An Enhanced Feature Extraction Method and Classification Method of EEG Signals using Artificial Intelligence

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ABSTRACT
Emotion Recognition from EEG signs permits the immediate appraisal of the "internal" condition of a client, which is viewed as an essential figure human-machine-connection. Numerous systems for feature extraction have been mulled over. Their suitability for emotion recognition, be that as it may, has been tried utilizing a little measure of particular capabilities and on distinctive, typically little information sets. In the proposed work NN based Classification will be done on EEG Signal dataset that has been collected from FORTIS HOSPITAL AND BCI Competition. First feature extraction was applied to the raw data. Then the resulted feature vectors were used to train the classifiers. At last the classifiers were tested with the data not seen during the training to evaluate their classification accuracy. The results indicate that the NN classifier produces best classification accuracy than genetic algorithm.

Keywords
Emotion Recognition, EEG Signal, Feature Extraction, Classification, Neural network, BCI, FAR, FRR

1. INTRODUCTION
Recently, there has been a lot of interest in the area of Brain Computer Interface (BCI) research as it has the potential to provide communication and control capabilities to people with severe motor disabilities [1]. This is a multi-disciplinary research including specialists from neurobiology, brain research, building, arithmetic, and software engineering [2,3]. Any functional execution of BCI configuration requires an effective signal processing plan that incorporates signal pre-processing, feature-extraction and characterization [4].

Endeavors in human-machine-interaction (HMI) go for discovering approaches to better and all the more fittingly interface with PCs/people [5]. To make HMI more normal, learning about the enthusiastic condition of a client is viewed as an essential element. Emotions are essential for right understanding of activities and in addition correspondence. Enthusiasm for emotion recognition from distinctive modalities (e.g. face, stance, movement, and voice) has ascended in the previous decade and as of late picked up consideration in the field of brain computer-interfaces (BCIs), which has authored the term full of feeling BC [6,7,8].

In this paper, we stress on the classification and feature extraction part so it will be useful in emotion recognition [9]. Preferably, a great classifier for BCI ought to deliver high classification accuracy with minimal classification complexity and feature extraction procedure must concentrate includes accurately. In a matter of seconds, various direct and nonlinear classifiers have been suggested for this application. They incorporate measurable techniques, for example, Linear Discriminant Analysis (LDA), Hidden Markov Classifier and z-scale base Discriminant Analysis (ZDA) [10]. The fundamental downside of these techniques is that they don't function admirably for nonlinear order issues. As of late backpropagation neural systems (BPNNs) and Support vector machines (SVMs) have been indicated to enhance the classification accuracy and linear methods, for example, Linear discriminant analysis [11,12].

So, in this proposed work NN based Classification will be done on EEG Signal dataset that has been collected from forties hospital and from V BCI Competition III. First feature extraction was applied to the raw data [13]. Then the resulted feature vectors were used to train the classifiers. At last the classifiers were tested with the data not seen during the training to evaluate their classification accuracy. The results indicate that the NN classifier produces similar classification accuracy but requires more precisely feature extraction, so for feature extraction genetic algorithm used. [14].

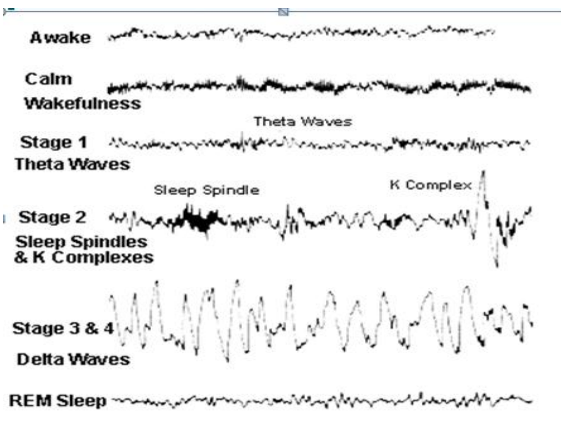

Figure 1 Different waves in EEG

Alpha wave frequency from 8-13 hz and amplitude is 20-60 µV. Easily produced when quietly sitting in relaxed position with eyes closed (few people have trouble producing alpha waves). Beta waves frequency is from 14-30 hz and amplitude is 2-20 µV. The most common form of brain waves are present during mental thought and activity. Theta wave frequency lies from 4-7 hz and amplitude is from 20-100µV. Believed to be more common in children than adults. Walter Study (1952) found these waves to be related to displeasure, pleasure, and drowsiness. Delta waves lies between5 to 3.5 hz and amplitude lies in 20-200µV. Found during periods of deep sleep in most people. Very irregular and slow waves pattern.

The paper is organized as follows. Section 2 gives a description of the EEG Signal classification problem. Section 3 presents the details of the proposed algorithm Section 4 gives the Performance evaluation using parameters. Conclusion and future scope from this study are summarized in Section 6.

2. EEG SIGNAL CLASSIFICATION

Below are the steps to compute the classification problem using AFNN and genetic algorithm .

2.1.Measuring EEG

EEG database has been collected from forties hospital and from V BCI Competition III.

For EEG dataset the electrode should be connected to head. The electrodes are connected to head by a EEG gel. In order to avoid artifacts, the participants should be in a relaxed mode. At last signals are recorded in raw form.

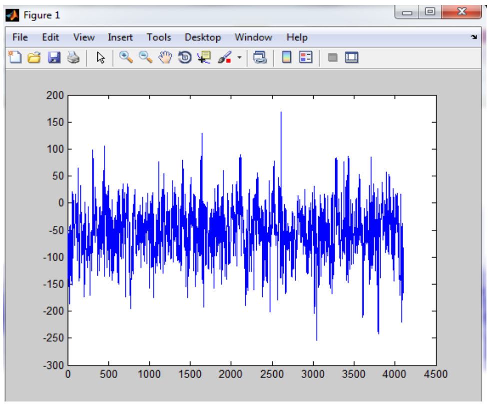

Figure 2 Normal signal of EEG

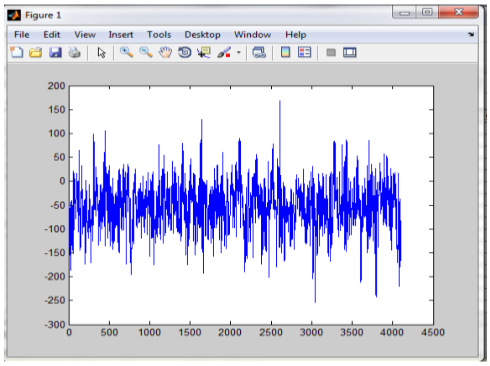

Figure 3 Abnormal signal of EEG

2.2.Feature extraction

Feature extraction of EEG signals mainly done using features like Time domain, Frequency Domain and Time-Frequency Domain. EEG signals are the rich source of information about brain activity. The information in EEG signals also includes information about emotions [15]. This has to extract the valuable information from the large amount of data. For this task, the system will first reduce the amount of data available. This process is known as feature extraction and extracts specified measures that are useful for the task. These features should contain enough information about the emotion. After reducing the size of the data, the emotion has to be detected from the features. The following processes are involved in successful emotion detection.

2.3.Optimization using genetic algorithm

Genetic algorithms are motivated by Darwin's hypothesis about development. Answer for an issue explained by genetic algorithms is advanced. Algorithm s begun with a situated of arrangements (spoke to by chromosomes) called population. Arrangements from one populace are taken and used to frame another population.

1. **[Start]** Produce arbitrary population of *n* chromosomes (suitable answers for the issues).
2. **[Fitness]** Assess the fitness *f(x)* of every chromosome *x* in the population.
3. **[New population]** Make another populace by rehashing after ventures until the new populace is finished.
   a) **[Selection]** Select two guardian chromosomes from a populace as indicated by their wellness (the better wellness, the greater opportunity to be chosen).
   b) **[Crossover]** With hybrid likelihood traverse the folks to shape posterity (kids). On the off chance that no hybrid was performed, posterity is an accurate duplicate of folks.
   c) **[Mutation]** With a transformation likelihood change new posterity at every locus (position in chromosome).
   d) **[Accepting]** Put new posterity in another populace.

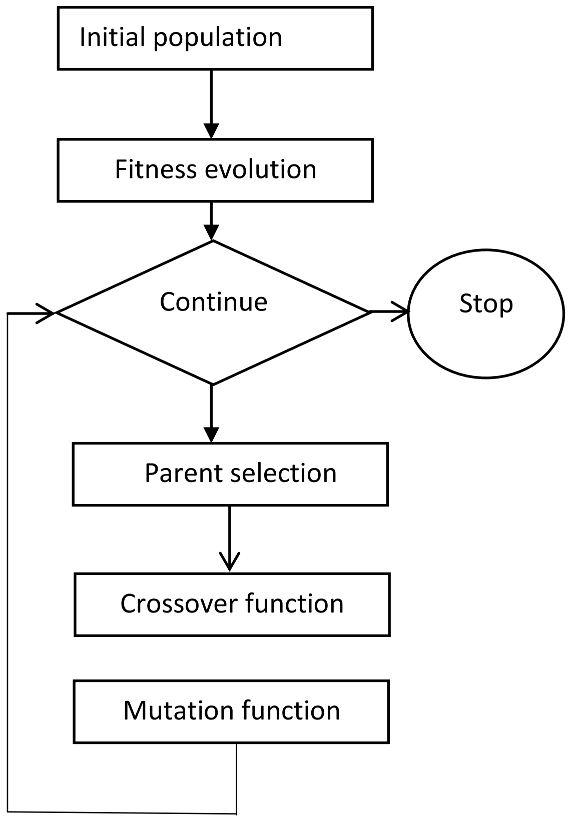

Figure 4 Flowchart of genetic algorithm

4. **[Replace]** Utilization new produced population for a further run of algorithm.
5. **[Test]** If the end condition is fulfilled, **stop**, and return the best arrangement in current population.

[Loop] Go to step **2.**

2.4 Classification

The classification of feature extracted method has been done using AFNN classifier. The AFNN works in the form of weights and the output values can be changes according to the weights inputted in the system.

Artificial neural network can be described as:

Y (k1) = F ($\sum_{i=0}^{m1}$(wi) k1 .xi $k1 + b$)

Where: Xik1is input value in discrete time.

Wi k1 is weight value in discrete time

B is bias,

F is a transfer function,

Y (k) is output value in discrete time

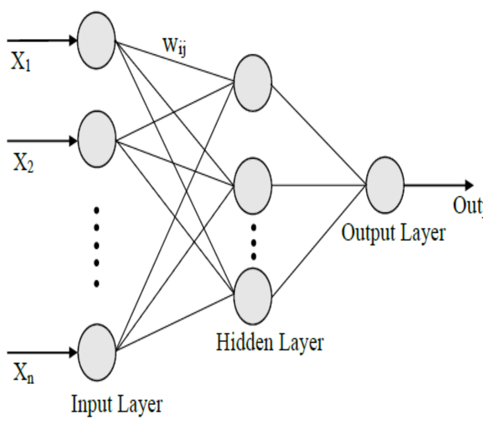

Figure 5 Neural Networks architecture

3. PROPOSED WORKING

Flowchart describes the steps that have been followed to classify the EEG signals into normal or abnormal signal of EEG.

In this genetic algorithm is used for classification and also for the comparison of accuracy with neural network.

Table no.1 Parameters of GA

Population size	**50**
Mutation	**0.05**
Crossover	**0.8**
Feature selected	**1 to 100**

EEG signals are the rich source of information about brain activity. However, since brain activity produces very weak signals and the EEG signals contain a lot of background noise therefore before using the signals for emotion detection, they have to be preprocessed, in order to remove unwanted noise.

The information in EEG signals also includes information about emotions. Below are the steps to compute the classification problem using AFNN and genetic algorithm.

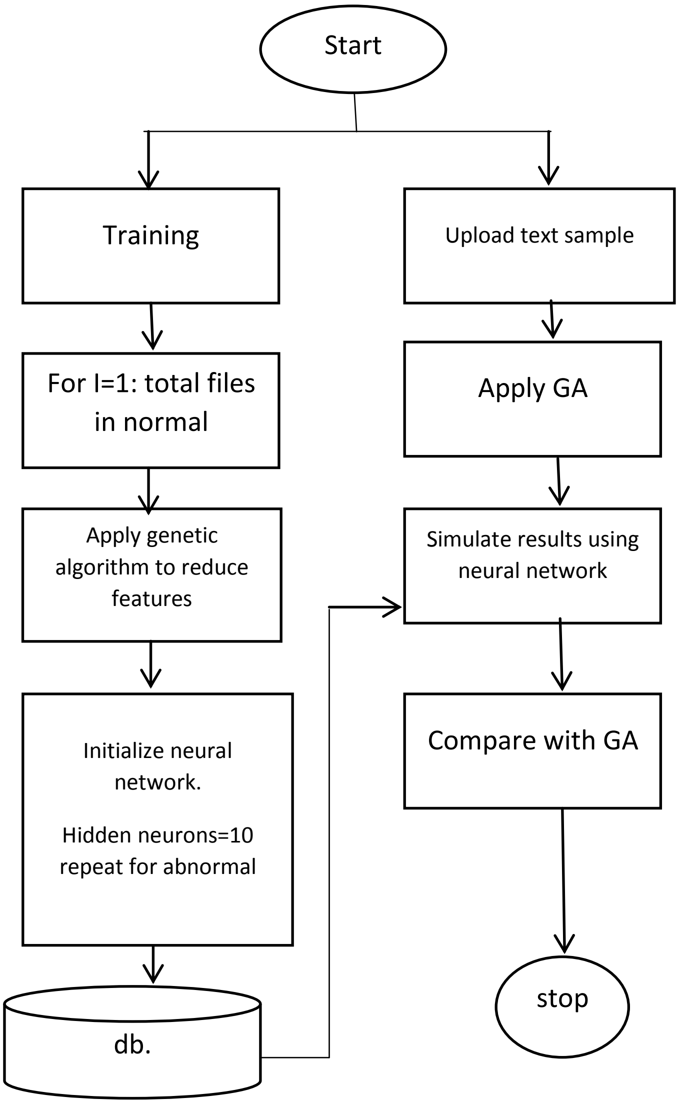

Figure 6 Proposed work Flowchart

4. RESULTS AND IMPLEMENTATION

The whole implementation has been taken place in MATLAB environment. Below figures shows the working of the proposed algorithm.

The testing of uploaded text file in which no. f epochs taken are 50, gradient value is 1.22, Mu value is, .001 and 6 validation checks has been used to test the uploaded file.

Performance plots for EEG signals: - performance plot shows mean sq. Error dynamics for all the data sets in logarithmic scale.

Training MSE is always decreasing. Validation fails are iteration. MATLAB automatically stops training after 6 fails in row. Regression gives the idea of how close the output from your model to the actual target values. Mu is the training gain or control parameter of the algorithm.

4.1 Feature extraction of normal signal and abnormal signal of EEG in time and frequency domain

Feature of EEG signals can be extracted in time domain as well as frequency domain. In this work features are extracted in both domains. In time domain feature extraction a sine wave forms. This sine wave represents with one cycle per second..

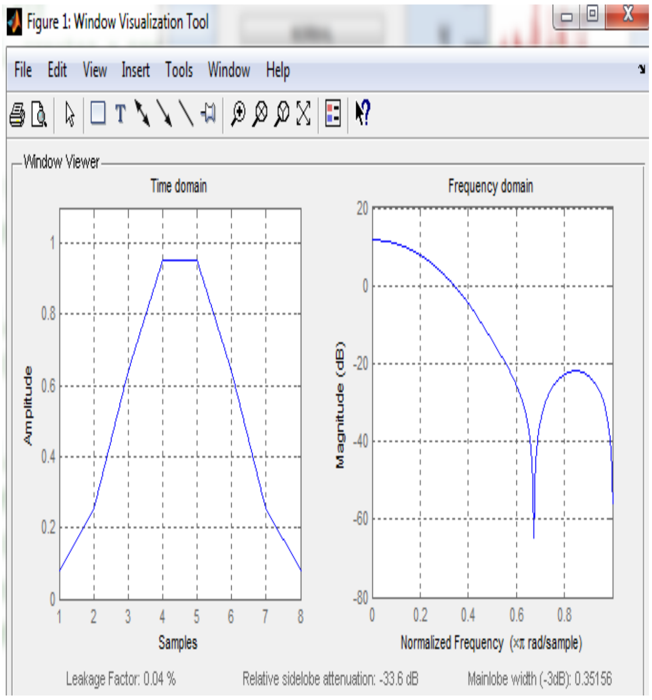

Figure no.7 feature extraction of normal signal

In frequency domain peak of the signal represent frequency component of sine wave. The tail of signal represents the artifacts on signal.

Frequency domain method may not provide high quality performance for some EEG signal.

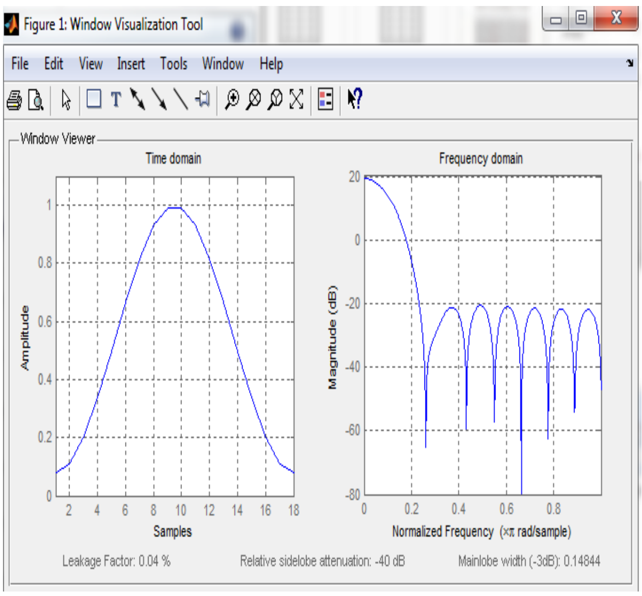

Figure no.8 feature extraction of abnormal signal

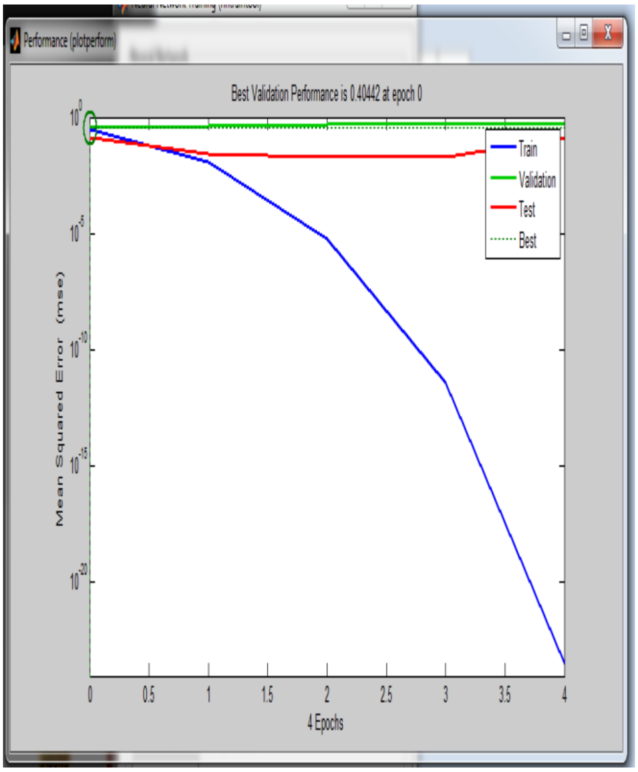

Figure 9 Performance plot for normal signal of EEG

4.2 Test using neural network

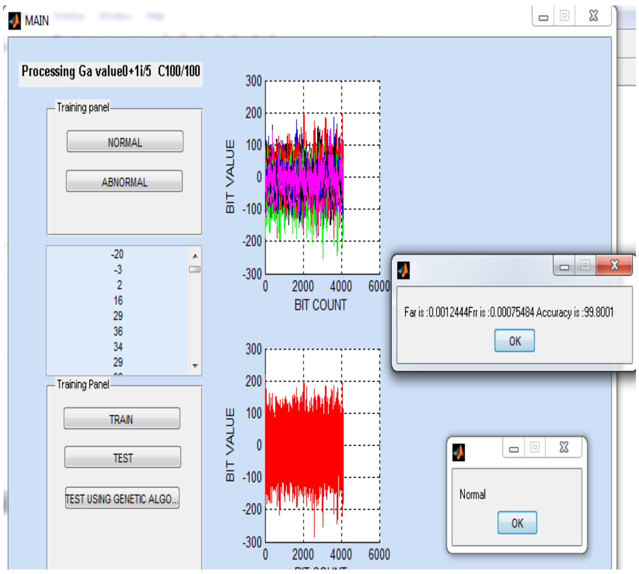

Figure 10 For normal EEG signal

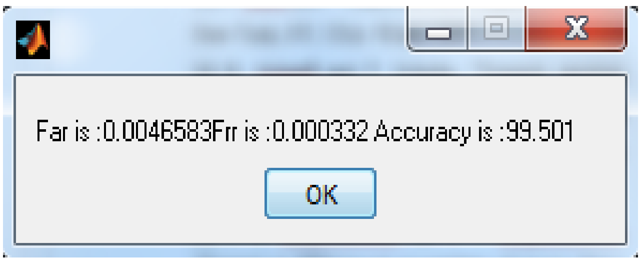

Fig.11 Evaluated Parameters by testing neural network

4.3 Testing using genetic algorithm

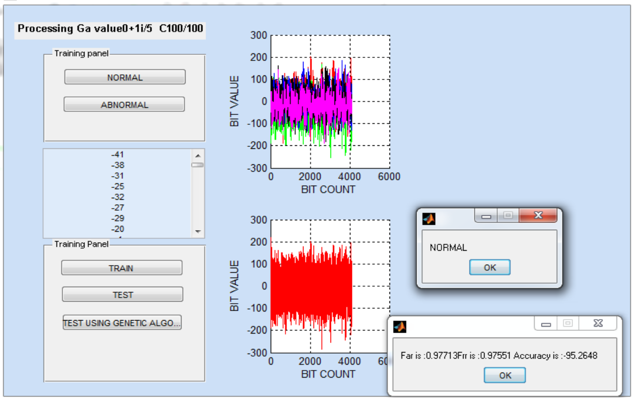

Figure 12 Test using GA for abnormal EEG signal

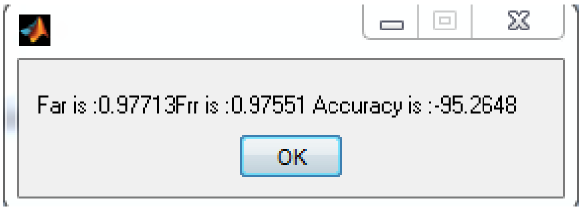

Fig.13 Evaluated Parameters by testing Genetic algorithm

Table no.2 results after testing with different algorithm

s.no.	TESTING	FAR	FRR	ACCURACY	SIGNAL
1	Using neural network	0.010313	0.00094637	98.8	NORMAL
2	Using neural network	0.0082742	0.00053832	99.1	ABNORMAL
3	Using genetic algorithm	0.98466	0.98357	-96.8	NORMAL
4	Using genetic algorithm	0.85757	0.84865	-70.6	ABNORMAL

The proposed algorithm working has been verified using three parameters i.e. FAR (False Acceptance Ratio), FRR (False Rejection Ratio) and Accuracy. It has been concluded that 99.501 % efficiency has been achieved by the neural network technique and by genetic it gives negative values.

5. CONCLUSION AND FUTURE SCOPE

This paper has presented the feature extraction and classification of EEG signals using machine learning algorithm. Genetic algorithm is used to select the best combination of features that minimize classification error. An important disadvantage of using genetic algorithm in practice is the long time it requires to complete calculations. Neural network as well as genetic algorithm feature extraction techniques have been used in this method too. Using these features, it has been concluded that which of the EEG data is normal or abnormal. This emphasize on the classification as well as feature extraction part so that it will be helpful in emotion recognition. Ideally, a good classifier for BCI should produce high classification accuracy with minimal computational complexity and feature extraction technique must extract features precisely. So in this work neural network and above mentioned features has been extracted to get high accuracy. From the results it has been concluded that by obtaining values for FAR= .004, FAR= .0003 and accuracy = 99.55 shows that proposed algorithm is good working technique for this type of problem specification.

Further work suggestions include the use of the BPNN (Back Propagation Neural Network) for training purpose. As in the present work training has been done using Levenburg Neural Network. As it have wide range of operating conditions and less complexity. If the signal is non-stationary, time-frequency methods can bring up additional information by considering dynamical changes.

6. REFERENCES

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