ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

Energetic EEG Signal Analyzer Based on Feature Extraction and Classification Strategies

Arun Chavan[1], Dr.Mahesh Kolte[2]

Associate Professor, Vidyalanklar Institute of Technology, Mumbai, India[1]

Professor & Dean R&D, Maharashtra Institute of Technology, Pune, India[2]

ABSTRACT: The main objective of the paper is to extract the prominent features from the EEG Signal, by using multi-wavelets and with the help of these features the different emotions are classified and detected by using a novel algorithm with the help of Neural Networks. The input EEG signals are collected from the sensor which is a single point core reference from the forehead's skin part and the reference voltage from the ear. The two are subtracted through common mode rejection to serve as a single EEG channel, and amplified 8000x to enhance the faint EEG signals. The signals are passed through analog and digital low and high pass filters to retain signals generally in the 1-50Hz range. After correcting for possible aliasing, these signals are ultimately sampled at 128Hz or512Hz. Each second, the signal is analyzed in the time domain to detect and correct noise artifacts as much as possible, while retaining as much of the original signal as possible, using NeuroSky's proprietary algorithms. Collecting the EEG signals and performing the sampling operation and the resulting of sampling is applied to the normalization procedure to get a normalized/optimized signal outcome. The filtering methodology is applied to eliminate the unwanted noises or interferences presented into the signal. The wavelet transformation is performed to EEG signal for every channel, it will be then broken down into sections or epochs for the purpose of wavelet transform as well as numerous parent wavelets will be used for pre-processing. The final resulting unit will be produced by means of Artificial Neural Network schema, because each network has different number of input nodes, variable number of hidden layer neurons and one output neuron.

KEYWORDS: EEG, Normalization, Signal, Brainwave, Artificial Neural Network, Wavelet Transformation.

I. INTRODUCTION

The single dry sensor and reference pick up potential differences (voltages) on the skin at the forehead and the ear. The two are subtracted through common mode rejection to serve as a single EEG channel, and amplified 8000x to enhance the faint EEG signals. The signals are passed through analog and digital low and high pass filters to retain signals generally in the 1-50Hz range. After correcting for possible aliasing, these signals are ultimately sampled at 128Hz or512Hz. Each second, the signal is analyzed in the time domain to detect and correct noise artifacts as much as possible, while retaining as much of the original signal as possible, using NeuroSky's proprietary algorithms. A standard FFT is performed on the filtered signal, and finally the signal is rechecked for noise and artifacts in the frequency domain.

The acquired EEG signal which is in the format of .xls is loaded to the MATLAB workspace and converted to .csv format for further processing. The formatted EEG dataset is analyzed by using wavelet transform to extract all the fundamental frequency components of EEG signal i.e. alpha, beta, gamma, delta and theta. EEG frequency bands which relate to various brain states. The aggregate of these electric voltage fields create an electrical reading which electrodes on the scalp are able detect and record. The prominent features from the EEG signal are extracted by using multi-wavelets and with the help of these features the different emotions are classified and detected by using a novel algorithm with the help of Neural Networks.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

II. DESCRIPTIVE ANALYSIS

The methodology which will be followed for the proposed research work is summarized as follows:
a. Data collection and selection
b. Waveform transformation
c. Neural network training and testing.

Data Collection and Selection:

(i) Digitized EEG will be collected from hospitals for at least hundred subjects.

(ii) Will be then categorized into different groups.

(iii) The information will be then preprocessed to separate the 20-channel waveform and stored in a separate file.

Wavelet Transform:

(i) EEG for every channel will be then broken down into sections or epochs for the purpose of wavelet transform.

(ii) Different mother wavelets will be used for preprocessing.

(iii) Will tries and tests a new mother wavelet and compares the processing capability with existing mother wavelets.

(iv) Will then store the wavelet coefficients for further processing by ANN

Artificial Neural Network Training and Testing:

(i) ANN will be trained and tested using wavelet transformation coefficients obtained.

(ii) Each network has different number of input nodes, variable number of hidden layer neurons and one output neuron.

(iii) Will try to compare results after ANN training for standard wavelets and a new wavelet introduced.

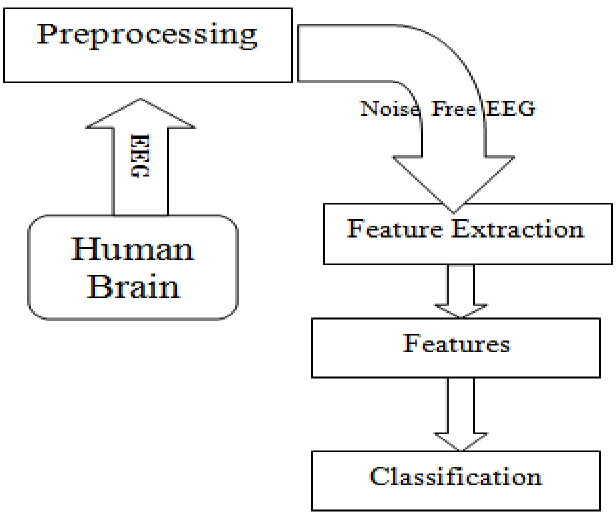

Fig. 1 System Design

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

III. FEATURE EXTRACTION

In the feature extraction process the analysis of input EEG signal is processed based on the following criteria's such as:

A. *Discrete Wavelet Transformation*

When the input data to an algorithm is too large to be processed and it is suspected to be redundant then it can be transformed into a reduced set of features (also named features vector). This process is called feature extraction EEG feature extraction is done by using wavelet transform. But there are multiple wavelets available in the wavelet family therefore a suitable wavelet has to be chosen for the efficient extraction of different feature of EEG. EEG features mainly contains the different frequency bands they are:

- Alpha
- Beta
- Gamma
- Theta
- Delta

Wavelet transforms has the advantages of time frequency localization, multi-rate filtering, and scale-space analysis. Wavelet transform uses a variable window size over the length of the signal. The DWT is often introduced in terms obits recovery transform: Here k is related to a as: a = 2k; b is related to l as b = 2k l; and d (k,l) is a sampling of W(a,b) at discrete points k and 1.

B. *Biorthogonal Wavelet*

A biorthogonal wavelet is a wavelet where the associated wavelet transform is invertible but not necessarily orthogonal. Among the different wavelets bior 5.5 has been chosen for the EEG feature extraction. The properties of Bior wavelet are discussed below.

Let fk and gk belongs to H then fk and gk are said to be biorthogonal if

$$(fj\ , gk\ ) = \delta jk \quad (2)$$

In order to construct two sets of wavelets that is

$$\varphi_{j,k} = 2^{\frac{j}{2}}\varphi(2^j x - k)\ \ldots\ldots\ldots\ldots\ldots\ldots(3)$$

$$\tilde{\varphi}_{j,k} = 2^{\frac{j}{2}}\varphi(2^j x - k)\ \ldots\ldots\ldots\ldots\ldots\ldots(4)$$

To construct (3) and (4) g, h, gbar, hbar filters are needed.

The two decomposition sequences are gn and hn and two sequences to act as a reconstruction sequences If C1n is a dataset, then it can be decomposed as

$$c_n^0 = \sum_k g_{2n} - kc_k^1 \ldots\ldots\ldots\ldots\ldots\ldots(5)$$

$$d_n^0 = \sum_k h_{2n} - kc_k^1 \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

For reconstruction

$$C_l^1 = \sum_n \widetilde{h_{2n-1}} c_n^0 + \widetilde{g_{2n-1}} d_n^0 \ldots\ldots\ldots\ldots\ldots\ldots(7)$$

The condition for the perfect reconstruction is

$$g_n = (-1)^{n+1}\widetilde{h_{-n}}$$

and

$$\tilde{g}_n = (-1)^{n+1}\widetilde{h_{-n}}\ \ldots\ldots\ldots\ldots\ldots\ldots(8)$$

The scaling function is defines as

$$(x) = \Sigma n\ \sqrt{2}\Sigma nhn\varphi(2x - n)$$

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

and

$$\tilde{\phi}(x) = \sqrt{2}\,\Sigma\, hn\,(2x - n) \quad (9)$$

C. Analysis by Using DWT

The different bands of raw EEG signal are extracted by using bior 5.5 wavelet functions. The flowchart of the DWT algorithm is as shown in the Fig. 10 The algorithm flow chart for EEG feature extraction contains the following steps:

(a) Collecting the Raw EEG signal from the EEG acquisition set up.
(b) Raw EEG signal is converted into CSV format that is comma separated values in the Excel sheet.
(c) Load the signal into the MATLAB platform.
(d) Set the sampling frequency (fs)
(e) Use bior 5.5 wavelet for decomposition and reconstruction of a signal to extract the frequency components. Bior 5.5 at 8levels is used for the decomposition.

After 8 level decomposition the coefficients which lies in the suitable frequency bands off EEG only those coefficients are selected and they represents the different frequency bands of EEG.

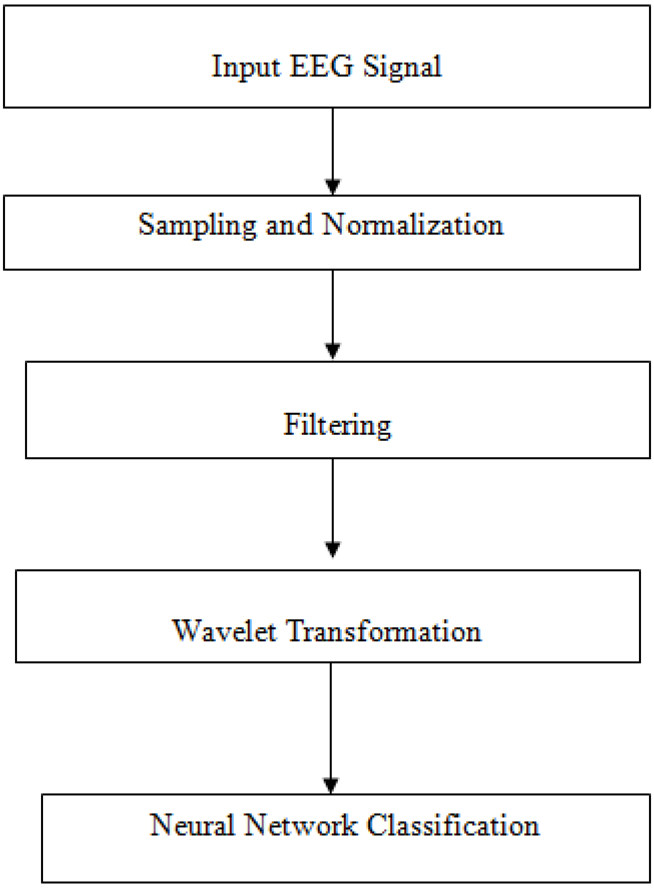

Fig.2 Block Diagram

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

Algorithm Flow Model:

a. Signal reading from .XML file
b. Framing of samples with 14 subdivisions
c. Filtering of frames with high pass filter coefficients
d. Windowing is done using hamming window function
e. Fast Fourier transform, logarithmic conversion, IFFT was carried out
f. Signal normalization
g. Wavelet filter bior 5.5 is applied to make low and high pass filter coefficients.
h. Wavelet decomposition to 8-levels
i. cD1, cD2, cD3, cD4, cD5, cD6, cD7, cD8 detailed coefficients splitting
j. Approximate coefficient cA8
k. D5-Gamma frequency wave
   D6- Beta frequency wave
   D7- Alpha frequency wave
   D8- Theta frequency wave
   A8- Delta frequency wave
l. Computing FFT to get frequency of feature
m. Feature vector of Trained Data
n. Neural network feed forward Training and Validation
o. Testing with Test feature and Train feature
p. Classification and performance calculation
q. TP,TN,FP,FN and accuracy estimation

Analysis of DWT:

DWT successfully analyses the multi-resolution signal at different frequency bands, by decomposing the signal into approximation and detail information. The method for frequency band separation is implemented in MATLAB2013.EEG requires feature extraction from the acquired signal in specific frequency range of delta, theta, alpha, beta, and gamma. After a first level decomposition, two sequences representing the high and low resolution components of the signal are obtained. The low-resolution components are further decomposed into low and high resolution components.

After a second level decomposition, seven more decompositions are done as CA1, CA2, CA3, CA4, CA5, CA6, CA7 and CA8 are the approximate coefficients andCD1, CD2, CD3, CD4, CD5, CD6, CD7 and CD8 are the detailed coefficients obtained after successive decomposition. The multi-resolution analysis, using five levels of decomposition, yields five separate EEG sub-bands. The main objective of the proposed method of is Wavelet Transform the division of the original EEG signals into different frequency bands.

Table I. Decomposition of EEG signals with the sampling frequency of 500 Hz

Frequency Range	Frequency Bands	Decomposition Level
0-4	Delta	A8
4-8	Theta	D8
8-16	Alpha	D7
16-32	Beta	D6
32-64	Gamma	D5

Neural Networks (NN) Classification

Neural Networks (NN) are highly interconnected and simple processing units which is designed to model the way human brain performs a particular task. Each unit is called a neuron. It forms a weighted sum of its inputs and a

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

constant term called bias is added. This sum is passed through a transfer function such as linear, sigmoid or hyperbolic tangent. In the construction of neural architecture, the choice of number of hidden layers and the number of neurons in each layer is one of the most critical problems. In order to find the optimal network architecture, several combinations should be evaluated. These combinations include networks with different number of hidden layers, different number of units in each layer and different types of transfer functions.

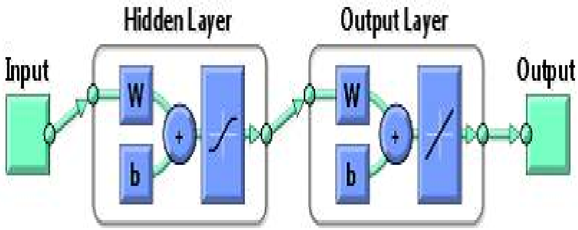

Figure 3 Neural Network Architecture

A neural network is a computational model based on the neuron cell structure of the biological nervous system. With a training set of data, the neural network can learn the data by using learning algorithm; here, the most common algorithm, back-propagation, is used. Through back-propagation, the neural network forms a mapping between inputs and desired outputs from the training set by altering weighted connections within the network.

IV. EXPERIMENTAL RESULTS

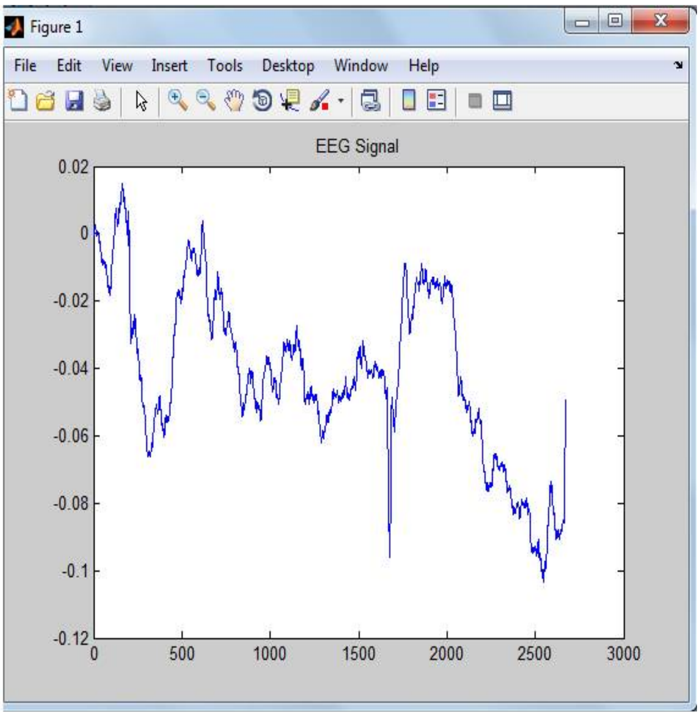

Fig.3. EEG Signal

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

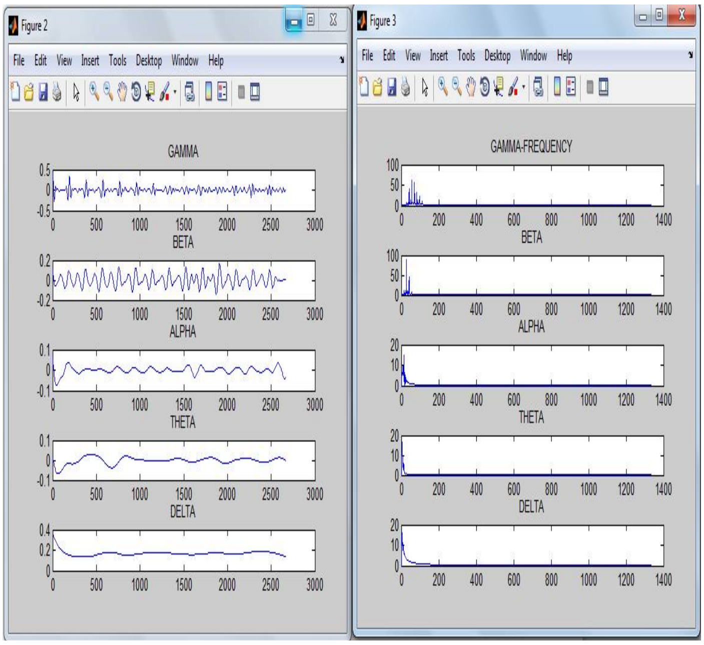

Fig.4. Gamma and Gamma Frequency

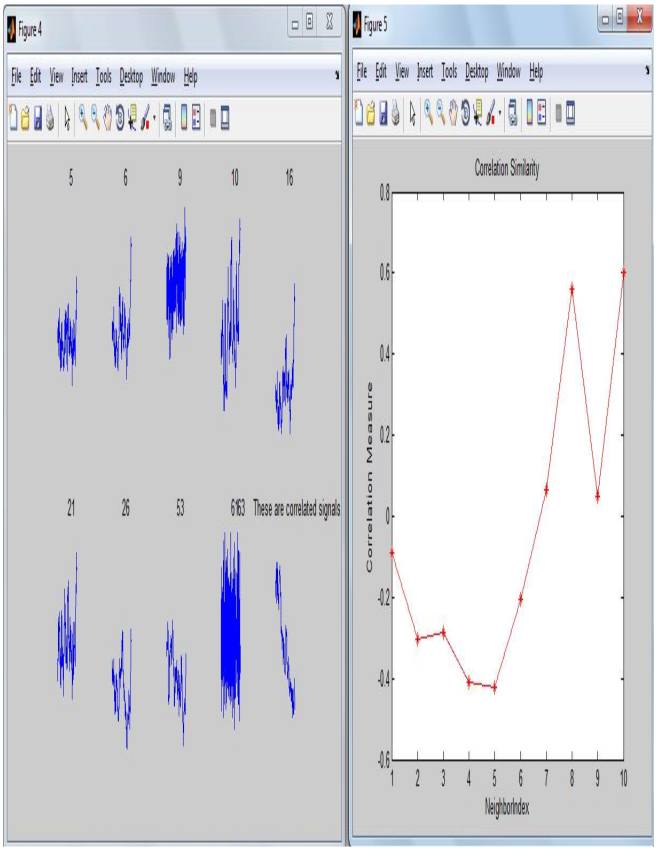

Fig.5. Correlation Similarity

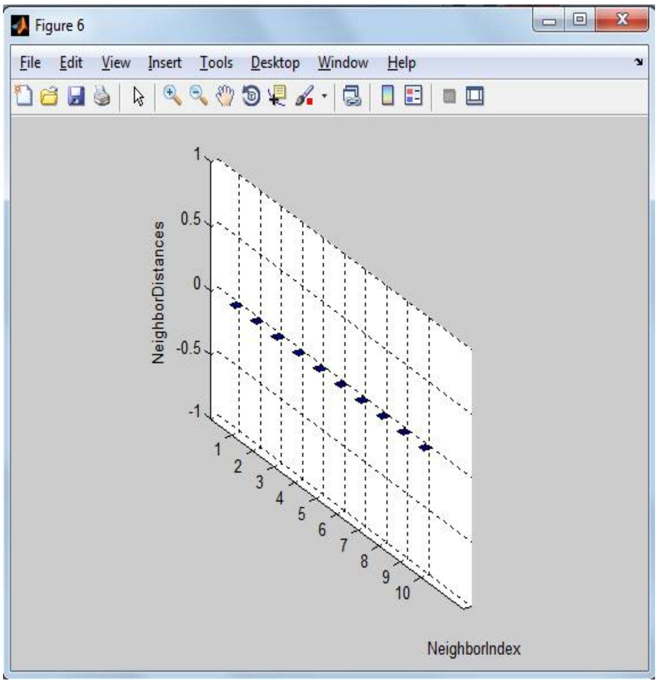

Fig.6.Neighborhood Distances

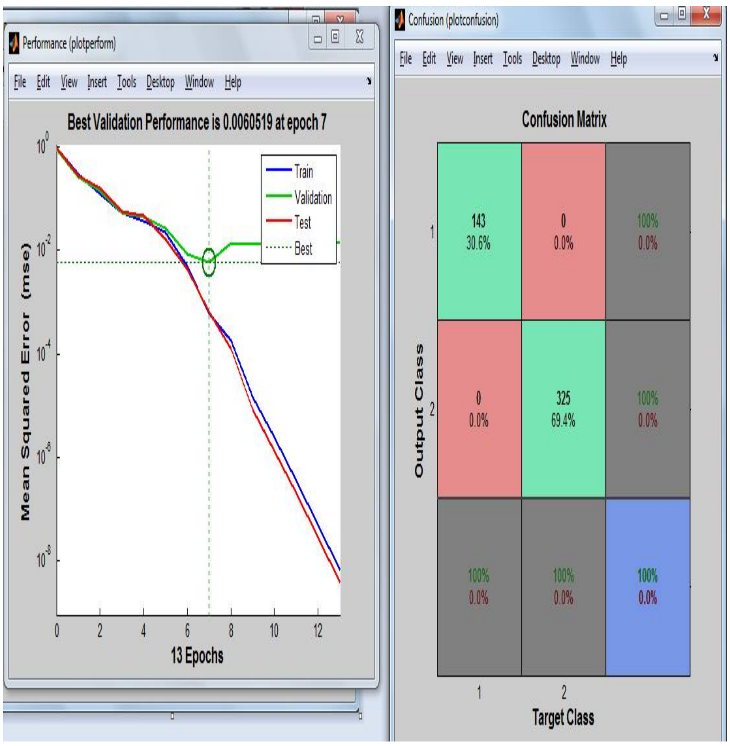

Fig.7. Performance Validation and Confusion Matrix

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

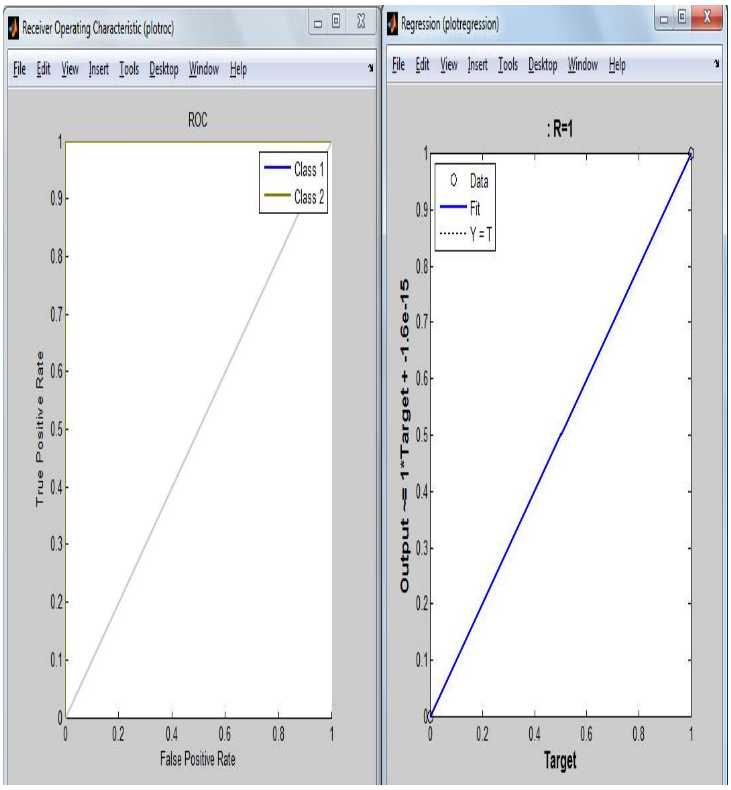

Fig.8. True Positive and False Positive Rates

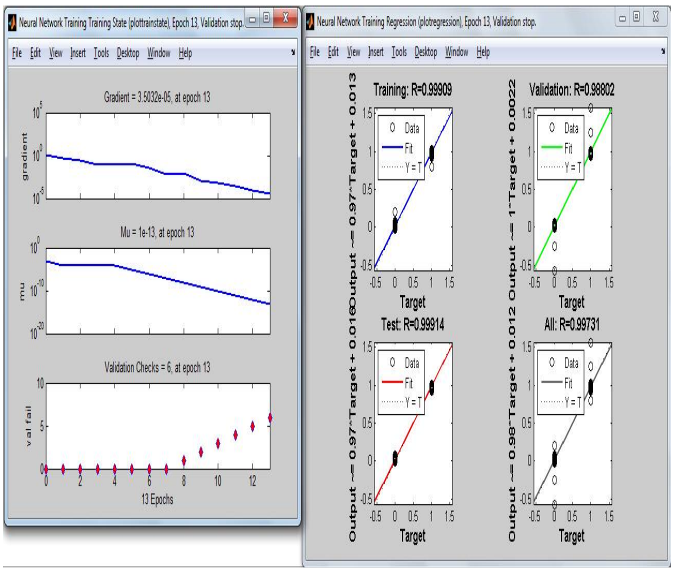

Fig.9. Gradient Form and Target Results

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

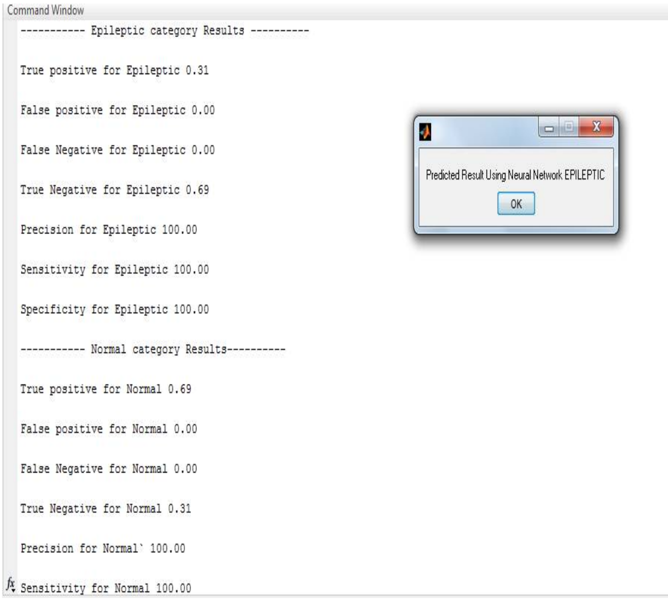

Fig.10. Prediction Results

V. CONCLUSION

For all the formatted EEG dataset is analyzed completely by using wavelet transformation and to extract all the fundamental frequency components of EEG signal that is alpha, beta, gamma, delta and theta. The complete analysis of EEG frequency bands which relate to various brain states are completed successfully. The aggregate of these electric voltage fields create an electrical reading which electrodes on the scalp are able detect and record. The prominent features from the EEG signal are extracted by using multi-wavelets and with the help of these features the different emotions are classified and detected by using a novel algorithm with the help of Neural Networks.

REFERENCES

[1] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, "Face recognition: A literature survey," ACM Comput. Surv., vol. 35, no. 4, pp. 399–458, Dec. 2003.
[2] J. Ni and R. Chellappa, "Evaluation of state-of-the-art algorithms for remote face recognition," in Proc. IEEE 17th Int. Conf., Image Process., Sep. 2010, pp. 1581–1584.
[3] M. Nishiyama, A. Hadid, H. Takeshima, J. Shotton, T. Kozakaya, and O. Yamaguchi, "Facial deblur inference using subspace analysis for recognition of blurred faces," IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 4, pp. 838–845, Apr. 2011.
[4] D. Kundur and D. Hatzinakos, "Blind image deconvolution revisited."
[5] A. Levin, Y. Weiss, F. Durand, and W. T. Freeman, "Understanding blind deconvolution algorithms," IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 12, pp. 2354–2367, Apr. 2011.
[6] T. Ojala, M. Pietikäinen, and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 971–987, Jul. 2002.
[7] R. Basri and D. W. Jacobs, "Lambertian reflectance and linear subspaces," IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 2, pp. 218–233, Feb. 2003.
[8] R. Ramamoorthi and P. Hanrahan, "A signal-processing framework for reflection," ACM Trans. Graph., vol. 23, no. 4, pp. 1004–1042, 2004.
[9] K.-C. Lee, J. Ho, and D. J. Kriegman, "Acquiring linear subspaces for face recognition under variable lighting," IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 5, pp. 684–698, May 2005.
[10] H. Hu and G. De Haan, "Adaptive image restoration based on local robust blur estimation," in Proc. Int. Conf. Adv. Concep. Intell. Vis. Syst., 2007, pp. 461–472.
[11] W. H. Richardson, "Bayesian-based iterative method of image restoration," J. Opt. Soc. Amer., vol. 62, no. 1, pp. 55–59, Jan. 1972.
[12] A. Levin, "Blind motion deblurring using image statistics," in Proc. Adv. Neural Inform. Process. Syst. Conf., 2006, pp. 841–848.
[13] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman, "Removing camera shake from a single photograph," in Proc. ACM SIGGRAPH Conf., 2006, pp. 787–794.
[14] T. Ahonen, E. Rahtu, V. Ojansivu, and J. Heikkilä, "Recognition of blurred faces using local phase quantization," in Proc. 19th Int. Conf. Pattern Recognit., Dec. 2008, pp. 1–4.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

[15] R. Gopalan, S. Taheri, P. K. Turaga, and R. Chellappa, "A blur-robust descriptor with applications to face recognition," IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 6, pp. 1220–1226, Jun. 2012.
[16] V. Ojansivu and J. Heikkilä, "Blur insensitive texture classification using local phase quantization," in Proc. 3rd Int. Conf. Image Signal Process., 2008, pp. 236–243.

BIOGRAPHY

Arun Chavan, Associate Professor at Vidyalanklar Institute of Technology, Mumbai. Has 24 years of teaching experience. Had guided 50 UG projects, 4 PG projects. Has keen interest in field of embedded system design and development as well as Signal Processing. Has number of publications in the National/International Conferences/Journals.

Dr. Mahesh Kolte, Professor & Dean R&D at Maharashtra Institute of Technology, Pune. Has 25 years of teaching experience. Had guided 50 UG projects, 10 PG projects and 4 PhD's. Has keen interest in field of Digital Signal Processing. Has 30 publications in the National/International Conferences/Journals.