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ANN based Epilepsy detection using EEG

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ABSTRACT
Brain is the most complex organ amongst all the systems in human body. ElectroEncephaloGraph EEG is a technique which is used to identify the neurological disorder of brain. Epilepsy is one of the most common neurological disorders of brain. Epilepsy needs to be detected efficiently using required EEG feature extraction such as: variance, power spectral density, energy and entropy. This paper proposes classification system for epilepsy based on neural network. Classification is done for normal and epileptic subjects. Normal subjects are further classified for eyes open and eyes closed. In classification of normal and epileptic, results obtained exhibited an accuracy of 99.2% and for eyes open and eyes closed an accuracy of 100% is obtained.
KEYWORDS: Electro Encephalo Graph, Discrete wavelet transform, Epilepsy, Artificial Neural Network.

INTRODUCTION

Brain is the most complex organ amongst all the systems in human body. In medical terms, human brain is also called an encephalon and the medical technique that reads scalp electrical activity of the encephalon is called ElectroEncephaloGraph (EEG). EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes. EEG is measured using 10-20 electrode placed on the scalp as shown in Figure 1 [1].

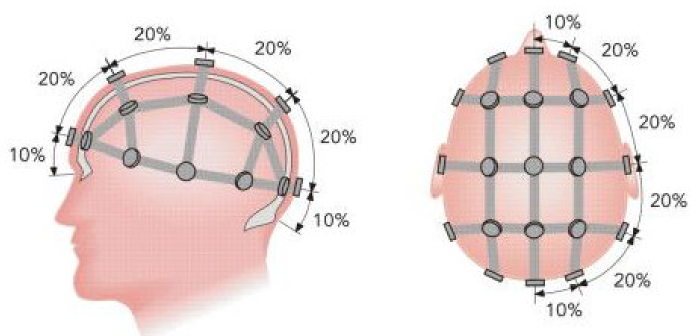


Figure 1: EEG Electrode placement system

EEG signals contain a great deal of information about the functioning of the brain. Since early, Fourier transform has been most commonly used for the EEG processing. This approach is based on some characteristic waveforms with five frequency bands: Delta (1-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz) and Gamma (30-60 Hz).

The main diagnostic application of EEG is detection of epilepsy. Epileptic activities can create clear abnormalities on a standard EEG study. The patient suffer from epilepsy has different EEG as compare to the normal human brain. EEG is the most common and most useful test performed in evaluating patients suspected of epilepsy. Apart from this EEG is also used for the diagnosis of coma, encephalopathy, and brain death.

Epilepsy is a neurological condition in which chronic abnormal bursts of electrical discharge in the brain are observed. A seizure is usually defined as a sudden alteration of behaviour due to a temporary change in the electrical functioning of the brain, in particular the outside rim of the brain called the cortex. It is usually diagnosed after a person has had at least two seizures that were not caused by some known medical condition like alcohol withdrawal or extremely low blood sugar. An epileptic attack may result in a series of involuntary contractions of the voluntary muscles, abnormal sensations, abnormal behaviours, or some combination of these events.

Our work involves classification of data obtained from Department of Epileptology University of Bonn. This EEG data consists of five sets A-E. Set A and Set B are normal subjects having eyes open and eyes closed data, whereas

Set C, D and E are epileptic subjects. Set C and Set D both come under seizure free interval, where in set C is from the hippocampal formation of opposite hemisphere of the brain and set D is from the epileptogenic zone. Set E contain seizure activity [2].

The **hippocampal formation** is a compound structure in the medial temporal lobe of the brain. There is no consensus over which brain regions are encompassed by the term, with some authors defining it as the dentate gyrus, the hippocampus proper and the subiculum [3]. The hippocampal formation is thought to play a role in memory, spatial navigation and control of attention. The neural layout and pathways within the hippocampal formation are very similar in all mammals.

The **epileptogenic zone** is an area of cortex that is necessary and sufficient for initiating seizures and whose removal (or disconnection) is necessary for complete abolition of seizures [4].

DATA USED

The EEG data considered for this work was obtained from EEG database of University of Bonn. It contains three different cases: 1) healthy, 2) epileptic subjects during seizure-free interval and 3) epileptic subjects during seizure interval. The complete data set consists of five sets A-E. Each data set contained 50 single channel EEG signals. Each segment is of 23.6 sec duration which contains 4096 samples. Set A and Set B both are for the healthy subjects, whereas Set C and Set D both are for epileptic subjects with seizure-free interval and Set E epileptic subject with seizure interval. Sets A and B recording was obtained from the surface of EEG recording that was carried out on five healthy volunteers using a standardized 10-20 electrodes.

Set A is for healthy volunteers who are in awake-state with eyes open while Set B is with eyes closed. Recordings in set C were from the subjects with the hippocampal formation of opposite hemisphere of the brain and set D were from the epileptogenic zone. Both Set C and D were measured during seizure free interval. Set E only contains seizure activity. All signals were recorded with 128-channel amplifier system, using an average common reference. After 12 bit analog-to-digital conversion, the data were written continuously onto the disk of a data acquisition computer system at sampling frequency of 173.6 Hz. Band pass filter settings were 0.53-40 Hz [2]. In this work, we use all the five data sets A-E for training and testing of neural network.

DISCRETE WAVELET TRANSFORM

There are no general methods of EEG analysis. Usually time and frequency domains have been considered for analyses of EEG signals. In both time and Frequency methods, an EEG signal is considered as a realization of a random process features of signal are: means, variances, power spectral density and skewness. It may have a high degree of complexity and only a description of statistical terms may be justified.

The discrete wavelet transform (DWT) is an active tool for Time-Frequency analysis of signals. Discrete wavelet transform (DWT) is a spectral analysis technique used for analyzing non-stationary signals, and provides time-frequency signals. Wavelet transform is a spectral estimation technique in which any general function can be expressed as an infinite series of wavelets. The decomposition of the signal results in a set of coefficients called wavelet coefficients. Decomposition of the signal analysis is depending on the high-pass and low-pass filter. Wavelet transform uses a different window size, which allows the wavelet to be stretched or compressed depending on the frequency of the signal. The important property of DWT is that this technique is used for analyzing the non-stationary signals like EEG signals.

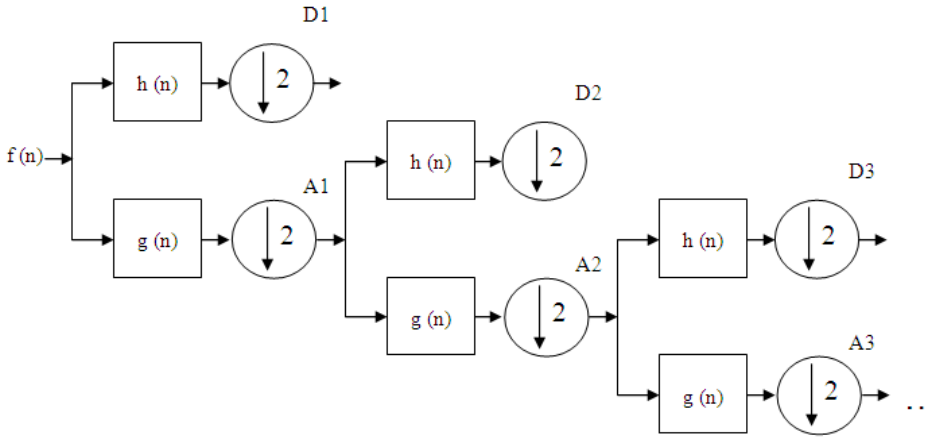


Figure 2: Multi-resolution decomposition of signal

DWT analyzes frequency bands with different resolution by means of multi-level decomposition into a coarse frequency band. This results in excellent feature extraction from sub-bands of the non-stationary EEG signals. In this study, by using the DWT with Daubechies wavelet of order 2 (db2) the EEG signals is decomposed into sub-bands which results in the classification of the signals. The process decomposition is replicated from the earlier work done by Mandeep Singh and Sunpreet Kaur. Five sub-bands are obtained, namely Delta (0-4.05 Hz), Theta (4.05-8.1Hz), Alpha (8.1-12.15 Hz), Beta (12.15-32.5 Hz) and Gamma (>32.5 Hz) [5].
The decomposition of the signal into different frequency bands is obtained by low-pass and high- pass filter of the EEG signal. Here the study has adopted multilevel decomposition of DWT, in order to filter the signals. A model of this multi-resolution decomposition procedure is shown in figure 2. Each stage of the process consists of two filters and two down samples by '2'. The first filter h(n) is high-pass filter and g(n) is low-pass filter. The output of first high-pass and low-pass filter gives the detail D1 and the approximation A1. The first approximation A1 is further decomposed and this process will continued until the particular level will not be reached by the user [6].

FEATURE EXTRACTION
The parameters derived for the epilepsy detection are: variance, energy, max power spectral density (PSD), min power spectral density (PSD) and entropy. All these parameters were extracted by using MATLAB R2011a and Microsoft Office Excel and used for epilepsy detection [1][5][7][8].

(1) Variance: Variance is defined as a measure of the dispersion of a set of data points around their mean value.

$$y^2 = \frac{\sum(X - \mu)^2}{n}$$

where μ is the mean value of the set X and n is the number of samples.

(2) Energy: The energy of the signal is defined as the sum of squared modulus of the sample values of any signal.

$$E = \sum_{n=0}^{N-1} |X|^2$$

where X is the samples values in each sub-bands and N is the total number of samples.

(3) Power Spectral Density (PSD): The PSD is the amount of power per unit frequency as a function of frequency. PSD is computed by squared modulus of the Fourier transform of the time series of the signal.

$$\max(\omega) = \frac{1}{n}|X(\omega)|^2$$

The Maximum and minimum values are estimated from the PSD of each EEG subbands can be considered as feature for classification.

(4) **Entropy:** Entropy is a numerical measure of the randomness of a signal.

$$(e) = -\sum_{1}^{n} X^2 \log(X^2)$$

Entropy can act as a feature and used to analyze psychological time series data such as EEG data. Entropy is a strong feature for epilepsy detection.
These features extracted from the five sub-bands of EEG signals are tabulated in table 1.
This work aims at achieving two different types of classifications:

i. To classify normal subjects and epileptic subjects (two-class classification).
ii. To classify normal subjects with eyes open and eyes closed (two-class classification).

From the 25 features extracted as given in table 1, it was observed that:

i. For 100 subjects in normal class and 150 subjects in epileptic class, none of the features had non-overlapping range. Thus a simple threshold based two class classification is not possible.
ii. For 50 subjects of normal eyes open and 50 subjects of normal eyes closed class, none of the features had non-overlapping range. Thus a simple threshold based two class classification is not possible.

In order to achieve two-class classification using the features extracted we propose an ANN based classifier.

Table 1: Features of sub-bands and their nomenclature

Sub-bands → **Feature** ↓	**DELTA**	**THETA**	**ALPHA**	**BETA**	**GAMMA**
	y1	y2	y3	y4	y5
PSD max	Max1	Max2	Max3	Max4	Max5
PSD min	Min1	Min2	Min3	Min4	Min5
Entropy	e1	e2	e3	e4	e5
Energy	E1	E2	E3	E4	E5

ARTIFICIAL NEURAL NETWORK

A neural network consists of hidden neurons arranged in layers, which convert an input vector into some output. Each neuron takes an input, applies a function to it and then passes the output on to the next layer, this show in figure 3. Generally the networks are defined to be feed-forward: a unit feeds its output to all the units on the next layer, but there is no feedback to the previous layer. Weights are applied to the signals passing from one unit to another, and these weights are modified to bring the network input-output behavior into line to adapt a neural network to the particular problem at hand [9].

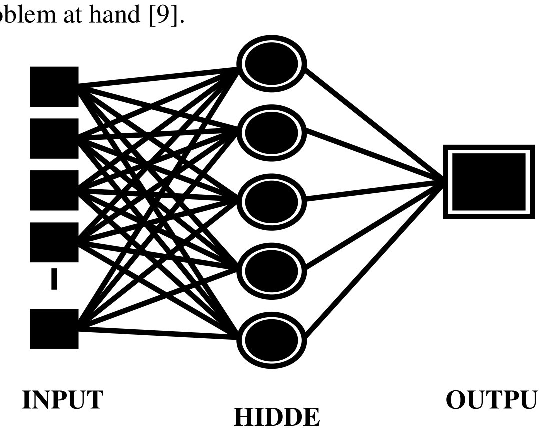


Figure 3: Artificial neural network architecture

The complete classification system is described in figure 4. From the decomposed EEG signal, the features are calculated for each sub-band. Total 25 features are considered for the classification. Neural network is designed with 25 input nodes, one output node and one hidden layer. We chose transfer function in all the layers as tansig. Further we chose 70% of the subjects for training, 15% for testing and 15% for validation. Since this is a two class classification, the target values are determined as 0 and 1. The topology chose is Feedforward back propagation neural network. Of 25 input parameters, combination of 10 input parameters are selected which gives good accuracy, sensitivity and specificity. This is done to keep the neural network light and computationally effective.

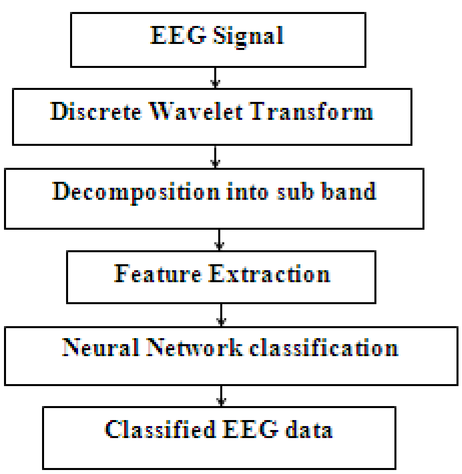
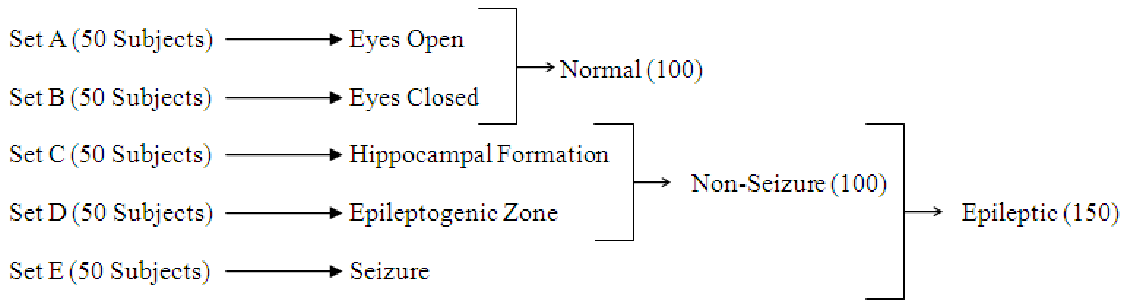


Figure 4: Classification of system

The data under analysis is as described below:



This paper outlines the classification of normal subjects and epileptic subjects in phase-I. Sub-classification of normal subjects into eyes open and eyes closed is done in phase-II.

Phase-I: Classification of normal subjects and epileptic subjects.

As described earlier, we have 100 normal subjects and 150 epileptic subjects. For optimizing the accuracy of ANN, we tried various possible combinations of extracted features from all five sub-bands, with different number of neurons in the hidden layer. The result of this exercise is given in table 2. It is found that ANN with seven neurons and 10 inputs, namely variance and entropy from all the five sub-bands gives maximum accuracy. This accuracy is 99.2% and is quite satisfactory.

Phase-II: Classification of normal eyes open and eyes closed subjects.

As described earlier, we have 50 eyes open subjects and 50 eyes closed subjects. For optimizing the accuracy of ANN, we tried various possible combinations of extracted features from all five sub-bands, with different number of neurons in the hidden layer. The result of this exercise is given in table 3. Here it is found that many possible combinations give 100% accuracy. Fortunately the topology and input vector chosen for phase-II, i.e. ANN with seven neurons and 10 inputs, namely variance and entropy from all the five sub-bands also gives accuracy of 100%.

Table 2: Accuracies achieved for classification of normal and epileptic dataset

Parameter → / Neurons ↓	Variance and PSD Max	Variance and PSD Min	Variance and Entropy	Variance and Energy	PSD Max and PSD Min	PSD Max and Entropy	PSD Max and Energy	PSD Min and Entropy	PSD Min and Energy	Entropy and Energy
2	86.40%	80.40%	97.60%	92.80%	66%	83.20%	94.80%	79.20%	91.20%	94.40%
3	82.40%	74.80%	98.80%	94.40%	57.20%	58.80%	92.80%	77.60%	92%	95.60%
4	76.80%	79.20%	98%	95.60%	68.80%	81.60%	95.60%	72%	93.60%	95.20%
5	84.80%	80.80%	97.20%	95.60%	78.80%	80.80%	93.60%	77.20%	94.40%	95.60%
6	82.40%	74.80%	98%	96%	64%	94.40%	94.40%	75.20%	92%	94.80%
7	84.00%	83.60%	99.20%	95.60%	64.40%	88%	94.80%	69.60%	96.40%	96.80%
8	86%	74.40%	96.40%	93.20%	67.60%	75.60%	95.20%	80.40%	93.60%	92.40%
9	84%	86%	94.80%	96.40%	71.60%	87.20%	95.20%	76%	94.80%	95.60%

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Table 3 : Accuracies achieved for classification of eyes open and eyes closed dataset

Parameter → / Neurons ↓	Variance and PSD Max	Variance and PSD Min	Variance and Entropy	Variance and Energy	PSD Max and PSD Min	PSD Max and Entropy	PSD Max and Energy	PSD Min and Entropy	PSD Min and Energy	Entropy and Energy
2	97%	97%	99%	98%	87%	100%	96%	86%	93%	96%
3	100%	97%	100%	67%	92%	100%	90%	52%	46%	56%
4	100%	96%	100%	98%	88%	100%	97%	83%	90%	95%
5	99%	92%	100%	97%	91%	100%	98%	72%	94%	95%
6	100%	96%	100%	100%	88%	100%	98%	73%	91%	95%
7	100%	99%	100%	99%	91%	99%	99%	96%	93%	95%
8	100%	99%	100%	99%	69%	99%	99%	87%	80%	98%
9	98%	95%	100%	99%	94%	100%	99%	93%	93%	95%

RESULTS AND CONCLUSION

From this study, we conclude that,

i. Variance and entropy from all the five sub-bands are optimum for classification of EEG signals.

ii. A hidden layer with seven neurons is best suited for this classification.

Let us elaborate the results further. General confusion matrix is given in table 4.

Table 4: General Confusion matrix

Predicted Class

Actual Class	**Class**	**Yes**	**No**
	Yes	TP	FN
	No	FP	TN

Accuracy = TP + TN / TP + TN + FP + FN
Sensitivity = TP / TP + FN
Specificity = TN / TN + FP

TP = True positive FP = False positive
TN = True negative FN = False negative

For epilepsy detection, we ask is the subject epileptic? Answer may be Yes or No. Our results for the chosen ANN are given in table 5.

Table 5: Confusion matrix for normal and epileptic detection

Predicted Class

Actual Class	**Class**	**Yes**	**No**
	Yes	148	2
	No	0	100

Accuracy = [(148+100)/ (148+100+0+2)] x 100 = (248/250) x 100 = 99.2%
Sensitivity = [148/ (148+2)] x 100 = (148/150) x 100 = 98.6%
Specificity = [100/ (100+0)] x 100 = (100/100) x 100 = 100%

For eyes open and eyes closed detection, we ask is it eyes open? Answer may be Yes or No. Our results for the chosen ANN are given in table 6.

Table 6: Confusion matrix for eyes open and eyes closed detection

Predicted Class

Actual Class	**Class**	**Yes**	**No**
	Yes	50	0
	No	0	50

Accuracy = [(50+50) / (50+50+0+0)] x 100 = (100/100) x 100 = 100%
Sensitivity = [50 / (50+0)] x 100 = 100%
Specificity = [50 / (50+0)] x 100 = 100%

The results are finally shown in table 7.

Table 7: Final result

Case	Accuracy	Sensitivity	Specificity
Normal and epileptic classification	99.2%	98.6%	100%
Eyes open and eyes closed classification	100%	100%	100%

Needless to mention, the results are very encouraging and need no more refinements.

SCOPE FOR FUTURE WORK

In this work, we have classified epileptic subjects (Set C, D and E) and normal subjects (Set A and B). The epileptic subjects can be further be classified as non-seizure (Set C and D) and seizure (Set E) case. To make this classification more specific, non-seizure case may be sub-classified as hippocampal formation (Set C) and epileptogenic zone (Set D).

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