IJITKM Volume 7 • Number 1 • December 2013 pp. 61-74

Comparison of Classifiers with Event Related Potentials as an Attribute in Emotion Quantification along Valence Axis Using EEG Signals

Dr. Mandeep Singh, Mr. Mooninder Singh, Nikhil Singhal
Department of Electrical & Instrumentation Engineering, Thapar University, Patiala, India
mandy_tiet@yahoo.com, mooninder@gmail.com, nikhilsinghal.729@gmail.com

ABSTRACT

Emotion exerts powerful force on human behavior. It is a complex state of feelings that results in psychological and physical change that influences the thoughts and human behavior. Psychological emotions correspond to the cognitive processes or state of mind such as happy, sad, depress, excited etc. Emotions can be detected by capturing the EEG signals using EEG cap. In this study EEG data from enterface website 06 was used and classified along the valence axis in two emotion classes namely high valence considered as pleasant emotion and low valence considered as unpleasant emotion state. P100, N100, P200, N200, and P300 are the Event Related Potential (ERP) features extracted from the raw EEG data of 3 participants over seven electrodes. The Naïve Bayes classifier when used over ERP as an attribute resulted in the accuracy of 56%. While with single hidden layer ANN the average accuracy obtained 57%. 100% accuracy has been obtained on using 2 hidden layer ANN classifier, the accuracy obtained for the ERP features showing the best of the results ever obtained in the classification of emotions.

As emotions play a very important role in daily life of human beings, so to recognize psychological emotions more clearly and sharply various recognition methods were introduced by various authors that were very affective. So in this paper, our objective is to analyze the ERP feature in different combination using ANN classifier and compare the classifier for emotion quantification using extracted features. This time also all above described features were included but on the basis of ERP features judgment was made on the better classifier's efficiency.

INTRODUCTION

Emotion is defined as a complex state of feeling that results in physical and psychological changes that influence thought and behavior. Emotionality is associated with a range of psychological phenomena including temperament, personality, mood and motivation. Human emotion involves "...physiological arousal, expressive behaviors, psychological valence and conscious experience." [1] [2]. To extract and classify the features, data is required which is the very first and crucial step. It has been obtained from the enterface website 06 [3]. This data was the raw EEG data prepared by the Savran et al on 5 participants, all were males and right handed at an enterface workshop. That data contained 4 files in the format of Biosemi Data Format (BDF). Entire data was grouped by the individual participants on valence- arousal scale using Self assessment Manikin (SAM) [4]. The data was divided into 3 classes-calm, positive exciting and negative exciting, after shown the images selected from International Affective Picture System (IAPS) [5]. But for our experiment only 3 participants (P3, P4, and P5) and 7 electrodes (Cz, Fz, Pz, FC1, FC2, F1, and F2) were considered and to reduce the dataset, data was down-sampled at a rate of 256Hz with the help of EEG LAB [6] which is a open source software.

Bradley M.M et al (2005) discussed the development and use of emotional colored picture stimuli that was incorporated in International Affective Picture System (IAPS). These pictures include pleasure, arousal, and dominance ratings made by men and women. The IAPS is currently used in experimental investigations of emotion by facilitating the comparison of results across different studies in combination to control the emotions across psychological and neuroscience research laboratories [5].

Jennifer Healey (2001) worked on the 8 emotional states namely no emotion, anger(High arousal negative valence), hate (Low arousal Negative valence), grief (High arousal negative valence or Low arousal Negative valence), love(Low arousal positive valence), romantic love(love for opposite sex- very high arousal positive valence), joy (high arousal positive valence)and reverence(for nature and God-low arousal and neutral valence) with the help of guidelines mentioned by Clynes [2]. To recognize 8 emotional states 5 sensors were used. The classification of these emotional states was done by using Fisher analysis and the accuracy lied between 80% and 90%. In his pioneer work Russell, J.A. (2003) discussed about the feelings like joy, happiness, fear, angry, depressed, displeasure and all were inter related. He worked on affective space model (Valence and Arousal) by representing them as a circle in a two dimensional space. He represented arousal dimension with pleased along the X-axis [7].

DATA COLLECTION

The analysis has been done on the EEG data available on the enterface 06 website [3] [8]. The emotions were elicited by using the stimulus provided by university of Florida called International Affective Picture System (IAPS) in NIMH center [5]. The participants were also asked to rate the images on the arousal and valence scale using self assessment manikin (SAM) method [4]. This work shows that the participants were showing the images from IAPS based on three classes namely clam, positive exiting, and negative exiting. To calculate the emotions, the arousal and valence scales have been rated from 1 to 9 [1]. The following criterion was adopted for the selection of images from the IAPS image set for the above said three emotions

Calm: Mean Arousal < 4
4 < Mean Valence < 6
Exciting Positive: Valence > 6.8
Variance (Valence) < 2
Mean Arousal > 5
Exciting Negative: Mean Valence < 3
Mean Arousal > 5

Each image was shows for 2.5 seconds and total of 5 images for evoking one emotion were shows at a time. So to evoke one emotion the EEG data was collected for 12.5 seconds. The data was available on enterface 06 website [8] which was a raw data in BDF (Biosemi Data Format) format obtained at a rate of 1024Hz, except the first session of participant 1 that was recorded at sampling rate of 256Hz. In order to reduce the data set, the EEG data was loaded into the EEG LAB [6] which is an open source software and then down-sampled to 256Hz. The sampled output obtained from eeglab for all 64 electrodes and the physiological variables were then saved into the memory of a computer for further analysis in case of each participant. The features has been extracted by acquiring the data for 20 marks for each session of a participant. Thus the data acquired from a total of 180 marks of the 3 participants namely P3, P4, and P5 with the 7 seven electrodes namely Cz, Fz, Pz, FC1, FC2, F1, and F2 was processed for the quantification into two classes.

FEATURE EXTRACTION

After getting sample values, the objective of quantification of emotions using three different classifiers has been achieved. To work with these classifiers the following features were extracted from the sampled data:

The latencies of the ERP features were ignored and only the potential values were considered. The chosen features for emotion quantification are P100, N100, P200, N200, and P300 [13] [14].
P100 is first positive peak observed from 80 to 12ms. N100 is first negative peak it also observed from 80 to 120ms. Here ERP value was chosen as a main attribute for classification. The N100 was also classified within the time limit of 80 to 120ms. P200 is a second positive peak observed about 200ms varying between 150 and 275ms. N200 in particular is a negative-going wave that peaks 200-350ms post-stimulus and is found primarily over anterior scalp sites. P300 is a positive peak observed at 300 ms varying between 250 and 500ms.
Then Naïve Bayes, Feedforward and Multilayer 2- Hidden Layer ANN classifier were trained using ERP features, to quantify the emotions along valence axis.

CLASSIFICATION

After extracting the desired features, classifiers were trained. Several methods for classification have been proposed. Some of the most well-known algorithms such as Naïve Bayes, Feedforward and Multilayer 2- Hidden Layer Neural Network ANN classifier have been used.

The Naïve Bayes algorithm is based on conditional probabilities. It uses Bayes' theorem, a formula that calculates a probability by counting the frequency of values and combinations of values in the historical data. It finds the probability of an event occurring given the probability of another event that has already occurred [12].

The algorithm of Naïve Bayes is shown below.

Posterior = (prior * likelihood)/evidence

For events r and s, Bayes rule is:

$$p(r,s) = p(r\square s) = p(r|s)p(s) = p(s|r)p(r)$$

$$p(r\square|s)p(s) = p(s|r\square)p(r\square)$$

$$p(r|s) = \frac{p(s|r)p(r)}{p(s)} = \frac{p(s|r)\,p(r)}{\sum_{\square\square=\square,\square\square} p(s|x)p(x)}$$

After the Naïve Bayes, ANN classifier was used. ANN is a neural network that consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation [15] [16]. MATLAB Tool nnstart was used to train the classifier through extracted feature of EEG.

Inputs→ NN→ Outputs

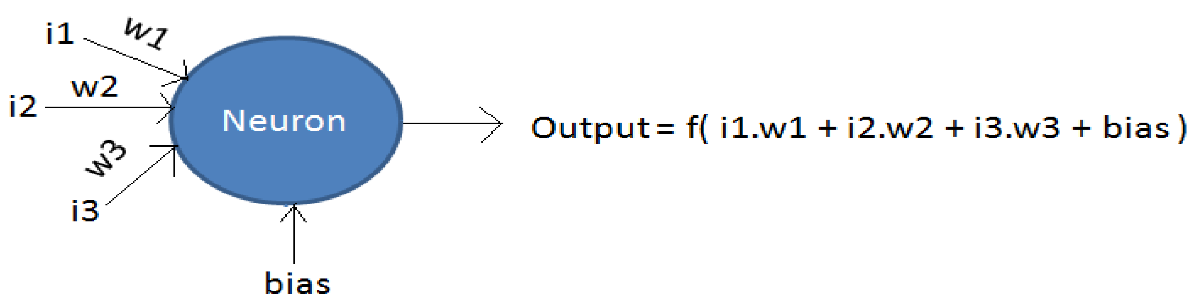

Figure 1.1: Structure of Neural Network

The classifier was also implemented using feedforwardnet inbuilt function in MATLAB R2011a version. Feedforward neural network is a biological inspired classification algorithm. It is the first and simplest type of artificial neural network (ANN). In this network, information moves in only one direction, forward, from the input node through the hidden node and to the output nodes. Since data flows only on forward direction with no feedback they are called feedforward neural network [16].

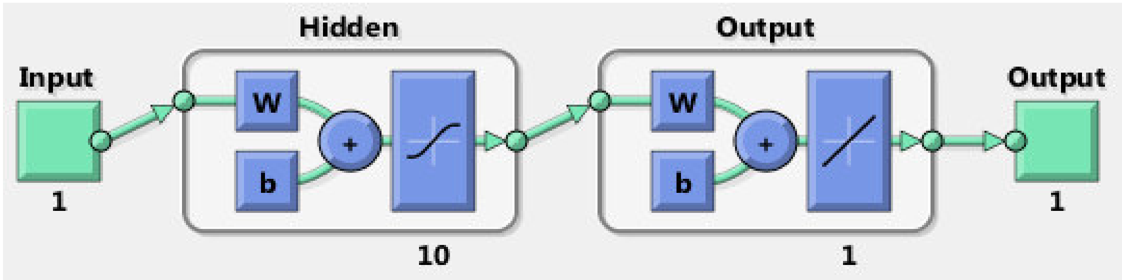

Figure 1.2: Feedforward Neural Network.

It is feedforward neural networks trained with the standard back-propagation algorithm. Generally only one hidden layer neural network is used for classification but we used 2-hidden layer neural network. By this we took 5 neurons in first hidden layer and 7 neurons in second hidden layer for classification. In this paper to determine the accuracy on emotional EEG data, built in MATLAB Tool 'nntool' of MATLAB version R2011 was taken under consideration [17][18] [19].

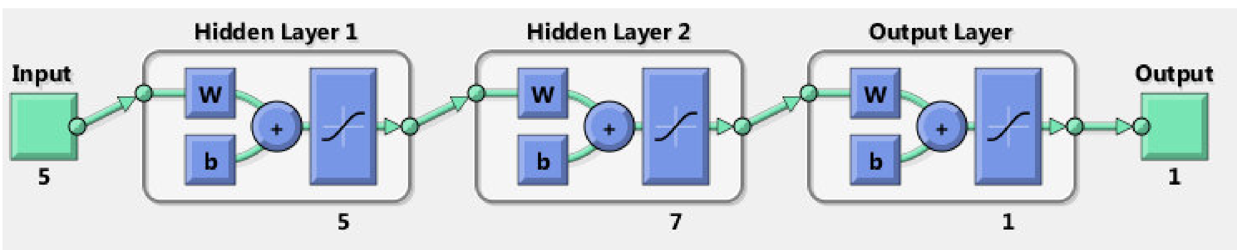

Figure 1.3: Multilayer 2- Hidden Layer Neural Network.

Generally in one hidden layer 10 neurons are used as an input to determine the classification rate of EEG data. In Multilayer Neural Network we used 2-hidden layer network with 5 or 10 neurons in first hidden layer and 7 or 40 neurons in second hidden layer for classification to improve the accuracy [20][21][22][23][24] .

RESULTS

For classification through Naïve Bayes, first ERP extracted features were used as attributes for classification. We took the entire data of 3 participants P3, P4, and P5, together and on classification, obtained the accuracy of **56%.**

Table 1.1 Accuracy obtained using Naïve Bayes Classifier.

Features	Accuracy
ERP	56%

Since the accuracy obtained using the Naïve Bayes classifier was pretty low, it was decided to use ANN based classifier. For this, again fed entire data of all 3 participants of ERP to ANN classifier (nnstart) and obtained the accuracy of **57%** which is similar to the one obtained using Naïve Bayes classifier. To improve the accuracy of ERP features different combinations of data were prepared and fed as an input to the GUI, obtained using nnstart function.

In first combination, the ERP attributes extracted from a particular participant per session for the selected electrode were used as input.

Table 1.2: Classification Rate for ANN Classifier is shown in the following table

PARTICIPANT SESSION ELECTRODE	TRAINING	VALIDATION	TEST	ALL
P3S1Cz	85.70%	100%	100%	88.90%
P3S1F1	78.60%	100%	100%	85%
P3S1F2	57.10%	66.70%	100%	65%
P3S1FC1	64.30%	100%	66.70%	70%
P3S1FC2	64.30%	100%	100%	75%
P3S1Fz	100%	100%	33.30%	90%
P3S1Pz	50%	100%	66.70%	60%
P3S2Cz	63.30%	100%	66.70%	70%
P3S2F1	71.40%	66.70%	66.70%	70%
P3S2F2	92.90%	100%	100%	95%
P3S2FC1	85.70%	66.70%	100%	85%
P3S2FC2	57.10%	66.70%	66.70%	60%
P3S2Fz	35.70%	100%	66.70%	50%
P3S2Pz	85.70%	100%	66.70%	85%
P3S3Cz	85.70%	100%	66.70%	85%
P3S3F1	42.90%	66.70%	66.70%	50%
P3S3F2	71.40%	100%	66.70%	75%
P3S3FC1	50%	100%	66.70%	60%
P3S3FC2	35.70%	100%	100%	55%
P3S3Fz	71.40%	66.70%	100%	75%
P3S3Pz	78.60%	66.70%	100%	80%
P4S1Cz	78.60%	100%	66.70%	80%
P4S1F1	85.70%	100%	66.70%	85%
P4S1F2	71.40%	100%	100%	80%
P4S1FC1	64.30%	100%	66.70%	70%
P4S1FC2	78.60%	100%	66.70%	80%
P4S1Fz	50%	100%	66.70%	60%
P4S1Pz	78.60%	100%	66.70%	80%
P4S2Cz	71.40%	100%	66.70%	75%
P4S2F1	78.60%	100%	66.70%	80%

P4S2F2	78.60%	100%	66.70%	80%
P4S2FC1	71.40%	100%	66.70%	75%
P4S2FC2	85.70%	100%	66.70%	85%
P4S2Fz	64.30%	66.70%	66.70%	65%
P4S2Pz	64.30%	66.70%	66.70%	65%
P4S3Cz	35.70%	66.70%	100%	50%
P4S3F1	64.30%	66.70%	66.70%	65%
P4S3F2	35.70%	100%	66.70%	50%
P4S3FC1	57.10%	66.70%	66.70%	60%
P4S3FC2	35.70%	66.70%	100%	50%
P4S3Fz	28.60%	100%	100%	50%
P4S3Pz	42.90%	66.70%	100%	55%
P5S1Cz	57.10%	100%	33.30%	60%
P5S1F1	50%	66.70%	100%	60%
P5S1F2	64.30%	66.70%	66.70%	65%
P5S1FC1	57.10%	100%	100%	70%
P5S1FC2	78.60%	100%	33.30%	75%
P5S1Fz	28.60%	100%	100%	50%
P5S1Pz	35.70%	100%	66.70%	50%
P5S2Cz	35.70%	66.70%	100%	50%
P5S2F1	64.30%	100%	66.70%	70%
P5S2F2	71.40%	100%	66.70%	75%
P5S2FC1	35.70%	100%	100%	55%
P5S2FC2	57.10%	66.70%	66.70%	60%
P5S2Fz	57.10%	100%	66.70%	65%
P5S2Pz	71.40%	66.70%	66.70%	70%
P5S3Cz	85.70%	100%	100%	90%
P5S3F1	35.70%	66.70%	100%	50%
P5S3F2	57.10%	100%	66.70%	65%
P5S3FC1	50%	100%	66.70%	60%
P5S3FC2	78.60%	66.70%	66.70%	75%
P5S3Fz	64.30%	100%	100%	75%
P5S3Pz	78.60%	100%	66.70%	80%

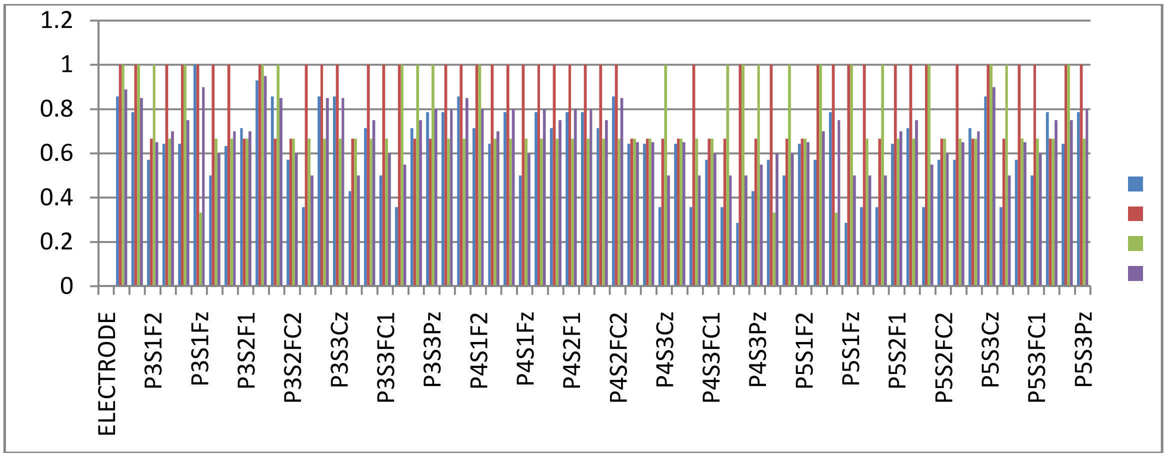

Figure 1.4 Accuracy Graph of Classification Rate for ANN Classifier

Table 1.3: The Averaged Accuracy Results over the Electrodes are shown in the following table.

Participant/ Electrode	P3			P4			P5			Average of each electrode
	S1	S2	S3	S1	S2	S3	S1	S2	S3	
Cz			77.8			77.8			77.76	77.78
F1			77.8			77.8			88.9	77.8
F2			88.9			88.9			66.7	77.8
FC1			77.8			77.8			88.9	77.8
FC2			88.9			88.9			55.53	74.08
Fz			66.6			66.6			88.9	77.78
Pz			77.8			77.8			66.7	74.1
AVERAGE of each participant			79.37			74.68			76.19	

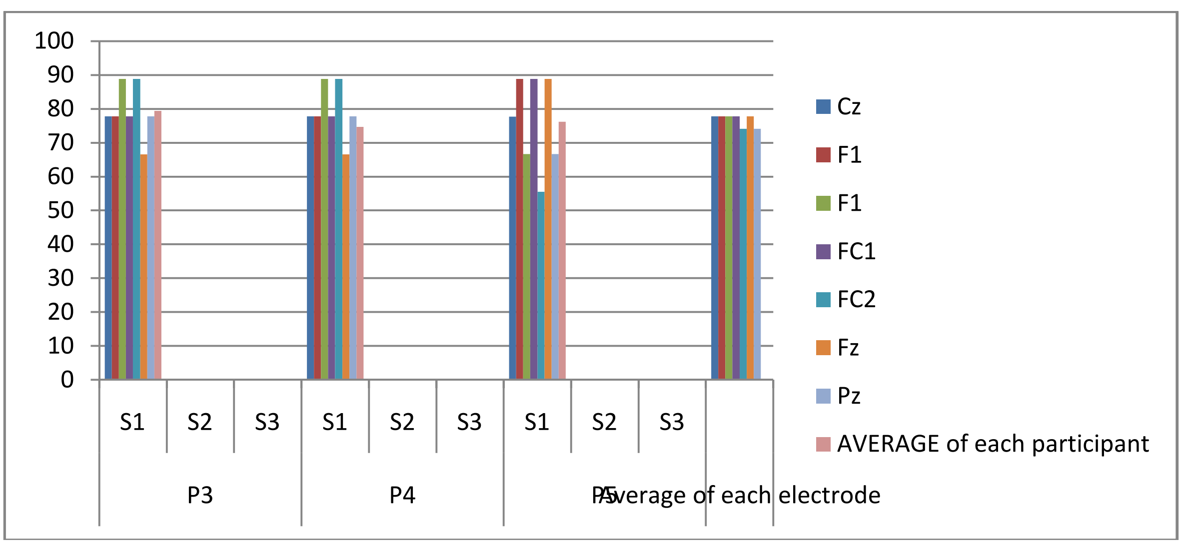

Figure 1.5 Graph of Averaged Accuracy Result over the Electrodes

Now in second combination, took data of each participant with one electrode and repeated the same method for all electrodes. On classifying obtained the following results.

Table 1.4: Accuracy for Each Participant for Each Electrode

Participant and Electrode	Training	Validation	Test	Overall
P3cz	66.7%	66.7%	55.6%	65%
P3f1	66.7%	66.7%	66.7%	66.7%
P3f2	54.8%	100%	44.4%	60%
P3fc1	47.6%	77.8%	66.7%	55.0%
P3fc2	54.8%	66.7%	66.7%	58.3%
P3fz	54.8%	77.8%	55.6%	58.3%
P3pz	54.8%	66.7%	55.6%	56.7%
P4cz	61.9%	66.7%	55.6%	61.7%
P4f1	57.1%	55.6%	77.8%	60%
P4f2	54.8%	55.6%	55.6%	55%
P4fc1	50%	77.8%	55.6%	55%
P4fc2	54.8%	55.6%	55.6%	55%
P4fz	40.5%	55.6%	88.9%	50%
P4pz	54.8%	55.6%	55.6%	55%
P5cz	54.8%	77.8%	66.7%	60%
P5f1	50%	55.6%	55.6%	51.7%
P5f2	42.9%	66.7%	77.8%	51.7%
P5fc1	66.7%	66.7%	44.4%	63.3%
P5fc2	42.9%	55.6%	77.8%	50%
P5fz	50%	66.7%	66.7%	55%
P5pz	64.3%	66.7%	44.4%	61.7%

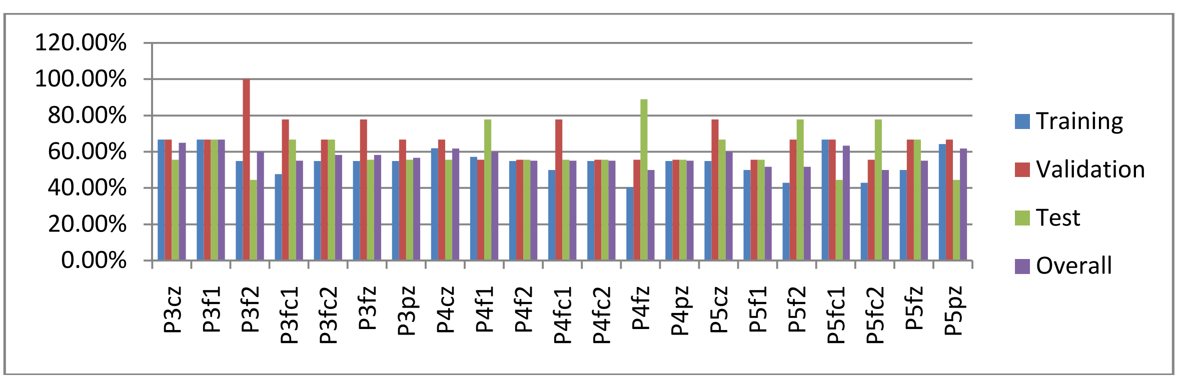

Figure 1.6 Graph of accuracy of Accuracy for Each Participant for Each Electrode

Table 1.5: Average Accuracy of Each Participant with One Electrode

Electrode/ Participant	Cz	F1	F2	FC1	FC2	Fz	Pz
P3	55.6	66.7	44.4	66.7	66.7	55.6	55.6
P4	55.6	77.8	55.6	55.6	55.6	88.9	55.6
P5	66.7	55.6	77.8	44.4	77.8	66.7	44.4
AVERAGE	59.3	66.7	59.26	55.56	66.7	70.4	51.86

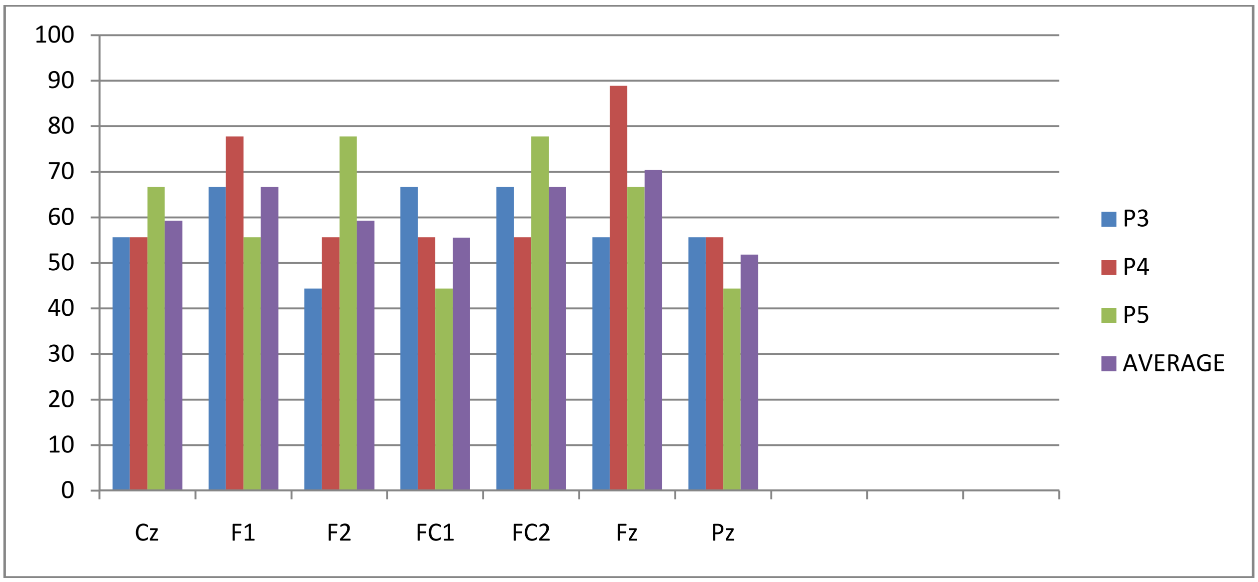

Figure 1.7 Graph of average Averaged Accuracy of Each Participant with One Electrode

Then in third combination, consider one electrode with all 3 participants and repeat same thing for other electrodes. From this got following results.

Table 1.6: Accuracy of all Participants with Each Electrode

ELECTRODE	TRAINING	VALIDATION	TEST	OVERALL
Cz	51.60%	59.30%	51.90%	52.80%
F1	47.60%	70.40%	63%	53.30%
F2	51.60%	51.90%	48.10%	51.10%
FC1	50.80%	55.60%	59.30%	52.80%
FC2	57.10%	51.90%	55.60%	56.10%
Fz	50.80%	59.30%	51.90%	52.20%
Pz	48.40%	55.60%	51.90%	50%

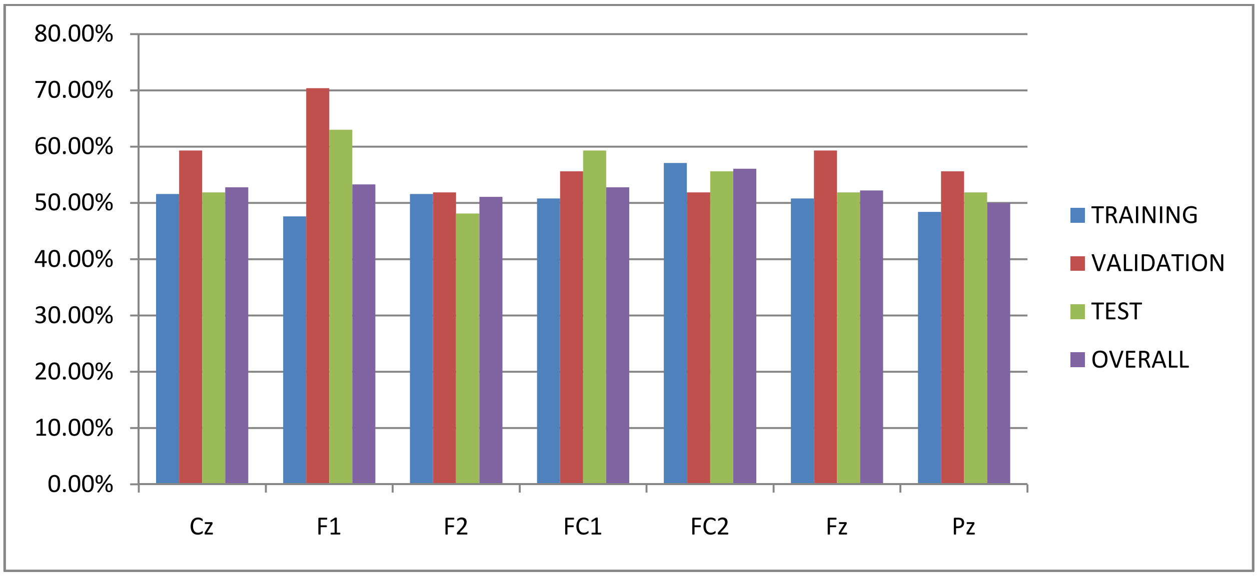

Figure 1.8 Graph of Accuracy of all Participants with Each Electrode

In final combination, took single ERP feature (P100, N100, P200, N200, P300) of all 3 participants with all 7 electrodes of all 3 sessions and then on classification and obtained the following results.

Table 1.7 Accuracy of One ERP Feature for all Participants

FEATURES	TRAINING	VALIDATION	TEST	OVERALL
P100	50.20%	56.10%	50.80%	51.20%
N100	51.50%	55%	50.80%	51.90%
P200	50.50%	51.90%	55.60%	51.40%
N200	48%	57.70%	54%	50.30%
P300	51%	57.10%	51.30%	52%

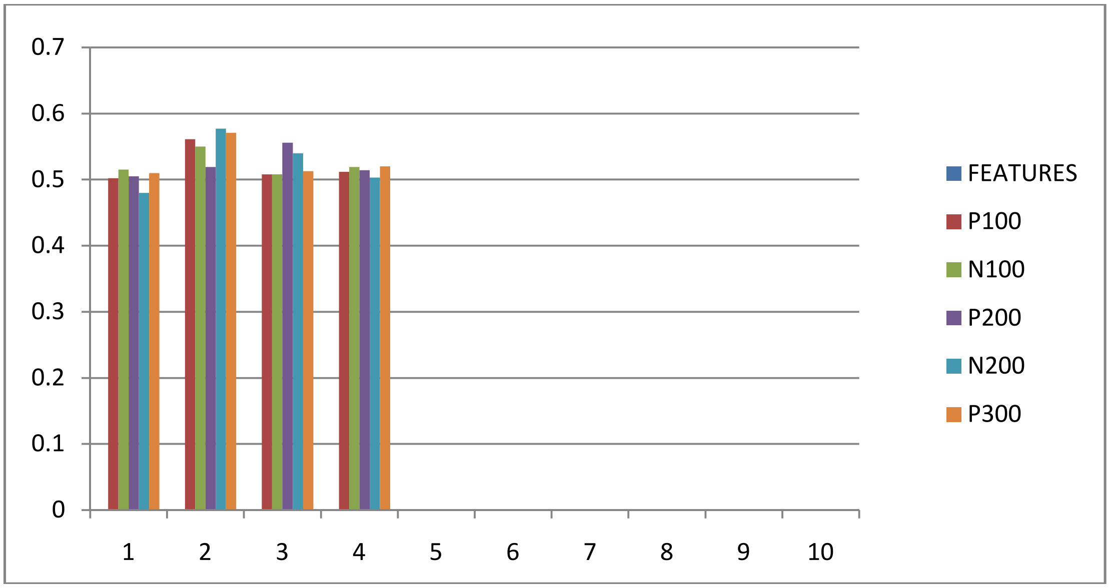

Figure 1.9 Accuracy Graph of One ERP Feature for all Participants

After ANN, feedforward neural network was trained. For this, feedforwardnet matlab tool was used for classification. In this 2 combinations were made to classify the features.

In first combination, fed entire data of each participant at a time to feedforwardnet tool and in second combination entire data of all 3 participants were considered. On classifying obtained the following results.

Table 1.8: Accuracy of Feedforward ANN Classifier

Participant	**Error**	**Accuracy**
Participant-3	29.78%	70.21%
Participant-4	34.04%	65.95%
Participant-5	27.66%	72.34%
Participant 3,4 & 5	23.40%	76.59%

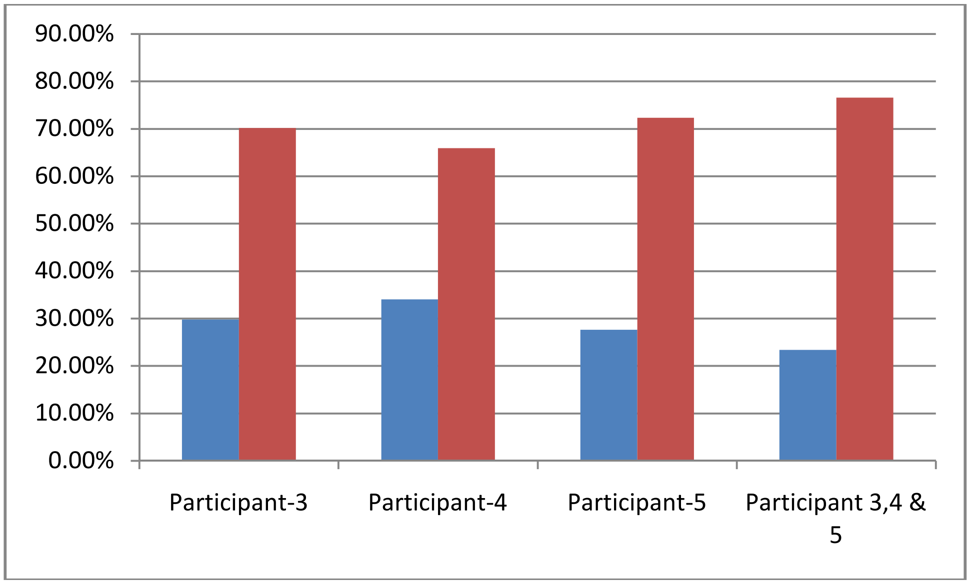

Figure 1.10 Accuracy Graph of Feedforward ANN Classifier

After feedforward neural network, multilayer 2-hidden neural network classifier was tried. For this classification nntool matlab tool was used. With the help of this, the data was analyzed in two combinations. First fed the data on single participant and then fed the combined data of all three participants together. Taking ERP features of EEG signals to classify the emotions in two classes Low Valence (negative) and High Valence (positive). The result obtained for these two combinations was **100%**.

Table 1.9: Accuracy of Multilayer 2-Hidden Layer Neural Network

Features	Accuracy
ERP of Participant 3	100%
ERP of Participant 4	100%
ERP of Participant 5	100%
ERP of Participants 3,4, and 5	100%

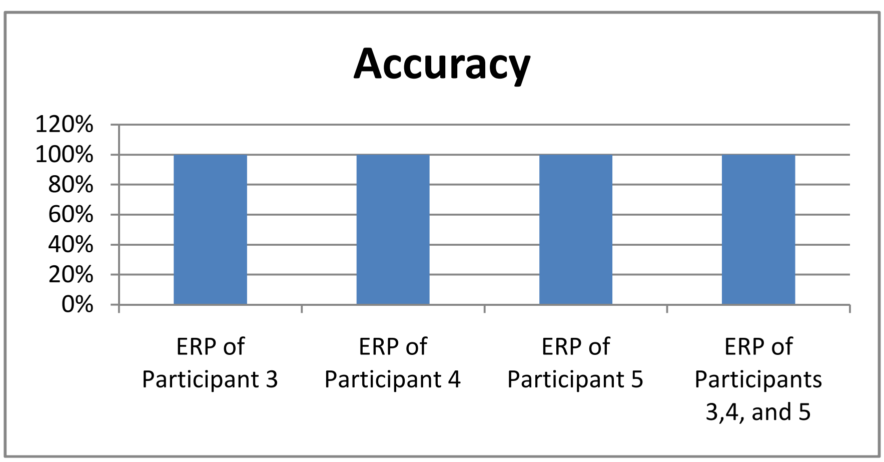

Figure 1.11 Accuracy Graph of Multilayer 2-Hidden Layer Neural Network.

CONCLUSION

In this study, classification of emotions using EEG signals was examined. The results obtained using the Naive Bayes classifier and single layer ANN for the different attributes were very low as compared to the two hidden layer classifier. The classification results obtained from the central electrodes were high as compared to the side electrodes. It can also be concluded that the classification results depend very much on the type of selected attributes, their combinations and the type of classifier used. The individual analyses of participants show that the emotions are a subjective affair. Since the results obtained for classification of emotion along the valence axis using Multilayer Neural Network (2 hidden layers) are 100%, it can be considered as a step forward in the direction of brain computer implementation. From above observed result it is concluded that multi layer neural network classifier gives best result among all other classifiers described in this paper.

REFRENCES

[1] Robert Horlings, "Emotion recognition using brain activity", Man-Machine Interaction Group TU Delft 27 March 2008.

[2] Rosalind W. Picard, Jennifer Healey "Toward Machine Emotional Intelligence: Analysis of Affective Physiological state", IEEE Transactions on Pattern Analysis and Machine Intelligence, 2001.

[3] Arman Savran, Koray Ciftci, "Emotion detection in the loop from brain signals and facial images", University of Geneva, 2006.

[4] M.M. Bradley and P.J. Lang, "Measuring Emotion: The Self-Assessment Manikin and the semantic differential," J. Behavior Therapy Experimental Psychiatry, vol. 25, no. 1, pp. 49-59, Mar. 1994.

[5] Bradley, M. M. & Lang, P. J., "The International Affective Picture System (IAPS) in the study of emotion and attention", Handbook of Emotion Elicitation and Assessment, Oxford University Press, 2007.

[6] Arnaud Delorme, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis", Journal of Neuroscience Methods 134, 2004.

[7] Russell, J. (1980). A circumplex model of affect. Journal of personality and social psychology, *39*(6), 1161-1178.

[8] Enterfacewebsite 06, http://www.enterface.net/

[9] Jaime F. Delgado Saa, "EEG signal classification using power spectral features and linear Discriminant Analysis: A brain computer interface application", Innovation and Development for the Americas, 2010.

[10]David Houcque, "Introduction to Matlab for engineering students", Northwestern University, 2005.

[11] Abdul-Bary Rouf Suleiman, Toka Abdul-Hameed Fatehi, " Feature extraction techniques of EEG signal for BCI applications", Faculty of Computer and Information Engineering Department College of Electronics Engineering, University of Mosul, Iraq, 2007.

[12] Omar AlZoubi, Rafael A. Calvo, "Classification of EEG for affect recognition: An adaptive approach", School of Electrical and Information Engineering,The University of Sydney, Australia, 2009.

[13] http://en.wikipedia.org/wiki/Event-related_potential.

[14] Glenn F. Wilson, Christopher A. Russell, "Real-time assessment of mental workload using psychophysiological measures and artificial neural networks", Human Factors, Vol.45, Winter 2003.

[15] C. M. Bishop, "Pattern recognition and machine learning", Springer, 2006.

[16] Daniel Svozil , "Introduction to multi-layer feed-forward neural networks" Chemometrics and Intelligent Laboratory Systems 39 (1997).

[17] Gaurang Panchal, "Behaviour analysis of multilayer perceptrons with multiple hidden neurons and hidden layers" International Journal of Computer Theory and Engineering, Vol. 3, No. 2, April 2011.

[18] Mandeep Singh, Mooninder Singh and Nikhil Singhal ―EMOTION RECOGNITION ALONG VALENCE AXIS USING NAÏVE BAYES CLASSIFIER , International Journal of Information Technology & Knowledge Management. Vol.7 no.1 Dec.2013 [in press].

[19] Mandeep Singh, Mooninder Singh and Nikhil Singhal ― ANN BASED EMOTION RECOGNITION ALONG VALENCE AXIS USING EEG, International Journal of Information Technology & Knowledge Management. Vol.7 no.1 Dec.2013 [in press].

[20] Mandeep Singh, Mooninder Singh and Surabhi Gangwar ―Emotion Detection Using Electroencephalography (EEG):A Review , International Journal of Information Technology & Knowledge Management. Vol.7 no.1 Dec.2013 [in press].

[21] Mandeep Singh, Mooninder Singh and Surabhi Gangwar, ―Feature Extraction from EEG for Emotion Classification, International Journal of Information Technology & Knowledge Management. Vol.7 no.1 Dec.2013[in press]

[22] Mandeep Singh, Mooninder Singh and Surabhi Gangwar ―Arousal Detection Using EEG Signal, International Journal of Information Technology & Knowledge Management. Vol.7 no.1 Dec.2013 [in press].

[23] Mandeep Singh, Mooninder Singh and Nikhil Singhal ―Emotion Recognition Along Valence Axis Using Naïve Bayes Classifier , International Journal of Information Technology & Knowledge Management. Vol.7 no.1 Dec.2013 [in press].

[24] Mandeep Singh, Mooninder Singh and Nikhil Singhal ― ANN Based Emotion Recognition Along Valence Axis Using EEG, International Journal of Information Technology & Knowledge Management. Vol.7 no.1 Dec.2013 [in press].