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ANALYSING EEG SUB-BANDS TO DISTINGUISH BETWEEN INDIVIDUALS WITH NEURAL DISORDER USING BACK PROPAGATION NEURAL NETWORK

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ABSTRACT

The electroencephalogram (EEG) signal plays a vital role in the detection of various types of neural disorders such as autism spectrum disorder, epilepsy, Alzheimer's, etc. Since EEG signals are lengthy and it contains a vast amount of useful data and artifacts analysing these signals by an expert using traditional methods are monotonous and time consuming. Recent years, many automatic diagnostic systems for examining EEG signals do exist. This paper proposes an automated system for analysing EEG signals using artificial neural networks to distinguish autism spectrum disorder subjects with normal subjects. We considered various statistical features of EEG signals as input for the proposed neural network model. The system is trained using back propagation neural network algorithm. The proposed method shows overall accuracy values as high as 88.8% can be achieved.

KEYWORDS: Electroencephalogram, Autism spectrum disorder, Back propagation neural network, Adaptive filter, discrete wavelet transform.

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INTRODUCTION

Autism is a developmental disorder that is generally observable in the early stages of life, preferably in the age groups of one to three years. The common deficiencies found in the autistic groups are social interactions, communication, controlled interests and recurring behaviour. The cause of autism is still enigmatic. Researchers are working to find out the various factors that cause autism. [1]Some of them believe that the changes in the environment and genetics might be the key cause. Clinicians adopt several methodologies to assimilate neural disorder subjects as a means of assisting and control. Two such approaches are non-invasive and invasive. Usually invasive techniques are more efficient compared to non-invasive. But they have risks such as impairment and infection. To perceive cognitive mental action of neural disorder subject clinicians prefer non-invasive technique such as EEG, ECG, MEG, etc. Specifically EEG is used since installation cost is inexpensive and reasonable time-based resolution. By attaching electrodes affording to international 10-20 system over the scalp of neural disorder subjects electrical signals of neurons are recorded. EEG contains five basic rhythms such as delta (up to 4Hz) associated deep sleep, theta (4-8Hz) relate to memory process, alpha (8-13Hz) allied with sensory and cognitive inhibition, beta (13-30Hz) linked to motor behaviour and gamma rhythm (>30). Abnormal EEG rhythm indicates neural disorders such as autism spectrum disorder, epilepsy, etc. EEG signal bands are analysed by extracting significant statistical features like standard deviation, mean, variance.

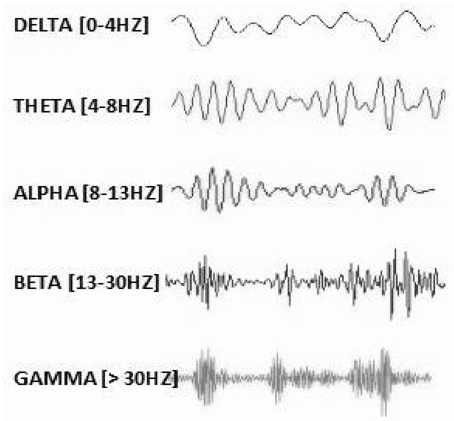


Figure 1
EEG rhythms

Ebtehal A Alsaggaf, Mahmoud I. Kamel[2]proposed a supervised learning model using filtering and windsorizing techniques to discriminate between autistic subjects from normal subjects. They obtained 80.27% classification accuracy with Fast-Fourier transform features using fisher linear discriminant classifier. Sharanreddy, P.K. Kulkarni [3] discussed a hybrid technique to detect epilepsy seizure. They used multi-wavelet transform and neural network in combination to classify epilepsy seizure with normal subjects. Their result has attained approximately 90% classification accuracy. Mandeep Singh, Mooninder Singh, Surabhi Gangwar [4] has developed a program using EEGLAB to extract data from raw EEG signals in text form. They applied discrete wavelet transform to decompose EEG signals into various sub-bands. Various features are extracted to classify emotional arousal state. Jolanta Strzelecka [5] provides an outline on the importance of various EEG rhythms and their role in subjects with autism spectrum disorder. Also the author discusses EEG abnormalities in ASD and relation between epileptiform abnormalities and cognitive dysfunction. Ali Sheikhania, Hamid Behnamb, Maryam Noroozianc, Mohammad Reza, Mohammad Mohammadid [6] analysed quantitative electroencephalography of 15 Asperger disorder subjects and 11 normal subjects using spectrogram as a tool. The authors found discriminations in various sub bands when subjects view stranger's picture, mother's picture. M. Hashemian, and H. Pourghassem [7] have grouped diagnosing EEG signals in autism into analysis based on comparison and pattern recognition techniques. The authors reported that result on these studies is contradictory and the degree of generalization of the diagnostic algorithm depends on the test data set size and cross validation methods. M. Murias, S. J. Webb, J. Greenson [8] studied EEG measures in ASD and control subjects in resting state and they found relative SPs of 3-6Hz and 13-17Hz ranges in ASD subjects are higher and this factor is lower for 9-10Hz.

METHODOLOGY

The entire process used for distinguishing individuals with neural disorders can be sub divided into various processing modules: Data Acquisition, pre-processing, sub-band decomposition, segmentation, feature extraction and classification.

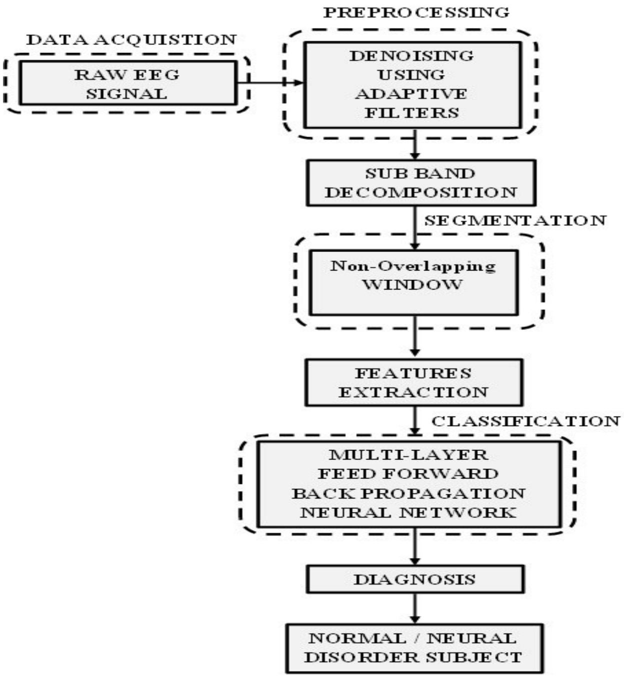


Figure 2
Proposed flow model

Data acquisition
The model was tested with fifteen artifact free EEG datasets of 2560 sec. Using international 16 channels (T3, C4, Cz, C3,T5,Pz, FP1,FP2,F7,F3,Fz,F4,F8,O1,O2 and Oz) 10-20 system [9] the EEG signals were recorded. The normal group consisted of six subjects without historical and existent neurological disorder. The neural disorders consisted of nine subjects.

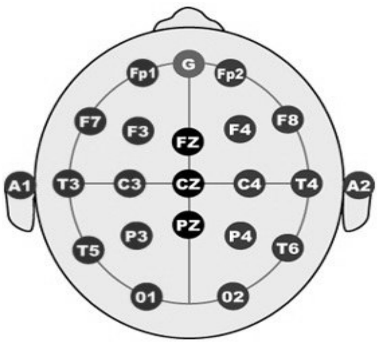


Figure 3
10-20 Electrode placement system

Pre-processing
When recording brain electrical signals using EEG numerous unsolicited signals such as inference from electronic devices (interference from power lines 50 0r 60 Hz), signals induced from muscle activity, artifacts due to eye blinking , heart beat and breathing are added. Clinicians infer indelicate decisions due to these artifacts. Removal of artifact is important in pre-processing of EEG signals to derive correct conclusions. An EEG signal mixed with various artifacts shown in the fig 4.

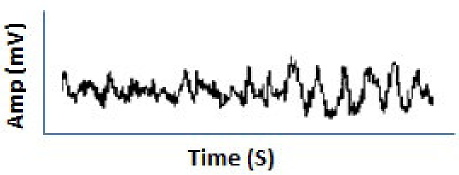


Figure 4
EEG mixed with artifacts
Since artifacts and EEG signal bands are mixed together simple filters cannot applicable to eliminate those artifacts. So we applied self- adaptable filters which alter its properties according to selected signal features.

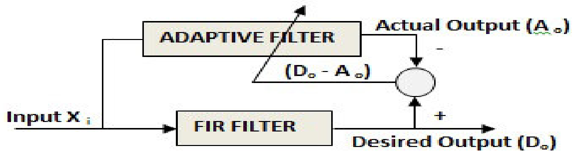


Figure 5
Adaptive filter
The adaptive filter generate signal similar to noise present in EEG signal by adjusting the co-efficient of linear filter. Here the adaptive transfer function Tf is adjusted based on error signal Es. Error Signal ES = (Do - Ao). The four reference signals are passed to adaptive filter along with noised EEG signal.[10] Adaptive filter estimates reference signal with input and gives output EEG signal without artifacts.

Sub band decomposition and segmentation
The pre-processed EEG signal is decomposed into different sub bands using discrete wavelet transform by applying low and high pass filters. We applied wavelet transform because it accounts both time and frequency unlike Fourier transform which consider only frequency. The discrete wavelet transform technique is effective in analysing EEG signals since it is highly random in nature.

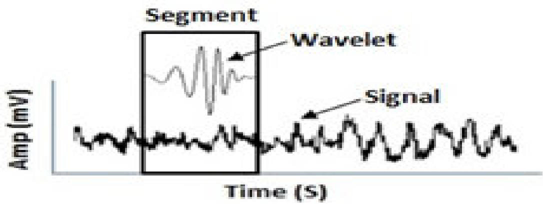


Figure 6
Wavelet evaluation

The basis functions are computed from primary wavelet Pw(t) using shifting and expanding. We applied two parameters namely shifting (Sh) and scaling (Sc). In each segment value x is computed that represents correlation between the signal within segment to given wavelet. Higher x value represents more similarity with the given wavelet. Once we reached the end of signal the wavelet is expanded and segment moved towards start. The signal is compared against expanded wavelet. Finally given signal is decomposed into various sub bands. This process continues till we reach the end of signal. [11] The frequency components in EEG signals above 30HZ contains no useful data, we are interested in decomposing frequency bands less than 40 Hz.

Feature Extraction
The selection of optimal features from extracted signal plays a vital role for accurate classification of EEG signals. Various statistical parameters such as mean, variance, standard deviation and changes in the frequency and power spectrum are calculated from the acquired sub bands.

Table 1

Subjects	Channel	Mean	Std dev.	Variance
1	F3	0.018	8.32	69.24
	F4	0.033	7.38	54.57
	C3	0.001	7.12	50.83
	C4	0.017	8.35	69.73
2	F3	0.054	13.68	187.1
	F4	0.079	11.73	137.6
	C3	0.085	8.16	66.61
	C4	0.121	8.90	79.33

Statistical features
Variance
It is a measure of how far each data in the set from typical value. Variance is calculated by taking the average of square root of deviations from the mean.

$$V = [(f – m) 2 / (n-1)]$$

Where f = values of given features, m = mean, n = number of pattern in the given set.

Mean
It is the arithmetic average of given features value represented by,

$$M= [f (1) + f (2) +\ldots..+ f (n)] / n$$

We are interested in extracting the above parameters from different sub bands. Finally the features values of each sub-band are normalized between 0 and 1.

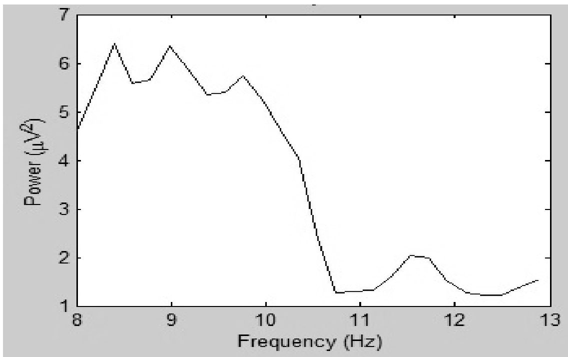


Figure 7
Channel F3 power spectrum

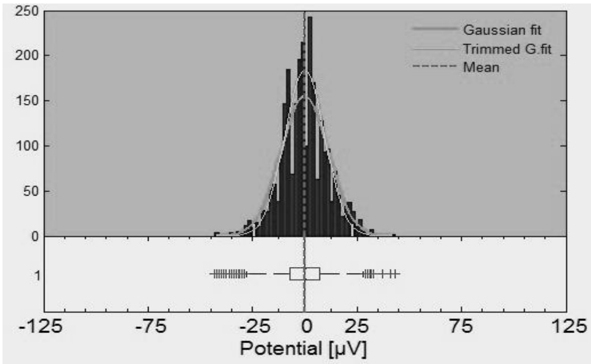


Figure 8
Channel F3 data histogram and fitted normal PDF

Classification
Each feature from delta and alpha sub-band are represented as vector in m-dimensional space. This feature vector is used as input for classifier. Different classification techniques such as Bayes classifier, hidden Markova model, and linear discriminant analysis and multi-layer perception neural networks are available. We choose non-linear classifier since the dimension of feature vector size is large.

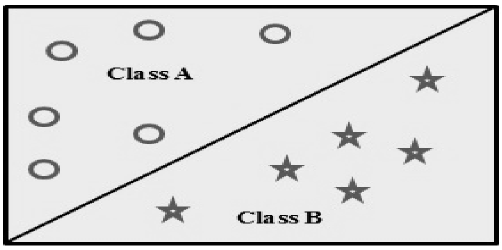


Figure 9
Linear classifier

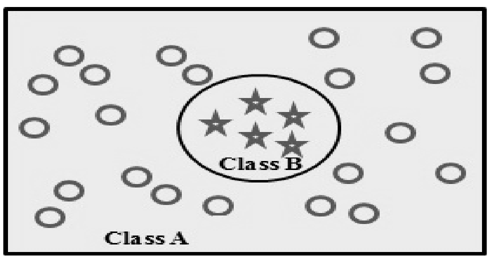


Figure 10
Non-linear classifier

NEURAL NETWORK MODEL

[12] Artificial neural networks are the best classifiers for the reason that of their properties likes adaptive learning and self-organization. It is suitable for an application where sufficient data are available to train the network and traditional simple classifier algorithms fails. The mathematical model of back propagation neural network contains input layer (I), output layer (O) and hidden layer (H). Depends on the necessities number of hidden layers may be altered. The output vector (OV) and hidden vector (HV) is calculated from input vector (IV) as,

$$HV = (IV) * (WM1) + B1$$
$$OV = (HV) * (WM2) + B2$$
$$HV = (IV) * (WM3) + B3$$
$$OV = (HV) * (WM4) + B4$$

Where WM , Bn are weight matrix and bias.
The computed (OV) must match with target vector (TV). This can be attained by selecting common WM and Bn for a particular input vector. The input (x) of neuron (k) is connected to its weight by an activation function to fix the state of the neuron. Unit step, sigmoid, piecewise linear, and Gaussian are some types of activation functions. For proposed method we have selected tangential-sigmoid activation function.

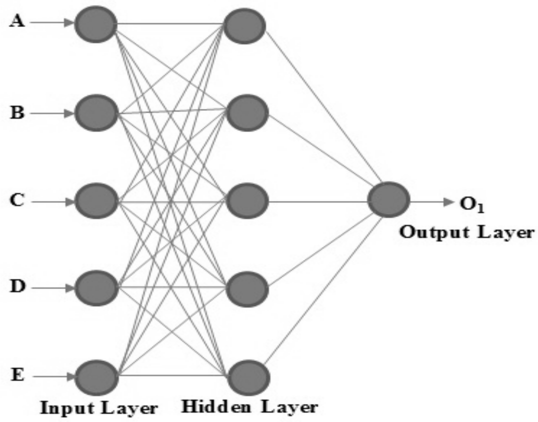


Figure 11
Neural network architecture

The inputs to neural network are various features extracted from EEG signals corresponding to neural disorder and normal subjects. Activation function used for hidden and output layer is tan-sigmoid. Here five hidden node and one output node is used. To train the network back-propagation algorithm with objective value 0 and 1 are used for normal and neural disorder subjects. The threshold value for classification of normal subject is set to (0.0 – 0.5) and for neural disorder subject (0.6- 1.0). For precise classification error value is set to (0.01).The tan-sigmoid (n) activation function calculates its output according to: n=2 / (1+exp (-2*n))-1

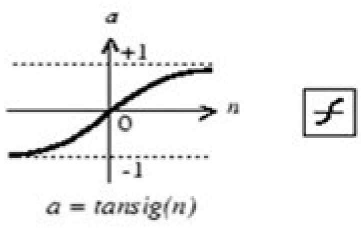


Figure 12
Tan-sigmoid activation function

RESULTS

Fifteen sets of EEG data of normal and neural disorder subjects are used. For training we used two normal and disorder subjects and remaining applied for testing. The mean and standard deviation and overall accuracy are calculated. The experimental result shows classification accuracy of 88.88% for disorder subjects and 83.33% normal subjects.

Table 2

Data Set	Percentage of correctness
Normal Subject	83.33% (5 out of 6)
Disorder Subject	88.88% (8 out of 9)
Average	**86.10 %**

Classification Result

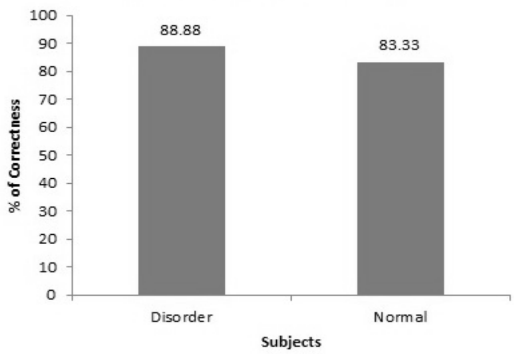
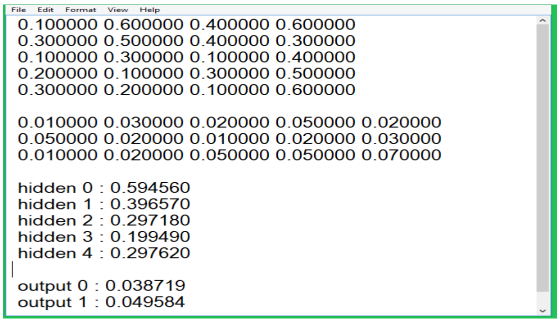


Figure 13
Classification accuracy



```
0.100000 0.600000 0.400000 0.600000
0.300000 0.500000 0.400000 0.300000
0.100000 0.300000 0.100000 0.400000
0.200000 0.100000 0.300000 0.500000
0.300000 0.200000 0.100000 0.600000

0.010000 0.030000 0.020000 0.050000 0.020000
0.050000 0.020000 0.010000 0.020000 0.030000
0.010000 0.020000 0.050000 0.050000 0.070000

hidden 0 : 0.594560
hidden 1 : 0.396570
hidden 2 : 0.297180
hidden 3 : 0.199490
hidden 4 : 0.297620

output 0 : 0.038719
output 1 : 0.049584
```

Figure 14
Feature Set

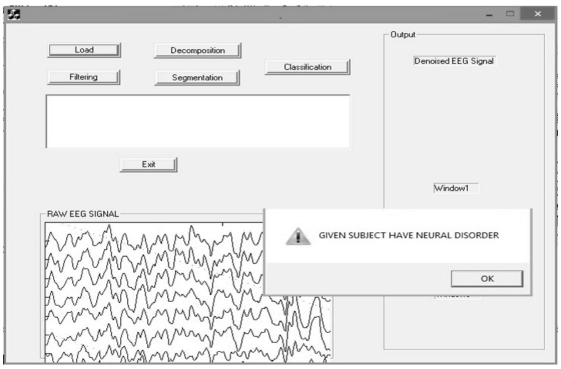


Figure 15
Sample screen shot

CONCLUSION

Diagnosis of neural disorder is a significant challenge for clinicians. Since EEG is an inexpensive and non-invasive technology, it seems to be right tool for clinician as diagnostic tool. This paper gives a brief description on a novel framework to discriminate between neural disorder and normal subjects. The proposed model is less complex and efficient since non-linear neural network classifier is applied. We obtained classification accuracy to (88.8%) for neural disorder subjects and (83.3%) for normal subjects. To improve the accuracy of proposed model the neural network will be trained with more subjects.

CONFLICT OF INTEREST

Conflict of interest declared None.

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