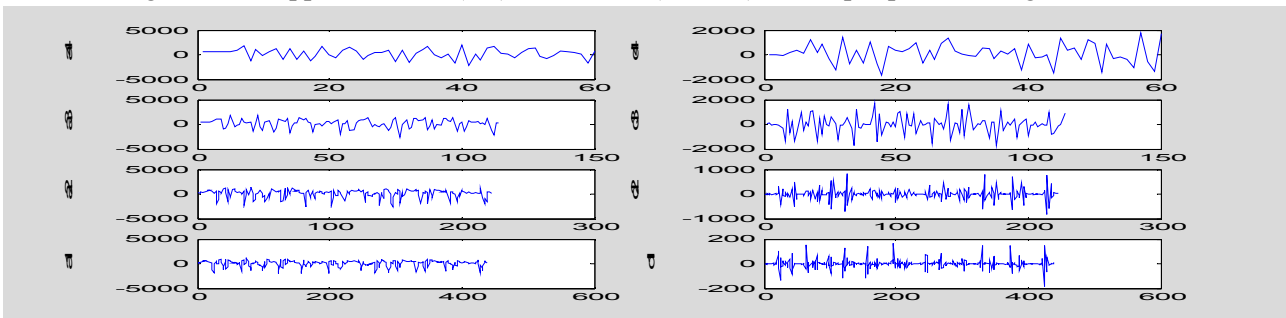


Fig. 1: Approximate and detailed coefficients of EEG signal taken from unhealthy subject (epileptic patient)

### 2.3. Feature extractions

I. Energy of the wavelet coefficients in each sub-band

$$E(l) = \sum_{i=1}^n x_i^2 \quad (5)$$

Where,  $x_i$  represents the value of signal,  $n$  is the total number of samples and  $l$  represents the decomposed level.

II. Coefficient of variation of the wavelet coefficients in each sub-band

$$\sigma^2 = \frac{\sum_{i=1}^n (x_i - \mu)^2}{n} \quad (6)$$

Where  $\mu = \frac{\sum_{i=1}^n x_i}{n}$  is mean the coefficient of variation is given by  $Cov = \frac{\sigma^2}{\mu^2}$  (7)

III. Inter quartile range of the wavelet coefficients in each sub-band

$$IQR = Q3 - Q1 \quad (8)$$

Where,  $Q1$  and  $Q3$  are the first and third quartile respectively. Median absolute deviation of the wavelet coefficients in each sub-band

IV. Median absolute deviation of the wavelet coefficients in each sub-band

$$MAD = \frac{1}{N} \sum_{i=1}^N |x_i - \bar{x}| \quad (9)$$

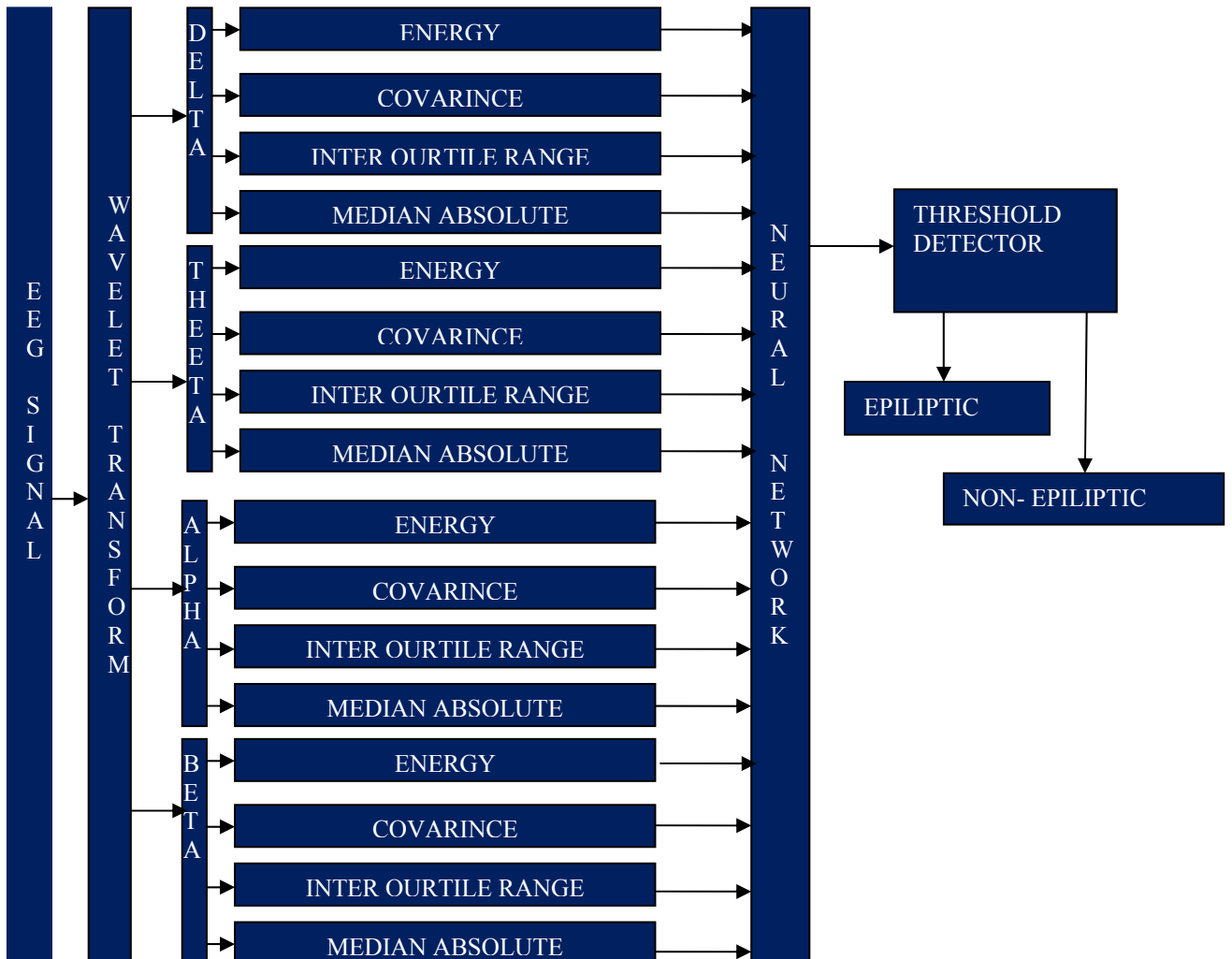


Fig. 2: Block: Diagram of Epileptic Seizure Classification systems

## 2.4. Neural networks

Artificial neural networks are computing systems made up of large number of simple, highly interconnected processing elements (called nodes or artificial neurons) that abstractly emulate the structure and operation of the biological nervous system. Learning in ANNs is accomplished through special training algorithms developed based on learning rules presumed to mimic the learning mechanisms of biological systems. There are many different types and architectures of neural networks varying fundamentally in the way they learn. In this paper, feed forward back propagation neural network considered

The architecture of BPN may contain two or more layers. A simple two-layer ANN consists only of an input layer containing the input variables to the problem, and output layer containing the solution of the problem. This type of network is a satisfactory approximate or for linear problems. However, for approximating nonlinear systems, additional intermediate (hidden) processing layers are employed to handle the problem's nonlinearity and complexity. The determination of appropriate number of hidden layers is one of the most critical tasks in neural network design. Unlike the input and output layers, one starts with no prior knowledge as to the number of hidden layers. A network with too few hidden nodes would be incapable of differentiating between complex patterns leading to only a linear estimate of the actual trend. ANNs' success depends on both the quality and quantity of the data.

The complete classification system is described in Figure 2 .From the decomposed EEG signal the features calculated for each sub band. Total 16 features are considered for classification. Neural network is designed with 16 input nodes and one output node. The network is trained with parameters a gradient descent algorithm with momentum factor included (TRAINGDM) was used for training. The stopping criterion was specified to be 0.001 Root Mean Square Error (RMSE). The training was stopped when the RMSE between the network outputs and the targets was lesser than or equal to 0.001. The learning rate was fixed at 0.5. The number of training epochs was fixed uniformly at 1000. . The output from threshold detector value is greater than threshold value the subject considered as epileptic otherwise normal. The threshold value of 0.5 is considered. In this work. Feed Forward back propagation and Elman backpropagation neural networks are used.

## 3. Results and Discussions

Each EEG signal is decomposed using DWT .from each sub band the four statistical features Energy, Covariance, Inter Quartile range (IQR) and Median absolute Deviation (MAD) calculated and average values are tabulated in Table-I. This table shows the deviation of values for different subjects. In each sub band the variation of values of features indicting the Presence of epilepsy

Table. 1: Average values of Extracted Features

	DELTA( A5) 0 --2.70Hz				THEETA( D5) 2.7-5.4				ALPHA( D4) 5.40-10.8Hz				BETA( D3)10.8-21.7Hz			
	E	C	I	M	E	C	I	M	E	C	I	M	E	C	I	M
Z	<b>639</b>	<b>249</b>	<b>19</b>	<b>11</b>	<b>73</b>	<b>65</b>	<b>9</b>	<b>5</b>	<b>68</b>	<b>40</b>	<b>7</b>	<b>4</b>	<b>71</b>	<b>26</b>	<b>6</b>	<b>4</b>
O	1092	428	26	15	152	136	11	7	286	156	13	8	296	109	13	7
N	1133	574	27	16	165	148	12	8	85	52	7	5	38	14	4	2
F	5049	3192	37	23	534	478	15	10	261	161	8	6	101	37	4	3
S	<b>24608</b>	<b>14183</b>	<b>143</b>	<b>80</b>	<b>9152</b>	<b>8051</b>	<b>94</b>	<b>57</b>	<b>7210</b>	<b>4393</b>	<b>68</b>	<b>43</b>	<b>5878</b>	<b>2161</b>	<b>40</b>	<b>28</b>

E=Energy in each sub band C= Covariance, I= Inter Quartile Range and M=Median absolute Deviation ;O-(Eyes open) healthy subjects data, Z( Eyes closed) healthy subjects data, N&F = Epileptic subjects during seizure-free interval (inter ictal) and S= Epileptic subjects during seizure interval (ictal)

Features of five different Subjects and each having 100 sets. Epoch duration of 1 second is considered for each type dataset. Therefore 2300 feature sets are generated from each subject and the total feature sets are 11,500. The target value are fixed as per the type of the subjects. For epileptic subject is assigned a maximum value of 0.9 and normal subject is assigned 0.1. These feature sets are arranged in random manner before neural network training. The trained network is simulated with normal and epileptic subject's data.

The performance of the classification is evaluated in terms of specificity, sensitivity and classification accuracy. The performance analysis is tabulated in Table II. The Fig2 shows the plot of classification performance of Feed Forward Back Propagation neural network.

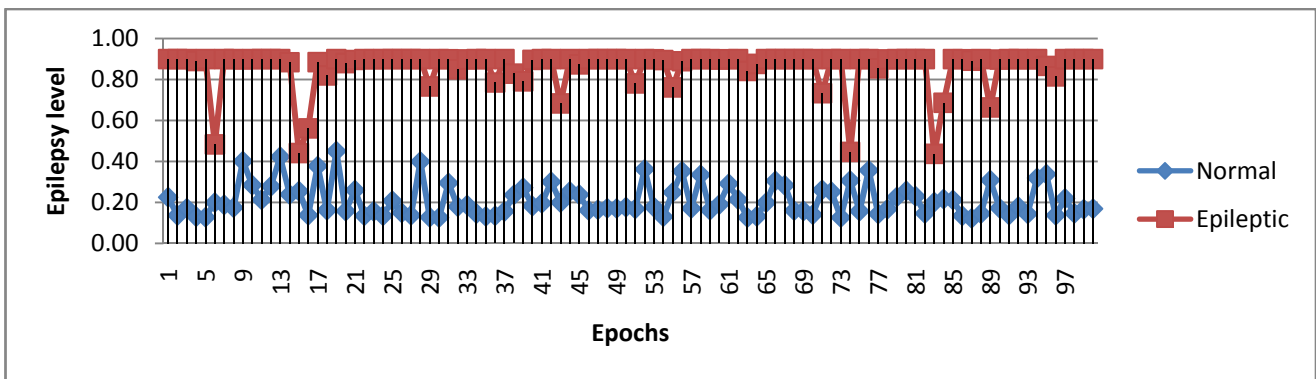


Fig. 3: Performance analysis of Epileptic Seizure Classification systems

Table. 2: Performance evaluation Neural network classifier

Neural network type	Specificity (%)	Sensitivity (%)	Over all accuracy (%)
Feed Forward Back Propagation	98.59	97.69	98.32
Elman Back propagation	98.7	97.78	97.79

For testing 4600 epochs are considered (2300 –normal and 2300 abnormal)

#### 4. Conclusion

Diagnosing epilepsy is a difficult task requiring observation of the patient, an EEG, and gathering of additional clinical information. An artificial neural network that classifies subjects as having or not having an epileptic seizure provides a valuable diagnostic decision support tool for neurologists treating potential epilepsy, since differing etiologies of seizures result in different treatments. In this work, classification of EEG signals was examined. The features are extracted using wavelet transform technique. Four features are extracted, the features Energy, Covariance, Inter quartile range (IQR) and Median absolute deviation(MAD). The generated data from wavelet technique are given to ANN for training of normal and abnormal EEG conditions. The ANN is used to discriminate between the two tasks with a success rate of 98%.

Further research is needed to find more elaborated memory architectures and its appropriate training algorithms. Neural networks as classifiers have here a high potential because they can compute in real time with a high numbers of features. This characteristic enable the development and construction of transportable devices, improving substantially the quality of life of epileptic patients intractable by medication and that must learn to live with seizures.

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