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EXTRACTING HUMAN EMOTIONS FROM EEG SIGNAL USING SVM IN FEED FORWARD NEURAL NETWORKS

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***Abstract*-The ability to recognize emotion is one of the hallmarks of emotion intelligence, an aspect of human intelligence that has been argued to be even more important than mathematical and verbal intelligence.EEG signal has a non stationary property and its frequency features also differ from individual to individual. The main objective of the proposed system is a six-layer biologically inspired feed forward neural network to discriminate human emotions from EEG.A total of six statistical features are computed from the EEG data and ANN (Artificial Neural Network) is applied for classification. The system is trained and tested with the statistical features from the psychological signal acquired under emotional stimulation experiments. The neural networks consist of a shift register memory after spectral filtering of the input layer. After the estimation of noise less signal, the correlation between all the pair of input signals are calculated from hidden layer. The arousal and valence level are used to discriminate the correct emotional output from the given EEG signal input. The accuracy of the proposed neural network is compared with various feature extracted methods and feed forward learning algorithm. High accuracy is achieved by using the proposed neural network with a type of support vector machine**

***Keywords*-Affective computing, arousal-valence plane, EEG-based emotion recognition, functional connectivity.**

I. INTRODUCTION

Emotion is a subjective, conscious experience characterized primarily by psycho physiological expressions, biological reactions, and mental states. Emotions are a complex state of feeling that results in physical and psychological changes that influence our behaviour. Emotions have been described as discrete and consistent responses to internal or external events which have a particular significance for the organism. Emotions are brief in duration and consist of a coordinated responses, which include verbal, physiological, behavioural, and neural mechanisms. Human bio signals are relatively more consistent across cultures and nations than face or voice features. Therefore, bio signal features produce more consistent results in estimating the emotion. The feed forward neural network is used to discriminate the emotions in the proposed method. Certain brain regions are associated in the processing of emotional stimuli.

The functional interactions between the brain regions can be explained using top–down or bottom–up approaches. Perception of emotional stimuli involves a deeper integration so that investigation of both top–down and bottom–up approaches are required. In the top– down approach, emotion is described as a product of a cognitive process that translates the emotional stimuli using appraisal theory. In the bottom–up approach, emotion is explained as a response to stimuli with intrinsic or learned properties and the reinforcement of them. The top–down approach is used for computationally mode. The bottom– up approach is also substituted with subject's feeling. The subject's feeling is based on his/her previous experiences and measured using Self-Assessment Manikin (SAM) questionnaire. Therefore, a biologically inspired model is developed considering both top–down and bottom–up approaches.

II . SYSTEM DESIGN AND MODULES

The proposed biologically inspired feed forward neural network is shown in Figure1. This neural network is construed to discriminate the emotions from EEG**.**The feed forward network consist of six layer for processing the input EEG data and the emotional values are extracted from the input EEG data. Emotional values are extracted depend upon the arousal levels and valence levels.The input is given from the training and testing data set to multichannel EEG.

Next four processes are done in the hidden layer. First apply the spatial filtering. Second layer is short term memory.

In third to extract the connectivity features. The feature ranking is used to select the features and given to the input of radial classification. Finally the output is evaluated using the output data and emotional status. The process of the emotional states discrimination in each layer of the proposed neural network is described below.

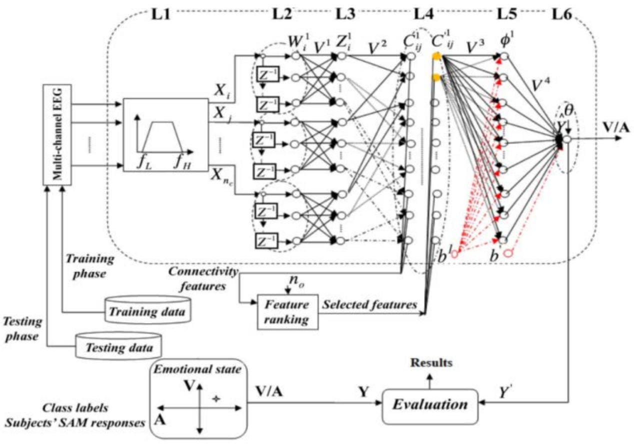

Figure:1 Six-layer feed forward neural network for EEG-based emotion recognition.

A. Functions of Each Layer :

The multichannel EEG data are the network input and the valence/arousal level is the output

1) First Layer- Spectral Filtering:In the first layer, spectral filtering is applied to the input signal to eliminate the noise from the input signal. The input signal is often contaminated by noises and artifacts such as AC(Alternative Current) power-line interference (50 Hz in Singapore), heartbeat, ocular, and muscular artifacts that are mainly located in lower frequencies .A spectral filtering is performed on the EEG using a band pass filter to extract the rhythmic activity using the following formula,

$$X_i^n = \sum_{k=0}^{n} \mathrm{H}_\mathrm{i}^\mathrm{n}\ \mathrm{E}_\mathrm{i}^{\mathrm{n-k}}$$

Where, $\mathrm{E}_\mathrm{i}^\mathrm{n}$ denotes the n^{th} sample of the i^{th} channel of the acquired EEG data, and X denotes the band pass filtered data.H denotes the transfer function of the filter.The output of the spectral filtering is given to the input of second layer.

2) Second Layer–A Short-Term Memory*:*It is the second layer of the proposed system. Emotion variations last for some time till the next emotional episode happens, and these variations are detectable using EEG. Typically, EEG data for a period of 1–4s is used to discriminate an emotional state because EEG is assumed to remain stationary during short intervals. In the proposed neural network, a serial-in/parallel-out shift register memory is used to accumulate the filtered EEG data for a period of 1 s using a rectangular window. The optimum length of EEG data is selected using a Particle Swarm Optimization (PSO). The spectral filtered EEG, X, is presented to a rectangular window f_w to produce W. The rectangular window function is calculated using the below formula

$$\mathrm{F_W(N)} \triangleq \begin{cases} 1, & \mathrm{S_{T} \le N \le N + S_T} \\ 0, & otHerwise \end{cases}$$

$$W_i^n = \mathrm{F_W(N)}\, X_i^n; \quad \forall_{\mathrm{N}} \in\ [\mathrm{S_{T,}}\ \mathrm{N + S_T}$$

Where W_i^n denotes the n^{th} sample of the $i^{\,th}$ hannel of windowed filtered EEG, and s_t is the start point of window, W is represented as input to the third layer.

3) Third and Fourth Layers—Connectivity Features:Cortical–sub cortical interactions and interaction between different brain regions play an important role in the perception of emotional stimulus.Therefore brain connectivity features would be very informative to investigate the relationship between emotion and cognition during the perception of emotional stimuli. In order to estimate the emotional stimuli the connectivity features are extracted from the brain region. Therefore the Magnitude Square Coherence Estimation (MSCE) is applied to compute the functional connectivity features between the brain regions.To compute the MSCE features, at third layer of the network, the windowed time series EEG data is transformed to frequency domain. The MSCE features are then computed in frequency domain with high resolution at the fourth layer.

The weight of each node is calculated using the below formula

$$V_{n_i,f_i}^1 = e^{\frac{-j2\pi n_i f_i}{N}}$$

Where,*J* denotes the imaginary unit, and *e*(.) is the exponential function. At fourth layer, the MSCE features are computed using the data transferred to frequency domain Z. The MSCE features are computed for all the pairs of EEG channels in all the frequencies. The transfer function of hidden nodes is fourth layer.The transfer function of f_i^{th} hidden node at third layer produces a response Z_i^{th} given as

$$z_i^f = \sum_{k=0}^{N} \mathrm{W_i^n}\, \mathrm{V^1_{n_{i,f_i}}}$$

Since the m^{th} hidden node at fourth layer computes the MSCE between the pairs of z_i^f and z_j^f , the transfer function for m^{th} hidden node at fourth layer $C'^{f}_{m} = C^{f}_{i,j}$ is computed using

$$C'^{f}_{m} = \frac{|z_i^{f*} z_j^f|^2}{(z_i^f z_i^f)(z_j^f z_j^{f*})}$$

where, z_i^{f*} denote the complex conjugate of the z_j^f.

Some of these extracted features (C'^{f}_{m}) have irrelevant or redundant negative effect on the accuracy of the classifier. The structure of neural network at the next layers is chosen based upon the number of features selected. Therefore, the network would be very computationally extensive in case of using the huge number of features. So in order to process the given network, significant number of features should be selected.

Several supervised and unsupervised methods can be applied. The Nonnegative Sparse Principal Component Analysis (NSPCA) is used to extract the significant features in unsupervised manner. NSPCA transforms the original features to a lower dimensional space. This transformation maximizes the variance of the transformed features using parts of the original coordinates and creates a sparse projection. Initially, the extracted features (C'^{f}_{m}) are centered by subtracting off the mean. The mean value is calculated during the feature extraction to obtain the needed data. By using the nonnegative principal components the centred features are calculated. Finally, significant number of feature n_{out} are selected. The n_{out} is a constant number and it is one of the network parameters that is selected using an optimization method. These selected features are the input of fifth layer and computed using the formula

$$c^{f}_{m} = I^f C'^{f}_{m} | I^f \neq 0$$

The most significant features are classified using a two layer Radial Basis Function (RBF) type learning algorithm.

4) Fifth and Sixth Layers—The Classification Stage:After choosing the most significant connectivity patterns between the brain regions, these patterns are correlated to emotional states in a feed forward manner at fifth and sixth layers. The SVM network is presented in a two-layer structure. The activated output from hidden nodes at fourth layer (C^{f}_{m}) is given to the input layer of this classifier. Each hidden unit at fifth layer implements a radial activated function. At the sixth layer, the output unit implements a hard limit function on the weighted sum of fifth layer's hidden units. The transfer functions of hidden nodes at fifth layer are calculated using the formula,

$$\emptyset(v^3_m, c, b'_m) = g_1(b^1_m \|c - v^3_m\|)$$

Where the c denotes the selected features and b^1_m denote the bias of m^{th} hidden node at fifth layer,

$$b'_m = \frac{\sqrt{In(2)}}{\sigma}$$

$g1(.)$ is also defined as

$$g_1(X) = e^{-X^T X}$$

where, σ denotes the spread of RBFs,and $ln(.)$ is a natural logarithm function ,$e(.)$ denotes the exponential function.The output unit function at the sixth layer is also calculated using the formula

$$\hat{Y} = \left(\sum_{m=0}^{<n_h} V^4_m \emptyset\,(V^3_m, c, b'_m) + b' \right.$$

Where, $\hat{Y}$denotes the estimated classes labels and b denotes the bias of output unit.

In addition, the output of our binary classifier $\hat{Y}$ is assigned to its class label using a hard threshold (step function) using

$$Y' = g_2(\hat{Y}, \emptyset) = \begin{cases} 1, & \hat{Y} \le \theta \\ 0, & \hat{Y} \ge \theta \end{cases}$$

Where,θ is calculated from training data using the formula

$$f(x) = \begin{cases} u_1 = & max(\hat{Y}) \\ u_2 = & max(\hat{Y}) \end{cases} \rightarrow \theta = \frac{u_1 + u_2}{2}$$

The procedure is started by computing the errors associated with input vectors using the formula

$$e = \frac{((p' * Y)'.)^2}{((\sum Y.*Y)' * (\sum P.*P)')}$$

Where

$$P = \varphi(C', C, b^1_m)$$

The actual error of network is calculated using mean-square-normalized error. The actual error of network is then compared with defined goal; if the goal been reached, another node is added. This process is continued until the sum squared of actual error falls below the defined goal error or the number of hidden layer nodes at the fifth layer reaches to maximum defined number n_h.

III RELATED WORK

B. Learning process

In our general definition a feed-forward neural network is a computational graph whose nodes are computing units and whose directed edges transmit numerical information from node to node. Each computing unit is capable of evaluating a single primitive function of its input. In fact the network represents a chain of function

compositions which transform an input to an output vector (called a pattern). The network is a particular implementation of a composite function from input to output space, which we call the network function. The learning problem consists of finding the optimal combination of weights so that the network function approximates a given function f as closely as possible.
The learning process consists of three stages which is show in figure

- Computing the parameters of neural network in first, second, third, and fourth layers in an unsupervised manner (computing the MSCE features).
- Selecting of active hidden nodes in fourth layer using an unsupervised method (NSPCA).
- Computing the network parameters for fifth and sixth layers in a supervised manner (classification of labelled data).
  In testing phase, stages 1 and 2 are repeated. The selected features are then classified using parameters calculated in learning phase. This network is, however, sensitive to value of σ and n_h

The radial basis networks even when designed efficiently tend to have many times more neurons than other comparable feed forward networks in the hidden layer.These parameters should be tuned properly to lead a high level of accuracy. Otherwise, network can converge to an optimum accuracy rates by applying a proper value for σ and large enough value for n_h. The network accuracy using all the mentioned methods is shown in Table 1. The results confirm that the SVM network works better than other possible networks.

The SVM network is fast and can be directly implemented in the network. Therefore, other feed forward learning methods are also applied, such as Extreme Learning Machine (ELM), General Regression Neural Network (GRNN), *K*-Nearest Neighbor (KNN) method, Naive Bayesian (NB) .

Table.1 Classification of accuracy for EEG-based arousal and valence recognition

Classification methods	CLASSIFICATION ACCURACY		PARAMETER
	AROUSAL	VALANCE	
FFNN	70.83	71.43	$n_h = 2n_a$ or $2n_v$ $\sigma = 3.83$, $n_{out} = 12$
MSCE-KNN	62.53	62.86	$n_{k=5}$
MSCE-ELM(sig)	65.22	65.71	Noise at 5^{th} layer = 10%
MSCE-SVM	66.67	68.51	Kernel rbf,$\sigma = 6$
MSCE-GRNN	56.52	57.14	$n_0 = 0.8$
MSCE –NB	65.22	68.57	_
HJ[66]-KNN	45.83	48.57	$n_0 = 24$, $n_k = n_0$
HJ-ELM(sig)	54.17	51.43	_
HJ-SVM	47.83	54.29	Noise at 5^{th} = 10%
HJ-GRNN	45.83	54.29	Kernel rbf,$\sigma = 6$
HJ-NB	47.83	51.43	$\sigma = 0.8$

The accuracy of network is also compared with higher order crossing and discrete wavelet transform , which are the two existing feature extraction methods for emotion recognition from EEG.The accuracy of the feed forward network is compare with different types of learning algorithms. Comparing to all other learning algorithm the feed forward algorithm has high accuracy, the noise in the signal is reduced, processing time is less, the result produced by the network is high, and also the performance of neural network is good compared with other method.

C. *Emotional states*

Emotion theories and researches have suggested a number of basic emotions. Basic emotions are defined as the emotions that are common across the cultures and selected by nature because of their high survival factors. The most commonly accepted basic emotions include: happy, sad, fear, anger, surprise, disgust, and complex emotions such as shame and disappointment are a combination of these basic emotions . Emotions can also be measured by two axes of valence and arousal plane. Valence measures unpleasant to pleasant, and arousal measures calm to excited levels. Basic emotions can then be mapped onto the valence–arousal space.Different human may feel may feel differently when they are exposed to similar emotional stimuli. Therefore, the emotional responses of human have to be ascertained using questionnaires. The above task is performed using the SAM (Self-Assessment Manikin) in proposed method. The SAM is a nonverbal pictorial assessment technique that directly measures the valence, arousal, and dominance levels associated with a person's affective reaction to a wide variety of stimuli. The proposed neural network is applied to discriminate the changes of the cognitive process in response to emotional stimuli.These changes in human emotions are interpreted from the changes in EEG and mapped to subjects' SAM responses in terms of valence and arousal..Emotions collected during emotional stimulus using EEG signal is processed using feed forward neural network. The SAM response is also provided in order to get the pictorial response. Emotions collected during emotional stimulus using EEG signal is processed using feed forward neural network. The SAM response is also provided in order to get the pictorial response. The arousal and valence levels are discriminated simultaneously using a parallel structure.The EEG data is provided to feed forward network to discriminate the emotion. The feed forward network estimate the emotion depends on the valance and arousal level. The SAM response is used to provide the emotion in non verbal representation.

D. Experimental Protocol

The duration of emotion elicited can be categorized into three categories: full blown emotions that last from seconds to minutes, moods that last from minutes to hours, and emotional disorders that last for years or an entire lifetime. An emotion recognition system should be able to discriminate the emotional states from the EEG as fast as possible. Full blown emotions whereby the emotional stimuli are presented for 1 min in a counterbalanced and random order is proposed here. The data are collected with subjects seated in a comfortable chair in a registration room whereby the experimental procedure is explained to them. The subjects are then asked to fill in a handedness questionnaire. The EEG is recorded using the BIMEC from Brain marker(BV). The BIMEC has one reference channel plus eight EEG channels with a sampling rate of 250 Hz. The impedance of the Ag/AgCl electrodes is kept <10 k. Considering the cerebral lateralization during emotional perception , the eight Ag/AgCl electrodes are attached bilaterally on the subjects' scalps using the 10/20 system of electrode placement where the $C_z$is the reference channel . EEG data are collected for a 6-min period that comprised arousal and valence levels. The visual stimuli are displayed on a 19-inch monitor positioned 1 m far from the participant's eyes and the audio stimuli are played by the speakers with a constant output power. The categories of emotional stimuli are presented randomly such that each stimulus category is observed one time for every subject.

E. Subjects

EEG data were collected from 57 healthy patients (age: 17–33, nine women and 48 men). The valence and arousal levels measured from SAM questionnaire are used for labeling the EEG data. The valence and arousal levels provide a dynamic representation of the emotional states. The valence–arousal plane provides a dynamic representation of the emotional states. The valence and arousal levels are evaluated separately. The boundaries between different classes are determined from the subjects' answers to the SAM questionnaire. Negative emotions are labeled when Valence $\leq$ 3 and positive emotions are labeled when Valence $\geq$ 7. Calm emotions are labeled when Arousal $\leq$ 3 and excited emotions are labeled when Arousal $\geq$ 7.

IV SIMULATION RESULTS

The biologically inspired feed forward neural networks consist of two main processes to extract the human emotion. In the proposed method the emotional states are recognized based on the valence and arousal levels. The negative and positive states from valence dimension calm and highly exited states from arousal dimension are investigated in classes' labels. The collected EEG signals are then labeled with SAM responses. The two main processes are,

- Training
- Testing

A. Training

The training process is done with known input signal to train the system in order to extract the human emotion when an unknown signal is provided to the system. The EEG signals are acquired during watching audio–visual stimuli through an explained paradigm. The subjects' emotional states are scored using SAM questionnaire. A single-trial EEG data of 1 s is used to test the proposed neural network and classification accuracy of the network for valence/arousal level identification is computed. The input is taken from DEAP (Database For Emotion Analysis using EEG, Physicological signal)data base and process using MATLAB tools. In the proposed method the input is taken from 57 healthy patients to estimate and analyses the human emotion. The input signal is collected from different brain region and from different location. In order to collect the EEG signal from the brain, electrodes are placed along the scalp The input of neural network is the normalized EEG data in range (0–1)s. After extracting the input the next step is to remove the noise from the input signal.

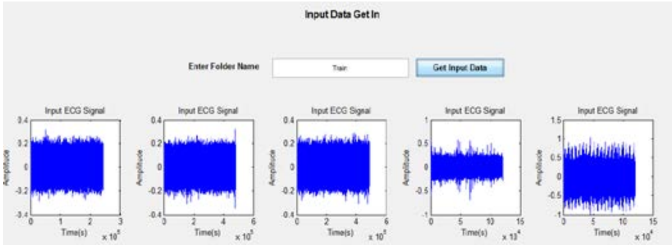

Fig:2 Input signal for training

The input EEG signal is spectral filtered inorder to eliminate the noise from the input signal.

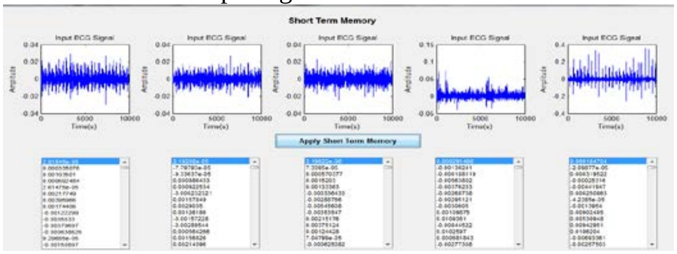

Figure:3 Output of short term memory and spectral filtering

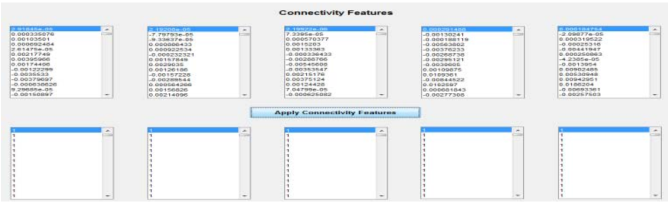

Figure: 4 Connectivity features

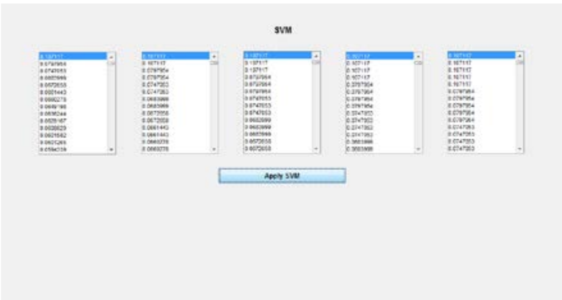

Figure :5 Output wave form of emotions in training process and some selective feature.

After eliminating the noise from the input signal the connectivity features and the emotional features are extracted inorder to express the required emotion.The obtain emotion is then compared with various aurosal and valance level.

B. Testing

The steps involve in the testing process is similar to the training process. At the output of the feed forward network the exact emotion of given input is produced as the output. Also the performance of the feed forward network is improved. After the training phase is completed, the given system is tested using the unknown EEG signal. From this signal the emotion are estimated. First the input signal is spectral filtered in order to remove the noise and other DC components. Similar to the training phase the connectivity features and the short term memory values are estimated. Here also the correlation between different pair of input signal is calculated. After calculating the values for the connectivity feature, the next process is estimating the correct feature using feature ranking method.

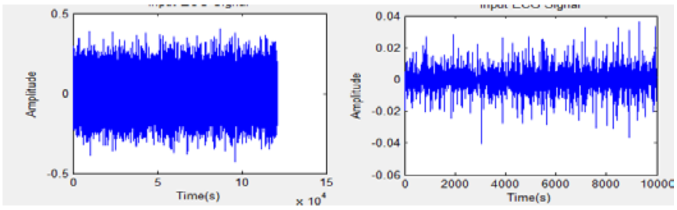

Figure : 6 Input signal and Spectral filtered signal

The unknown signal is taken for testing,where the noise is eliminated using spectral filtering.

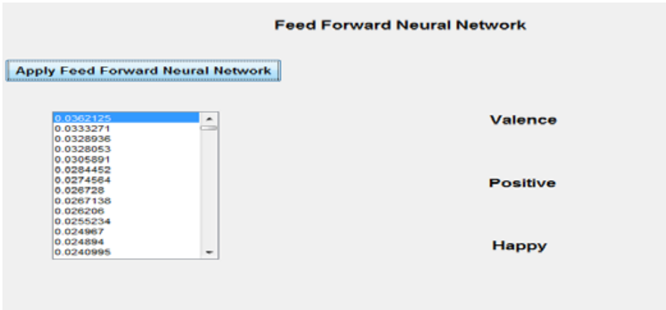

Figure:7 Output from feed forward neural network

After the elimination of the noise the connectivity feature and the required emotion values are extracted in order produce the required emotional value

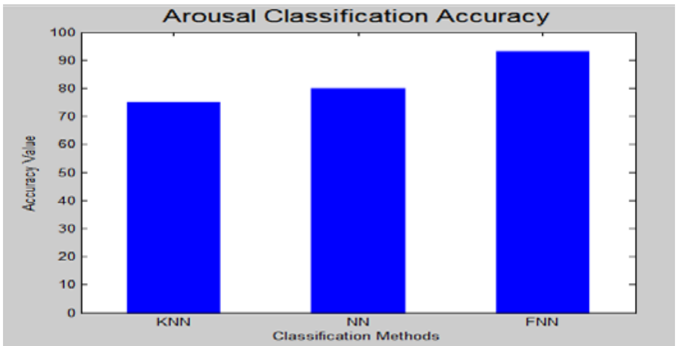

Figure:8 Performance depend on arousal level

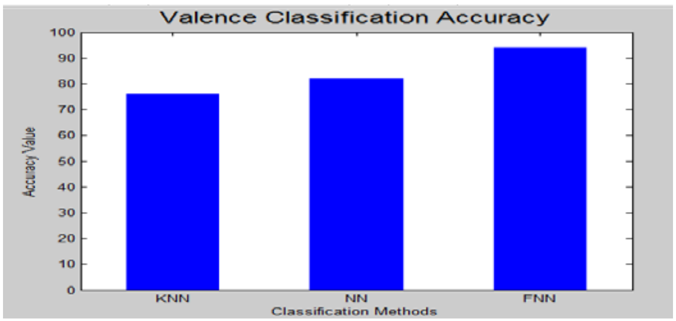

Figure: 9 performance depend on valence level

The above two figure indicate the comparison result of feed forward network with different network technologies.

V CONCLUSION

The proposed system presents a biological inspired feed forward neural network to discriminate the emotion from EEG based on valence and arousal levels. The EEG data from the perception of emotional stimuli in healthy participants are collected. The top-down approach is formulated and bottom-up approach is bypassed using SAM answers. Also the performance of the proposed neural network for discriminating emotions is evaluated using the EEG data and SAM responses. The results show that there are patterns of brain regions connectivity in the perception of individual emotional stimuli. These patterns are detectable by estimating the connectivity between different brain regions from the EEG data. Nevertheless, the feed forward architecture is presented by considering a constant level of attention, mood, and mental health for all the subjects. Therefore, further assessment for understanding the impact of attention level, moods, and mental disorders on the perception of emotional stimuli should be done. The arousal and valance level are used to discriminate the level of emotion (either positive or negative).High accuracy is obtained by using feed forward algorithm. The accuracy of feed forward network is compared with many feature extraction method.

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