Classification of Human Emotion from Deap EEG Signal Using Hybrid Improved Neural Networks with Cuckoo Search

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Abstract

Emotions are very important in human decision handling, interaction and cognitive process. In this paper describes that recognize the human emotions from DEAP EEG dataset with different kind of methods. Audio – video based stimuli is used to extract the emotions. EEG signal is divided into different bands using discrete wavelet transformation with db8 wavelet function for further process. Statistical and energy based features are extracted from the bands, based on the features emotions are classified with feed forward neural network with weight optimized algorithm like PSO. Before that the particular band has to be selected based on the training performance of neural networks and then the emotions are classified. In this experimental result describes that the gamma and alpha bands are provides the accurate classification result with average classification rate of 90.3% of using NNRBF, 90.325% of using PNN, 96.3% of using PSO trained NN, 98.1 of using Cuckoo trained NN. At last the emotions are classified into two different groups like valence and arousal. Based on that identifies the person normal and abnormal behavioral using classified emotion.

Keywords: DEAP EEG; Feature Extraction; Band Selection; Discrete Wavelet Transform; Valence; Arousal.

1. Introduction

Human emotions play in important role in affective computing and Human Machine Interaction. The emotions may be happy, sad, surprise, angry etc, which are used to find the mental stress and mental disorders. In Human Brain each and every cell has performed the particular functions like, occipital lobes perform visual tasks and temporal cell performs auditory task. EEG power has decreased during the sad emotion and increased during the happiness. The region that shows the difference between sadness and happiness is the frontal pole with left CBF being higher during sadness and lower during happiness Reza Khosrowbadi, Kai Keng Ang (2014). So that we can identify the positive and negative emotions from the past experience. The emotions can be classified by using two ways, implicit memory and explicit memory. The implicit memory the emotions and decision making analysis only the present incident and explicit memory is used to analysis the past experience proposed by Reza khosrowbadi, Kai Keng Ang (2014). Emotion has determined by various ways. First kind focus on analysis the Facial expressions or speech. The audio – visual based techniques used to detect the emotion. The Second kind of approaches focuses on peripheral physiological signal. Different emotional state has identified by using the Electrocardiogram, Skin Conductance. Third approach uses EEG signal. The EEG based emotions are very accurate.EEG power has decreased during the sad emotion and increased happiness. The region that shows the difference between sadness and happiness is the frontal pole with left CBF being higher during sadness and lower during happiness. In order to stimulate the emotion of interest, the user calmly sat in front of a computer and is viewing an image to inform him/her which type of emotion she has to think of. EEG has measured by using electrode which was placed on the

scalp with the help of the Ag/Al the recording was carried out for each and every brain activity. The impedance of the electrodes was kept below 5KΩ.The International Affective Picture System related images and videos are used to find the EEG recordings. EEG data have collected from desirable subjects. Each and every EEG signal has different kind of bands like Alpha, Beta, Gamma, Theta, and Delta. Each band stores the particular information about the emotions. Alpha band (8-13 Hz) which located in Frontal Occipital, Beta band (13-30 Hz) which located in Frontal Central, Gamma band (30-100 Hz), Theta band (4- 7 Hz) which located in Midline Temp, Delta band (0-4Hz) which located in Frontal Lobe. Before processing the EEG signal and extracting these bands, preprocess the signal and reduce the noise. The basic brain figure is shown in below.

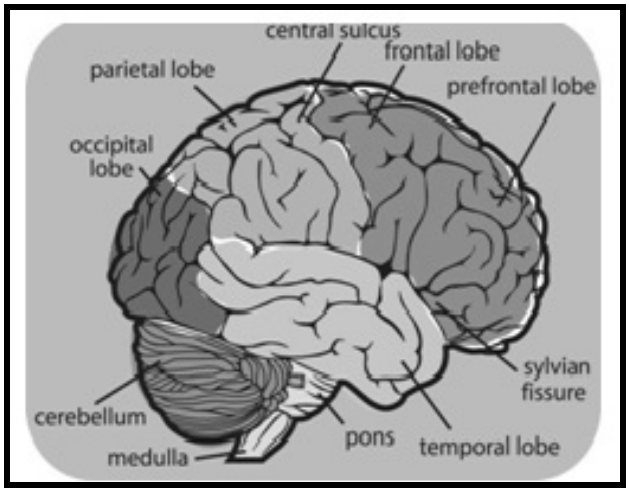


Figure 1. Brain Structure

To remove redundancy the process of feature extraction and selection is done. There are many techniques for feature extraction. *Discrete wavelet transform Murugappan*, (Ramachandaran, 2010), *Higher Order Crossing Method* (Petrantonais, 2010), *Statistical Transform* (Petrantonais, 2012). These techniques vary through their searching strategy and extracting criteria. Extraction methods are highly depending on the statistical features like mean, average, power, Euclidean distance. And also different features or band selection methods are used to select the best features, like Genetic Algorithm, Particle Swarm Optimization, and Ant colony. Once the band selection is performed, then those data have to be a classification of emotion. Neural networks Ubeyli (2009) and Radial Basis Function Networks Reza khosrowbadi, Kai Keng Ang (2014) are well suited for classification as they can both visualize and compute the results. The classification results are compared to various feature extraction and classification method for accuracy. There are several work exists related to human emotion analysis. In Ubeyli (2009) Relate the different kind of emotions and their EEG features and find the exact feature for emotions, identify the accuracy for the emotion using different machine learning techniques like DWT, SVM. DWT includes the time scale signal analysis, signal decomposition and signal compression Murugappan & Ramachandaran (2010). Murugaappan et al and Mohan Kumar et al (2010) paper describes with the Wavelet Transform are the Non- Parametric method of feature extraction based on multi resolution analysis. In Xiao-Wei Wang et al. (2013), the wavelet function is chosen based on the time location properties. This function decomposes the signal into different time frequency. Wavelet function is calculating the different shapes of particular time, frequency then that total energy has to be estimated.

$$P_j = \frac{E_j}{E_{total}} \tag{1}$$

Mohan Kumar et al. (2008) extract wavelet energy co-efficient gives a representation of EEG signal in time and frequency. It has decomposed the different level of frequency signals like

alpha, beta, gamma, theta, and delta. Here the emotions are grouped based on enjoyment and disagreeable The emotions can be identified using LDA, KNN. The features are extracted using discrete wavelet Transform and Statistical Features. *Chai Tong Yuen et al.,* (2010) paper describes with that, statistical based features are used to classify the human emotion from EEG signals. Each Statistical features are used to classify different types of emotions. The signals recorded from the EEG is X, then the Nth Sample of signal is X_n where N=1024, The Mean of the raw signal is

$$\mu_x = \frac{1}{N}\sum_{n=1}^{N} X_n \tag{2}$$

And also find Standard Deviations,

$$\sigma_x = \left(\frac{1}{N}\sum_{n=1}^{N}\left(X_n - \mu_n\right)^2\right)^{1/2} \tag{3}$$

And also find the mean absolute values of raw signal, normalized signals. Here few combinations of Statistical Feature Vectors are,

$$X1 = \left[\mu_x, \sigma_x\right] \tag{4}$$

$$X2 = \left[\delta_x, \gamma_x\right] \tag{5}$$

C. Petrantonais [2] paper, Statistical Feature Vector (FV) is used to classify the emotion from the EEG signal. FV is calculated by using the mean, standard deviation and etc. The corresponding FV is defined by,

$$FV = \left[\mu_x, \sigma_x, \delta_x, \gamma_x\right] \tag{6}$$

It describes with both symmetric and asymmetric levels of emotions Garrett, D., Peterson (2013).The emotions can be identified by using the signal segmentation and extracts the feature using HOC and Cross correlation method. SVM are used to classify those emotions into different group like negative and positive emotions. By using this method we have to get the best accuracy of emotions and multidimensional data also used. Karpagachelvi.S (2010) present Emotion classified from different optimized techniques and those emotions is related to the human machine interaction and other activities, which are used in the affective computing. The features are extracted from EEG using HOC. It supports different feature extraction techniques and provides better accuracy result. The proposed method used to calculate the human emotions and related emotional disorder and also analyze the accuracy of the classification. Section II presents the EEG data collection methods. Section III presents the methodology for processing the EEG. Section IV presents the result and its discussion. Section V conclusion and future works.

2. EEG data collection

This section describes that collection of EEG signals for different emotion recognition experiments. The electroencephalography signals of 32 participants were recorded during one minute videos. Based on that participants are rated in terms of valence and arousal, like/dislike, familiarities and dominance. Emotion related ratings are given based on the online self assessment which is 120 one minute extracted music videos, which are rated by 14-16 volunteers based on arousal and valence. The EEG signals were recorded using 64 electrodes, first 62 electrodes are active electrode, one for reference and remaining one is ground electrode. All the electrodes are placed on the scalp which is made up of the Ag/Ag-Cl. Figure 2 shown in below which is represent the basic EEG signal recording methods and emotion analysis process.

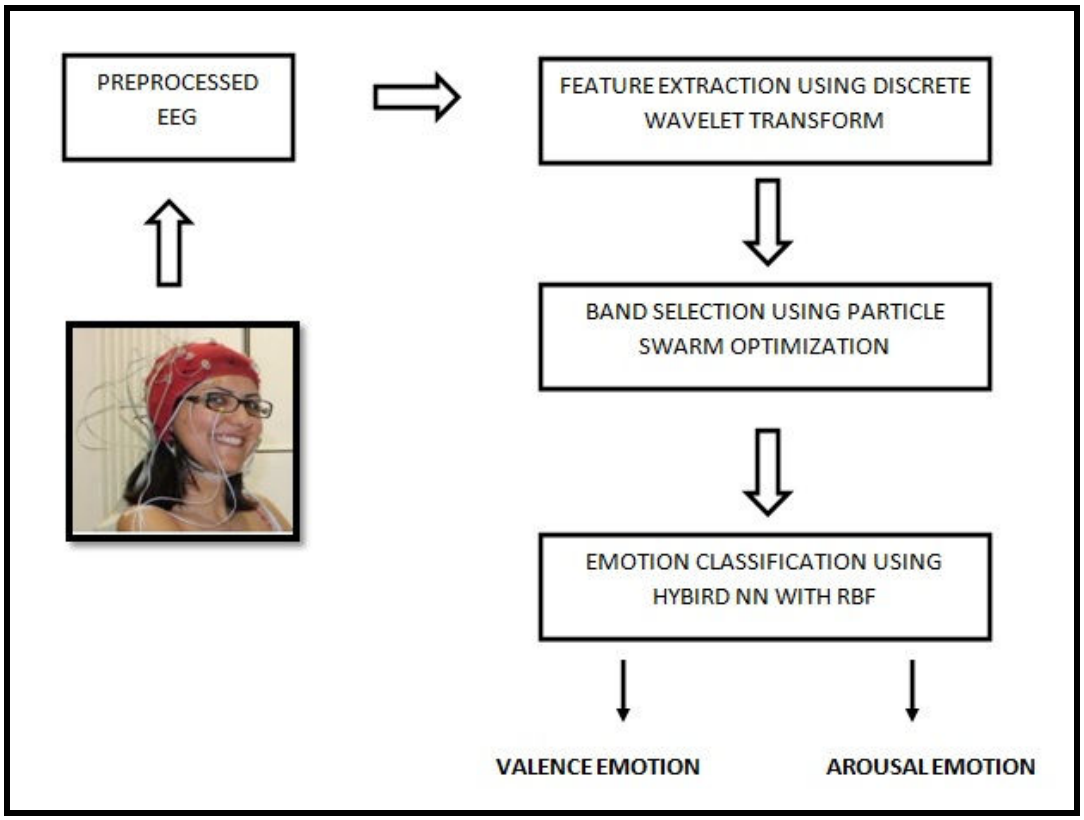


Figure 2. Emotion recognition using EEG

Reference electrode placed AFz placed in between AF1 and AF2 electrode and ground electrode Oz is placed between O1 and O2 electrodes. The impedance of the electrode range is 5KΩ. The sampling rate was fixed range between 256 samples per second for all the channels. Figure 3 shown in below which is represent the electrode placement diagram. The recorded EEG signal is used to recognize the different level of emotions.

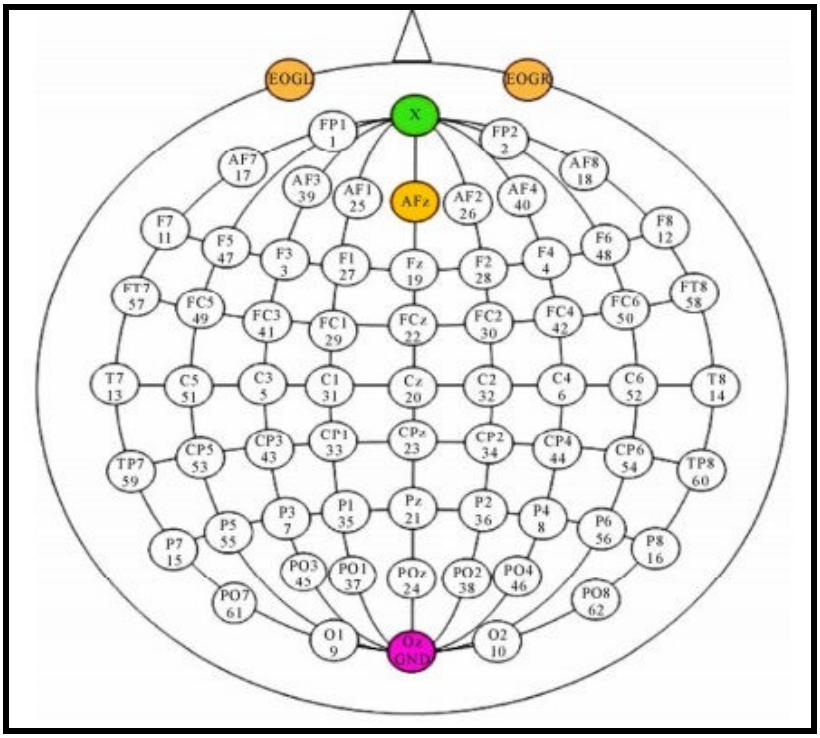


Figure 3. Electrode placement diagram

3. Processing methodology

EEG signal were recorded using different electrodes placed in the scalp. Normally the recorded EEG signal has noise. But here DEAP dataset is used to process the entire signal. So preprocessed dataset is used to recognize the emotion. The dataset has noise free, and it has filter 4 to 40 Hz to identify the accurate emotions for volunteers. This section describes with several approaches like feature extraction, band selection, emotion classification and person identification. The following section describes each and every approach.

3.1. Feature extraction

Feature extraction is the process of extracting related information or particular detail information from the raw information. Emotion identification from the EEG signal has multiple features for analyze the result. So that the EEG has to be analyzed the multi resolution way for that discrete wavelet transform has to be used.

3.1a. Discrete wavelet transformation

The EEG signal is non stationary signal so it has to be analyzed in detail and approximate coefficient. For that purpose discrete wavelet transformation is used to extract the EEG signal. Detcoef, wrcoef functions are used to extract the detail and approximated information from the signal and the time, frequency resolution has obtained by wavelet transform and then wavelet function has to be choosers

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}}\varphi\left(t - \frac{b}{a}\right) \tag{7}$$

Based on that coefficient, different bands have to be extracted. The bands are alpha, beta, theta, gamma, and delta. Figure 4 shown in below which is represent the different extract band diagrams.

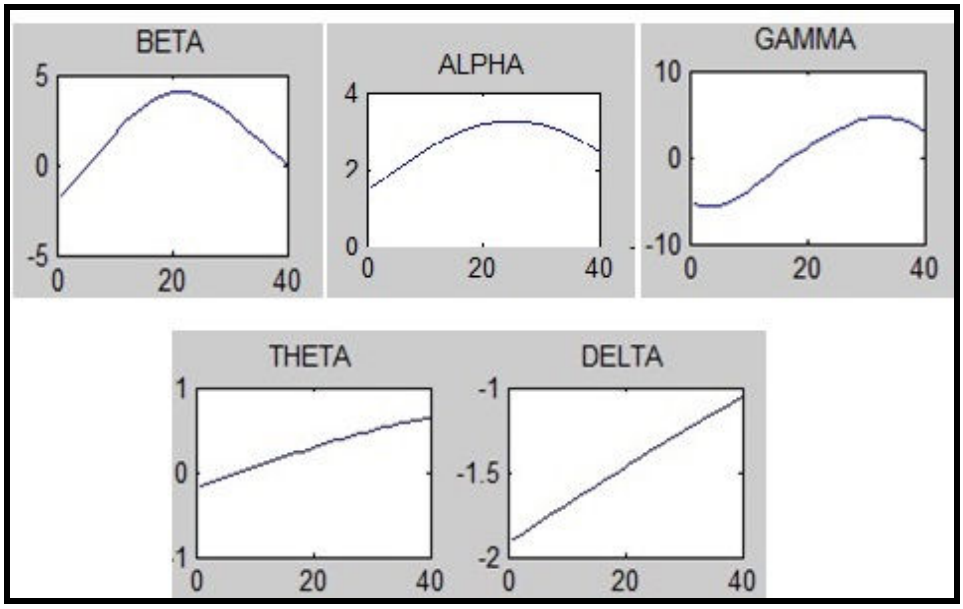


Figure 4. Extracted bands diagram

Every band has particular range of frequency bandwidth. For extracting the different bands db8 wavelet function is used. After extracting the bands related feature has to be calculated. Statistical and energy based features are extracted. Based on the power, entropy energy, standard

deviation, mean, average features are extracted and this features are used to classify the emotion. The features are list out in following table 1.

Table 1 Features List and Related Formula

LIST OF FEATURES	**FORMULA**
Standard deviation	$\sigma_x = \left(\frac{1}{N} \sum_{n=1}^{N} (X_n - \mu_n)^2 \right)^{1/2}$
Mean	$\mu_x = \frac{1}{N} \sum_{n=1}^{N} X_n$
Variance	$\mathrm{var}(x) = E\left[(x - \mu_x)^2 \right]$
Power	$P = s^2(t)$
Energy	$E_s = \int_{-\infty}^{\infty} \left| x(t)^2 \right| dt$

Feature related formals are used to extract the features from the EEG Signal. Then that features are trained and emotions are identified.

3.2. Band selection

Band selection is the process of selecting one single band from the list of bands. Gamma and alpha band provide the accurate result when classifying the emotion. Before selecting the particular band the set of features has to be trained for research. The feature set has to be trained by using different neural network based on the mean square error the band was selected.

3.2a. Particle swarm optimization

PSO is used to identify the best solution from collection of solution. It is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position but, is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions. PSO is a metaheuristic as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, metaheuristic such as PSO do not guarantee an optimal solution is ever found. The following Figure 5 explains the basic flow of PSO process.

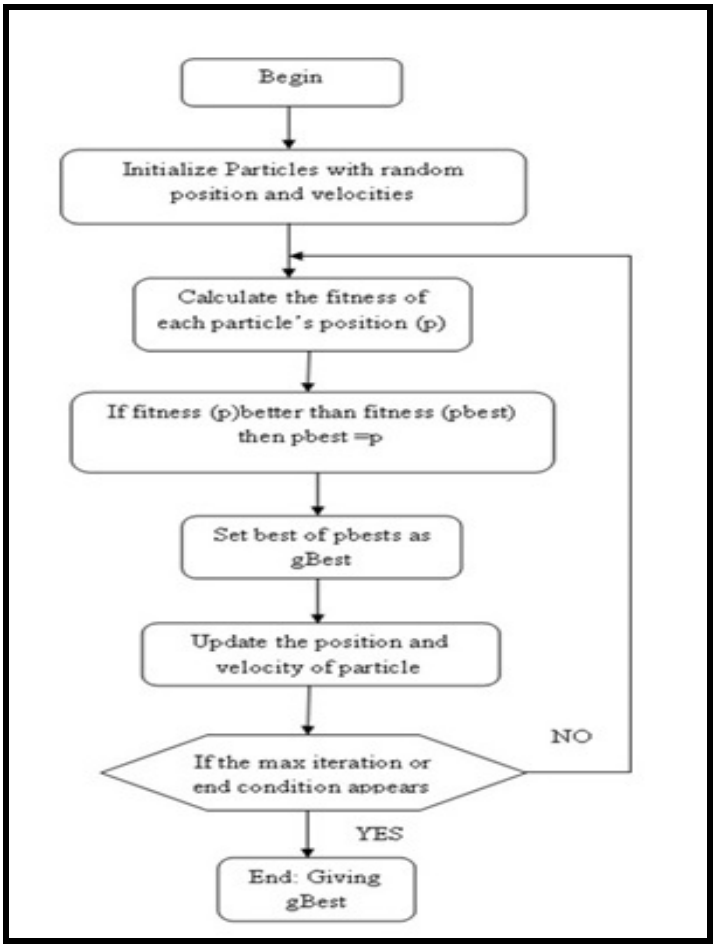


Figure 5. Process flow of PSO

Particle swarm optimization algorithm first optimizes the neural networks weight and bias and provides the minimum mean square error with nearer by zero. The following figure 6 has shown that minimum mean square error when training the particular band features.

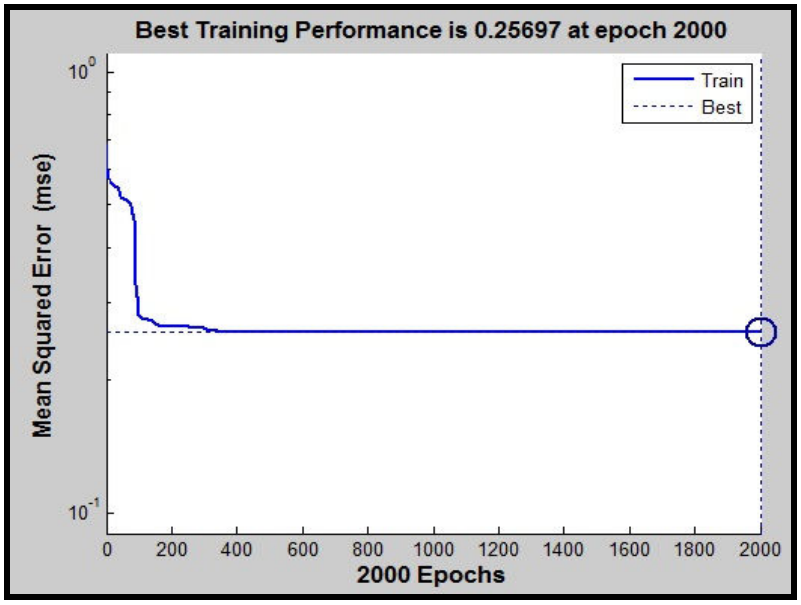


Figure 6. Mean square error of alpha band

Band has to be selected based on the minimum error. Gamma, beta, alpha bands are providing minimum error repeated training process. Depending on the features band has to be selected and then the feature related emotions are classified.

3.2b. Cukoo search

Cuckoo search is an optimized algorithm which is based on obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds (of other species). Some host birds can engage direct conflict with the intruding cuckoos. It is swarm optimization algorithm which is used to solve the complex classification problem. Cuckoo search is used to train the multi layer perceptron network. The cuckoo search is implemented with three important rules. First each cuckoo lays only one egg at a time, second one is the best egg is moved on best nest which is used to next generation. Final rule is number nest is fixed which is chosen based on the probabilities like 0 and 1. The MLP neural network is trained with using cuckoo search will provide the higher training efficiency and classification rate.

3.3. Emotion Classification

In this work, we have used feed forward neural networks with radial basis function and trained with particle swarm optimization classifier is used to classify the emotion. Neural network provides the optimize result when adapting the particular feature for the related result. It provides the fast and accurate result compared to other classifier. Minimum mean square error network will provide the more accurate classification result. The neural network has different layers like input layer, hidden layer, and output layer. The input layer receives the inputs and standardizes the range of values by subtracting the median and dividing its quartile values. The hidden layer process the values using the particular transform and training function like tansig and radbas called radial basis function which provide the high processing and accurate classification rate. The final output layer compares the target value into the predicted values. Based on the value the emotions are identified. Figure 7 shown in neural network architecture.

3.3a. PSO trained neural network

Neural Network has to be trained with particle swarm optimization. PSO tool box is used to train the Artificial Neural Network. PSO toolbox is designed with two main concepts which are used as the standalone function for optimizing, and it replaces the back propagation during the neural network training. PSO trained neural network provides the better classification accuracy and which is reduce the mean square error for best performance.

The training function format for the PSOt toolbox is

$$[W1, B1, W2, B2.....TE, TR] = TRAINPSO[W1, B1, F1, W2, B2, F2, ...P, T, TP] \quad (8)$$

Here W1, W2, W3, B1, B2, B3 represents the weight and bias of the neural networks. F1, F2,F3 represent the activation function used during neural network training. Tansig, logsig built-in functions are used. P, T is inputs and outputs of the neural networks.

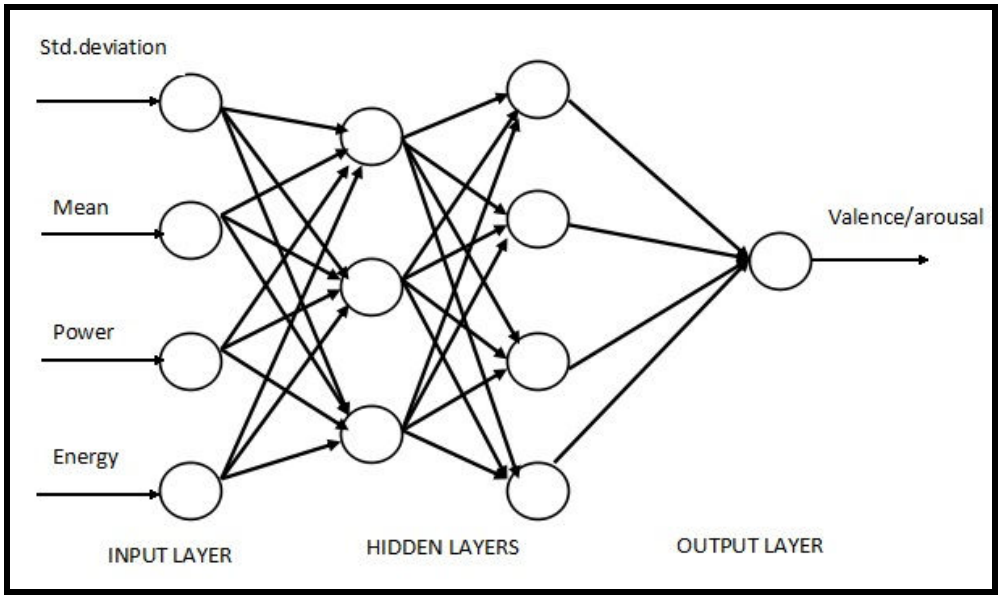


Figure 7. Neural Network model

3.3b. Probabilitistic neural network

In Probabilistic Neural Network the operations are organized into a multilayer feed forward neural network with four layers like input layer, hidden layer, pattern layer and output layer. PNN use the Euclidean distance measure the difference between one neuron to other neurons. The actual target values are stored in the hidden neuron and the optimized weighted values are fed into the same category hidden neuron. Then finally the output layer compared the weighted votes of each target values and the target votes are used to predict the emotions.

3.3c. Neural networks trained with Cuckoo search

Cuckoo Search (CS) algorithm is a meta-heuristic optimization algorithm which is suitable for solving optimization problems. Multi layer perceptron network is trained by using metaheuristic algorithm. When training the neural network with optimized algorithm which provide the better training efficiency result. Following code represent code for cuckoo search.

Define the objective function; $f(x)$
$x = (x_1, x_2, x_3, ...x_d)$
Initialize the n host nest;
Check whether t< max Generation or stop criteria
Get cuckoo randomly and replace its solution by performing levy flights;
Calculate the fitness value F_i
[for maximization , $F_i \propto f(x_i)$]
Choose next among n randomly;
If $F_i > F_j$
Replace j by new solution
End
Keep the best solution and rank the solution
Pass the current solution to next generation
Stop while.

Based on this algorithm neural network has to been trained and provide the better training and testing efficiency.

4. Result and discussions

For all the 32 participants the EEG signal has to be sampled and process their emotions. The emotions are depends on the music and video clips. In this paper the video clips are changed from one person to other person. Here hybrid feed forward neural networks with radial basis function; probabilistic neural network classifier is used to classify the emotions from EEG. PNN is very fast and insensitive neural network which provides the optimized classification result. Compare to the multi layer perception neural network it provide accurate result. It classifies the emotion into two different groups like arousal and valence. Figure 8 shows that the model implemented result of emotion classification and person identification.

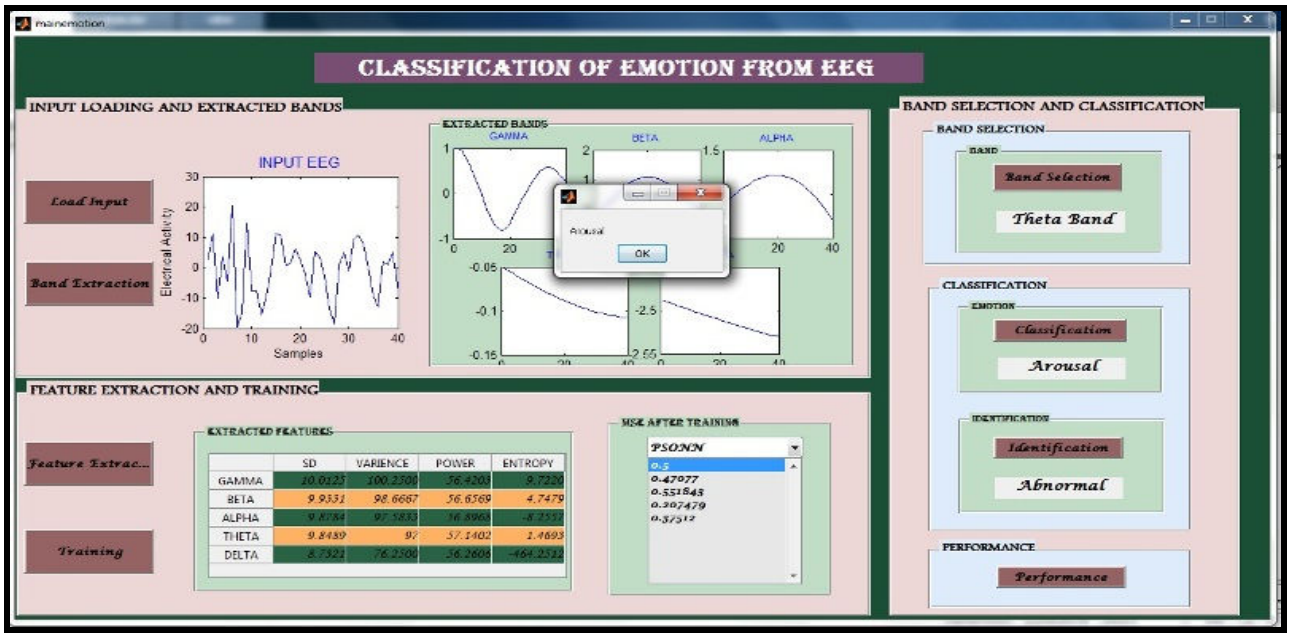


Figure 8. Sample Emotion Classification Result

In this paper we summarize that the neural network trained with particle swarm optimization provide better classification accuracy compared to other neural network. The maximum classification accuracy rate of 90.3% of NNRBF, 90.325% of PNN and 96.3% of PSONN obtained using statistical features and energy with 64 electrodes. The following

Table 1 has shown that different band performance for training the neural networks.

Table 2. Average Classification Accuracy using Hybrid Neural Networks

NEURAL NETWORKS	CLASSIFICATION	DIFFERENT BANDS				
		GAMMA	BETA	ALPHA	THETA	DELTA
NN WITH RBF	PERCENTAGE OF CORRECT CLASSIFICATION	58.06	90.32	12.9	90.322	38.7
	PERCENTAGE OF INCORRECT CLASSIFICATION	41.93	9.677	87.09	9.677	61.29
PNN	PERCENTAGE OF CORRECT CLASSIFICATION	41.93	67.74	83.87	83.87	80.24
	PERCENTAGE OF INCORRECT	58.06	32.25	16.12	16.12	19.35

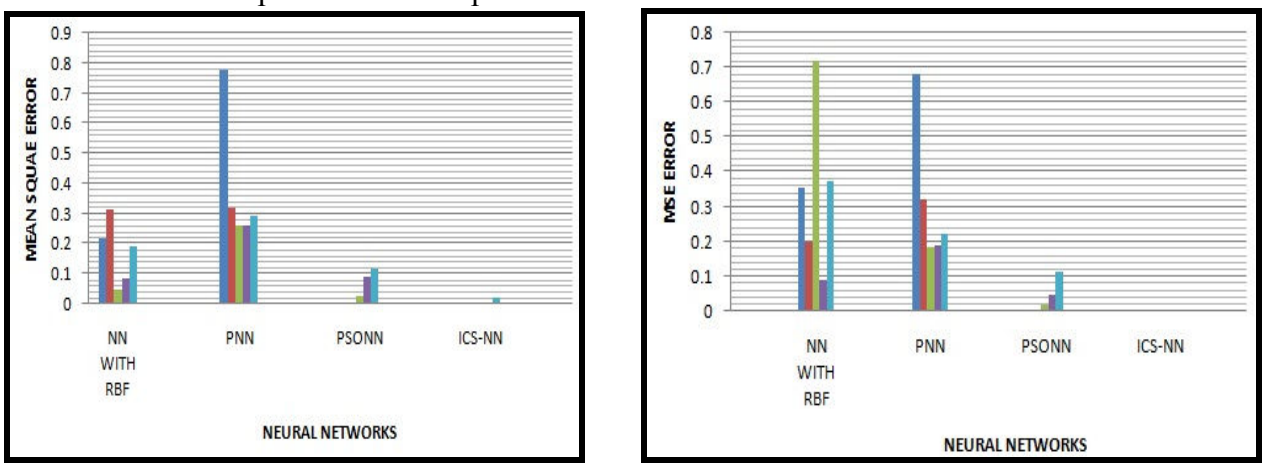
	CLASSIFICATION					
PSONN	**PERCENTAGE OF CORRECT CLASSIFICATION**	**96.77**	**95.01**	**94**	**93.548**	**87.09**
	PERCENTAGE OF INCORRECT CLASSIFICATION	**3.2**	**4.99**	**6**	**6.45**	**12.9**
ICS-NN	**PERCENTAGE OF CORRECT CLASSIFICATION**	**97.01**	**96.04**	**95.2**	**94.021**	**90.03**
	PERCENTAGE OF INCORRECT CLASSIFICATION	**2.99**	**3.96**	**4.8**	**5.979**	**9.7**

The above table explains that different classification accuracy using confusion matrix in the neural network. The following table 3 describes that different bands mean square error values which was obtained from different types of neural networks and neural network trained by particle swarm optimization, neural network trained with cuckoo search provide bests minimum error value which is used to band selection and emotion classification. Metaheuristic algorithms are providing the optimal and near optimal solution for many classification problem. When compared to the optimizing algorithm trained with neural network neural network trained with improved cuckoo search provides the better classification accuracy and minimum mean square error.

Table 3. Mean Square Error Values for different epochs

NEURAL NETWORK	**Training for 100 epochs**					**Training for 50 epochs**				
	Gamma	Beta	Alpha	Theta	Delta	Gamma	Beta	Alpha	Theta	Delta
NNRBF	0.21937	0.313	0.0504	0.083	0.193	0.35711	0.1983	0.7202	0.0869	0.3753
PNN	0.78	0.322	0.2612	0.261	0.293	0.68	0.322	0.1812	0.1861	0.2235
PSO-NN	**7.25E-14**	**0.002**	**0.0258**	**0.091**	**0.116**	**4.23E-05**	**3.0E-12**	**0.01674**	**0.0474**	**0.11383**
ICS-NN	**5.201E-12**	**0.0003**	**0.0004**	**0.006**	**0.021**	**3.21E-03**	**2.03E-9**	**0.002**	**0.003**	**0.005**

Figure 9 has shown in different epochs using neural networks with mean square error performance and the Table 3 shows that different bands mean square error values while training the neural networks with particle swarm optimization.



(a) MSE Error for 100 epochs (b) MSE Error for 50 epochs

Figure 9. Mean Square Error for different bands

In this figure ICS-NN has the minimum mean square error so that the neural network will provide the better average classification rate. After determining the mean square error, particular band is used to identify the emotion. From the classification sensitivity, specificity and accuracy values are calculated using following formulas.

$$SENSITIVITY = \frac{TP}{(TP + FN)} \tag{9}$$

$$SPECIFICITY = \frac{TN}{(TN + FP)} \tag{10}$$

$$ACCURACY = \frac{(TP + TN)}{(TP + TN + FP = FN)} \tag{11}$$

TP = True Positive FP = False Positive
TN = True Negative FN = False Negative

Using the equation $(9),(10),(11)$ below table values are calculated for analyze the performance of the network.

Table 4. Sensitivity and Specificity values for different networks

METHODS	**SENSITIVITY**					**SPECIFICITY**				
	Gamma	Beta	Alpha	Theta	Delta	Gamma	Beta	Alpha	Theta	Delta
SVM	66.7	68.571	47.83	54.29	54.17	54.29	56.62	57.14	56.62	57.14
KNN	45.83	45.71	54.17	51.83	54.2	47.8	54.29	62.50	62.86	61
LDA	70	78.33	41.67	54.16	62.5	30	71.67	62.5	45.83	39.58
NNRBF	55	89	80	40	66	61.5	50	82	78	48
PNN	40	30	50	30	40	70	75	76	77	58
PSO-NN	**98**	**97**	**82**	**68**	**78**	**88**	**91.5**	**96**	**87**	**91**
ICS-NN	**98.5**	**98.23**	**92.1**	**85.4**	**89.01**	**92.3**	**94.3**	**97.2**	**93.24**	**94.56**

Figure10 has shown in sensitivity and specificity of different neural network which is used to explain how exactly the emotions are classified into groups and accuracy value shown in above table 3.

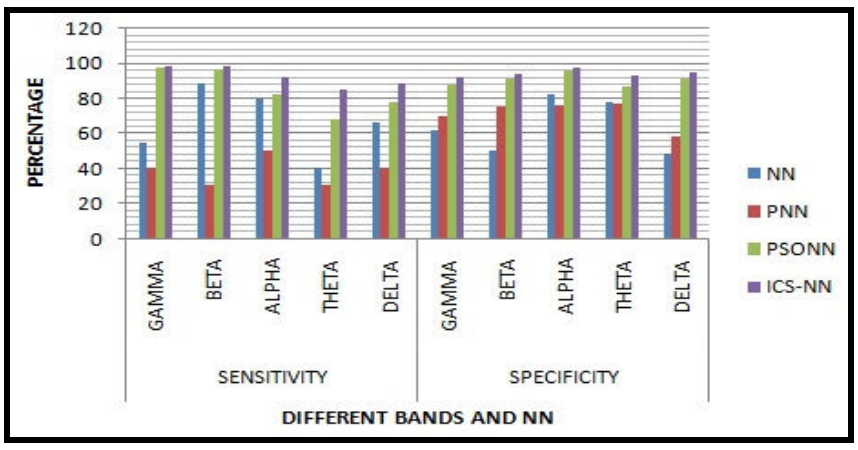


Figure 10. Sensitivity and specificity of different bands

Following table 4 describes that classification accuracy which was calculated using equation (10). Neural Network trained with improved cuckoo search optimization algorithm provides the higher classification accuracy and accurate emotion for different type of bands.

Table 5. Average classification accuracy for different bands

NETWORK	GAMMA	BETA	ALPHA	THETA	DELTA
NNRBF	70.9	55	50	38	38.7
PNN	41.9	67.7	73.4	83.4	80.6
PSONN	80.3	77.7	83.5	93.5	87
ICS-NN	85.6	89.3	93.2	96.4	95.45

5. Conclusion and future work

In this paper the emotions are analyze and related persons are identified from the EEG signals. But the processing EEG database is rare in public. Here the emotions are classified into two different groups using discrete wavelet transformation with statistical, power and entropy features and different hybrid neural networks. The weights are optimized with cuckoo search optimization with help of cs tool box when training the neural networks which are providing the accurate and fast classification rate. Based on the classification related mean square error, confusion matrix, sensitivity and specificity measures are used to identify the accuracy of the classifier. Here we just identify the normal or abnormal person based on the emotion. In future, it is interest to identify the mood of the particular person, disease for the person also identified using different optimization algorithm like Genetic Algorithm, Ant colony Algorithm. By using the emotions and emotion related disorder it is help to teach the accurate emotions and reaction to robots in the artificial intelligence, and fast identification of disease in medical applications.

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