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SVM in feed forward neural networks for emotion extraction from EEG data.

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Abstract

Emotion perception is a key component of emotion intelligence, a kind of human intelligence that has been argued to be more important than IQ in certain contexts.EEG signals are not static, and their frequency content and distribution will look different for each individual. In order to train a biologically-inspired, six-layer feed forward neural network, the proposed system relies on an EEG-based emotion categorization system.Six statistical features are computed from the EEG data, and then the information is fed into an ANN (Artificial Neural Network) for classification. The system is trained and evaluated using the statistical features of the psychological signal gleaned through experiments on emotional stimulation. The neural networks use a shift register memory after spectral filtering of the input layer. The hidden layer removes noise from the estimated signal before calculating the correlation between each pair of input signals. The arousal and valence levels of an EEG signal are used to generate an appropriate emotional response. Several methods of feature extraction and feed forward learning techniques are compared to the accuracy of the recommended neural network. When the recommended neural network is used in conjunction with a certain kind of support vector machine, remarkable improvements may be seen.

Keywords (K): 2-9 Keywords: functional connection, affective computing, electroencephalogram (EEG) emotion identification, and the arousal-valence plane.

I. INTRODUCTION

Emotions are characterized by the psychophysiological manifestations and biological reactions that accompany them, yet they are experienced consciously and subjectively by the individual. Emotions are complex mental and physical states with a wide range of effects. Emotions are thought to be individual and consistent responses to stimuli that have significance for the organism, whether those stimuli originate from inside or without.Momentary experiences of emotion set off a cascade of coordinated responses in the nervous system, the body, and the mind. Biosignals emanating from the human body are more universal than, say, a person's voice or appearance. This means that estimations of mood based on biosignal qualities may be trusted to be more accurate. The proposed method classifies emotional states using a feed forward neural network. Multiple brain regions collaborate on the task of interpreting emotional information.

The functional connections between brain regions may be explained in a number of different ways, including using both top-down and bottom-up approaches. Because of the complexity involved in processing emotional stimuli, research into both top-down and bottom-up approaches is required. The top-down approach analyses emotional inputs via the lens of an internal evaluation theory, which is then used to provide an explanation for the experience of emotion. In the bottom-up view, emotion is regarded as a confirmation of a stimulus's already existent inherent or learned features. The top-down methodology is used for the computational mode. Bottom-up approaches are represented by the individual's feelings. The subject's emotional state is evaluated using the respondent's life experiences in the Self-Assessment Manikin (SAM) questionnaire. In order to build a model that is true to biology, we consider both top-down and bottom-up approaches.

Subsequent Section: Components and Design

Figure1 shows how the proposed feed forward neural network draws inspiration from natural processes. This neural network is trained to recognize emotions by analyzing unique brainwave patterns.A feed forward network with six processing layers is used to extract emotional values from the input EEG data. The value of an emotion is determined by its arousal and valence levels.Training and validation data sets are used as inputs for multichannel EEG.

The last four stages are entirely performed below ground. Get started with the spatial filtering right now. In the second tier, working memory is used.

Third, we need to tease out the network's quirks. The ranking of features is used to choose features to include in the radial classification input. Finally, output is evaluated based on facts gathered about the recipient's emotional state and actions. The steps used by each layer of the proposed neural network to make this distinction between moods are described in detail below.

Since it is hypothesized that EEG would be steady between 1 and 4 seconds, this window might be used to differentiate between various emotional states. The proposed neural network employs a serial-in-parallel-out shift register memory with a rectangular window to store the filtered EEG data for 1 s. The best time to collect EEG data is calculated using particle swarm optimization (PSO). When the filtered electroencephalogram (EEG), X, is passed through a rectangular window (fRwR), W is the output. Obtaining the rectangular window function may be done with the use of the following formula.

JOURNAL OF CURRENT SCIENCE

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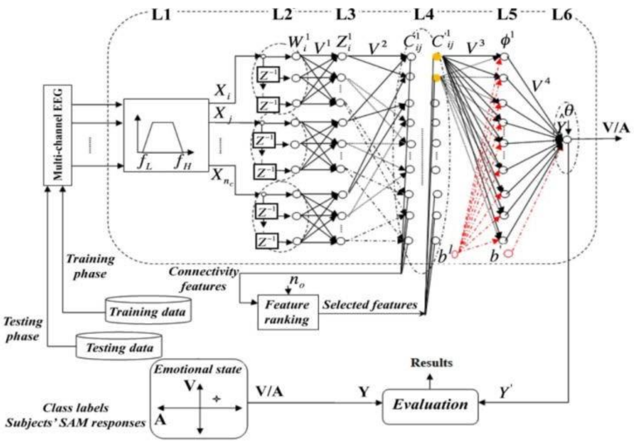

$\leq N + S_T$

$rwise$ $\qquad F_W(N) \triangleq$ �

$\forall_N \in [S_{T,} N + S_T$ $\quad i \quad i$

Where $W^n{}_i$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.

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 thevalence/arousal level is the output

1) In the first layer, spectral filtering is used to clean up the input signal by removing unwanted frequencies. Various sounds and abnormalities, often at lower frequencies, may contaminate the input signal. These include AC(Alternating Current) power-line interference (50 Hz in Singapore), cardiac, ocular, and muscle artifacts.The formula below describes how rhythmic activity is extracted from an EEG by spectral filtering using a band pass filter.3) Intermediate and Advanced LevelsConnectivity Characteristics:Interactions between various brain areas and between the cortex and the subcortex play a significant role in the interpretation of emotional stimuli.To that end, aspects of brain connection during the perception of emotional stimuli would be very illuminating. Extraction of connection information from a brain area allows for estimation of emotional stimuli. So as to calculate the functional connectivity properties between brain areas, the Magnitude Square Coherence Estimation (MSCE) is used.At the third layer of the network, the frequency domain is translated from the windowed time series EEG data used to calculate the MSCE features. At the fourth layer, the MSCE characteristics are calculated in frequency domain at a high resolution.

The formula below is used to determine the weight of each node.

$$\frac{1}{n_i, f_i} \qquad \frac{-j2\pi n_i f_i}{N} \qquad V \quad = e$$

$$n$$

$$X_i^n = \text{�}\ \mathrm{H}_i^n\ \mathrm{E}_i^{n-k}$$

$$k=0$$

Where, E_i^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 layerof 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 ofWhere,*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

JOURNAL OF CURRENT SCIENCE

ISSN NO: 9726-001X
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transfer function of hiddennodes is fourth layer.The transfer function of f^{th} hidden node at third layer produces a response Z^{th}_i given as

f N n 1
i $k=0$ i n_{i,F_i} z =� W V

Since the m^{th} hidden node at fourth layer computes the MSCE between the pairs of z^f_i and z^f_j, the transfer function

m m
using

here the c denotes the selected features and b^1_m denote the

$|z_i^{f*} z_j^f|^2 C$ =bias of m^{th} hidden node at fifth layer, $z^f z^f (z^f z^{f*}) f$ b' = $\frac{\sqrt{ln(2)}}{\sigma}$

where, z^f_i denote the complex conjugate of the z_j .m

Some of these extracted features (C'^f_m) have irrelevant orredundant negative effect on the accuracy of the classifier.$g1(.)$ is also defined as

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

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 inunsupervised manner. NSPCA transforms the original featuresto 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,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

$$\hat{Y}=(\sum_{m=0}^{nh} V^4_m \emptyset (V^3_m, c_m, b'_m)+ b'$$

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

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

Where,θ is calculated from training data using the formula

the extracted features (C'^f_m) are centered by subtracting off the $f(x) =$ � $u_1= max(\hat{Y})$ $\rightarrow$ $\theta = \frac{u_1+u_2}{2}$

mean. The mean value is calculated during the feature extraction to obtain the needed data. By using the nonnegativeprincipal components the centred features are calculated. Finally, significant number of feature n_{out} are selected.$u_2 = max(\hat{Y})$

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

The n_{out} is a constant number and it is one of the network F_F 2

parameters that is selected using an optimization method. These selected features are the input of fifth layer and computed using the formula

Where p *F .

e = $(\sum F.*F)^F*(\sum P.*P)^F$

m

ISSN NO: 9726-001X
Volume 08 Issue3 July2020

$$c_m^f = I^f C'^f_m | I^f \neq 0$$

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

4) The Layer 5 and 6 Classification Phase:Emotional states are connected with the selected patterns of connection between brain areas in a feed forward fashion at the fifth and sixth levels. The SVM network is shown as a two-tiered hierarchy. The input layer of this classifier receives the active output from the hidden nodes at the fourth layer (C f). At the fifth layer, each covert unit operates by a radially actuated mechanism. The output unit at the sixth layer applies a hard limit function to the weighted sum of the hidden units at the fifth layer. P=(C,,C, b1) is the formula used to determine the transfer functions of unseen nodes in the fifth layer.
Mean-square-normalized error is used to determine the true network error. When the network's actual error is compared to the predetermined target, new nodes are added only if the target has been achieved. This procedure is repeated until either the sum squared of actual error is less than the stated target error, or the number of hidden nodes in the fifth layer has reached the maximum defined value, nh.

III RELATED WORK

B. Learning process

According to our broad definition, a feed-forward neural network is a computational graph in which the nodes represent computing units and the directed edges carry numerical data from one node to the next. Each processor can only perform a single basic function evaluation on the data it receives. In reality, the network is a series of function compositions that take an input vector and produce a new vector, or pattern, as the output. In this context, "network function" refers to a specific realization of a composite function mapping input space to output space. Finding the best set of weights to make the network function closely match a target function f is the learning issue.
The three phases of the learning process are shown in Figure 1.

Computing the MSCE features (parameters of the first, second, third, and fourth layers of the neural network) in an unsupervised fashion.

• Using an unsupervised technique (NSPCA) to pick up dynamic hidden nodes in the fourth layer.

Supervised (data labeling) parameter computation for the fifth and sixth layers of a network.

The first two steps are repeated in the testing phase. The parameters determined during the learning phase are then used to categorize the chosen characteristics. This network, however, is very dependent on the parameters and variables.

			$n_{out} = 12$
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	_

ISSN NO: 9726-001X
Volume 08 Issue3 July2020

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

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 andvalence recognition

Classification methods	CLASSIFICATION ACCURACY		PARAMETER
	AROUSAL	VALANCE	
FFNN	70.83	71.43	$n_h = 2n_a$ or $2n_v$ $\sigma = 3.83,$

C. Emotional states

Numerous studies and perspectives on emotions have identified a core set of feelings. The term "basic emotions" refers to the range of feelings shared by people of different cultural backgrounds and that have been favored by natural selection. Happiness, sadness, fear, anger, surprise, and disgust are generally recognized as the fundamental emotions, although complex emotions like shame and disappointment are combinations of these. The valence and arousal axes provide another way to quantify emotional states. Both valence and arousal are scales that may be used to quantify emotional states. Then, the valence-arousal space may be used to plot the basic emotions.It's possible that various people's emotional responses to the same stimulus will vary. As a result, we need to use surveys to learn about people's feelings. The SAM (Self-Assessment Manikin) is used to carry out the aforementioned action in the suggested procedure. The SAM is a visual, nonverbal test that provides precise data on

degrees of valence, arousal, and dominance related with an individual's emotional response to various stimuli. The suggested neural network is used to identify whether there has been a shift in thought as a result of emotional arousal.Emotional states are deduced from EEG variations by correlating them with participants' SAM reactions, which are then analyzed for their valence and arousal levels.A feed forward neural network is used to analyze the EEG data gathered from an emotional input. For the graphic answer, we also provide the SAM response. A feed forward neural network is used to analyze the EEG data gathered from an emotional input. For the graphic answer, we also provide the SAM response. Using a parallel framework, we can separate apart the varying degrees of arousal and valence at the same time.In order to detect emotions from EEG data, a feed forward network is used. The valence and arousal level are used by the feed forward network to evaluate the emotion. SAM is utilized to convey a nonverbal depiction of the emotion.

Protocol for Experimental Design

There are three types of emotions based on their duration: fleeting feelings that fade after a few seconds, moods that linger for a few minutes, and emotional illnesses that may last a lifetime. An ideal emotion detection system would quickly and accurately differentiate between different EEG-based emotional states. Here, we recommend going all the way to intense feelings by presenting emotional inputs in a counterbalanced and unpredictable sequence for a whole minute. Subjects sit in comfy chairs in a

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Volume 08 Issue3 July2020

registration area where they are given a rundown of the experiment before data collection begins. After that, a handedness survey is given to the participants. Brain marker(BV)'s BIMEC is used to capture EEG data. One reference channel and seven EEG channels at 250 Hz are available on the BIMEC. Ag/AgCl electrodes maintain a constant impedance by

<10 k. Using the 10/20 electrode placement technique with the Czis as the reference channel, we inserted eight Ag/AgCl electrodes bilaterally on the participants' scalps to account for brain lateralization during emotional perception. Over the course of 6 minutes, subjects' arousal and valence levels are recorded by EEG. The music is broadcast via the speakers at a constant output level, while the visual stimuli are projected on a 19-inch monitor placed 1 m from the participant's eyes. Emotional stimuli are provided in categories, and each participant will experience each category once.

Topics (E)

Fifty-seven healthy individuals (aged 17–33, 9 females, 48 males) had their EEGs recorded. The SAM questionnaire's measures of valence and arousal are utilized to assign labels to the EEG data. Emotional states may be dynamically represented by valence and arousal levels. The emotional states are dynamically represented on the valence- arousal plane. Separate assessments of valence and arousal are made. Subjects' responses to the SAM questionnaire are used to draw dividing lines between demographic groups. When Valence is below 3, we name the feeling as negative, and when it is over 7, we describe it as positive. When Arousal 3, we call a state of calm, and when Arousal 7, we label a state of excitement.

The Simulation Outcomes

There are two primary steps involved in the biologically inspired feed forward neural networks' ability to extract human emotion. The suggested technique uses valence and arousal levels to identify emotional states. Class labels are studied to learn more about negative and positive valence states as well as calm and highly exited arousal states. EEG data are recorded and SAM responses are assigned labels. There are two primary procedures:

• Instruction

• Evaluation

A. Instruction

To enable the system to extract human emotion from an unknown signal, it is first trained using a known input signal. The EEG data are collected while the subject watches a described paradigm of audio-visual stimuli. The SAM questionnaire is used to quantify the individuals' emotional states. The proposed neural network is evaluated using 1 second long EEG trials, and the network's classification accuracy for identifying valence/arousal levels is calculated. The data is read from DEAP (Database for Emotion Analysis using Electroencephalographic and Physiological Signals) and processed with MATLAB. The data used to quantify and analyze human emotion in the proposed technique comes from 57 healthy patients. Various regions and locations in the brain provide the input signal. Electrodes are implanted on the scalp to pick up the brain's electrical activity (EEG). Normalized EEG data in the range of (0, 1s) is the input to the neural network. The following stage, once the input has been extracted, is to clean up the signal.

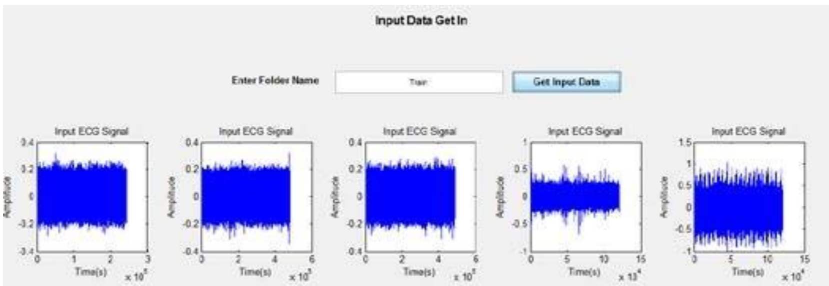

Fig:2 Input signal for training

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

ISSN NO: 9726-001X
Volume 08 Issue3 July2020
JOURNAL OF CURRENT SCIENCE

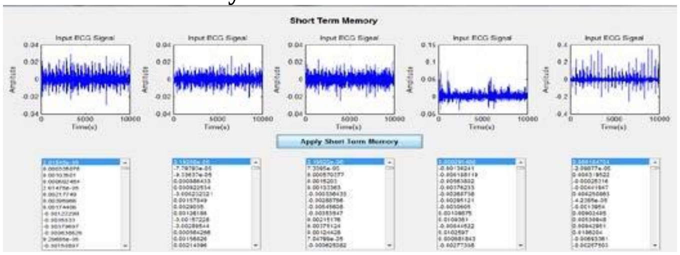

Figure:3 Output of short term memory and spectral filtering

Figure: 4 Connectivity features

Figure:5 Emotional learning's output waveform and a few specific features.

In order to communicate the necessary sentiment, connection characteristics and emotional features are extracted from the input signal after the noise has been removed.We then evaluate the obtained feeling on a spectrum of arousal and valence.

A. Trying Out

The testing procedure is quite similar to the training procedure in terms of the processes involved. In a feed forward network, the output corresponds exactly to the input emotion. The feed forward network's efficiency is boosted as well. After the system has been trained, it will be put through its paces using a fake EEG signal. The emotions may be inferred from this signal. The DC components and noise are first removed from the input signal via spectral filtering. The short-term memory values and connection properties are calculated in a manner similar to the training phase. Similar to the previous case, we now compute the correlation between each pair of input signals. Next, the proper feature is estimated using the feature ranking approach, based on the values calculated for the connection feature.

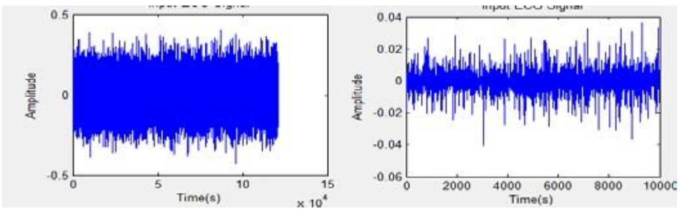

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Figure : 6 Input signal and Spectral filtered signal

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

ISSN NO: 9726-001X
Volume 08 Issue3 July2020

JOURNAL OF CURRENT SCIENCE

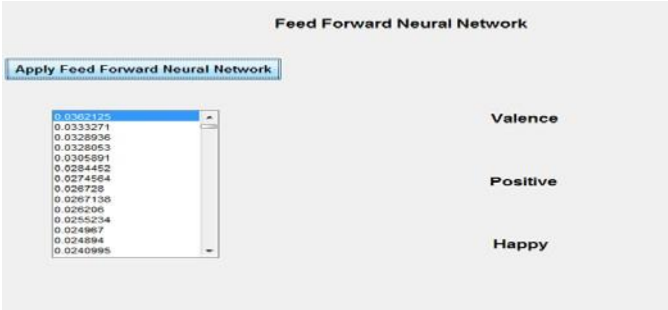

Figure:7 Output from feed forward neural network

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

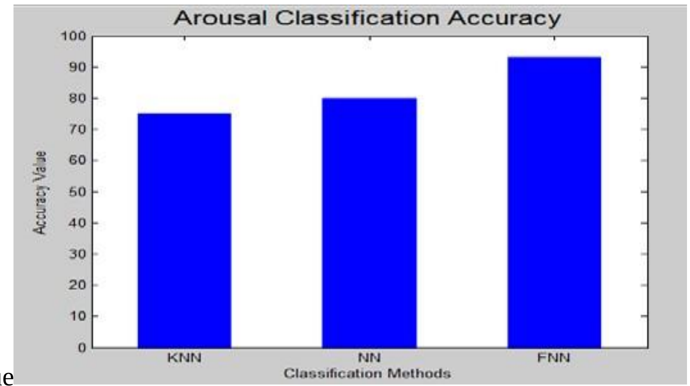

Figure:8 Performance depend on arousal level

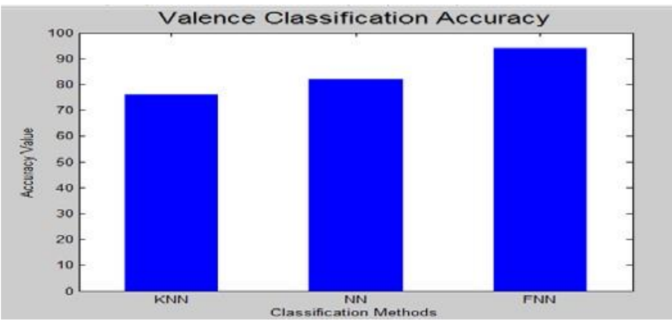

Figure: 9 performance depend on valence level

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

V CONCLUSION

To separate feelings of happiness or sadness from other EEG readings, the suggested approach uses a feed forward neural network inspired by biology. Emotional stimuli are shown to healthy subjects, and their brain waves in response to those stimuli are recorded. Using SAM replies, a top-down strategy is developed, skipping the bottom-up strategy altogether. Additionally, the EEG data and SAM responses are used to assess the effectiveness of the proposed neural network for emotion discrimination. These findings demonstrate that the way in which different brain areas communicate during the processing of emotional inputs follows predictable patterns. Estimating the connection between various brain areas using EEG data allows for the detection of such patterns. All participants are assumed to have a stable attention, mood, and mental health state while the feed forward architecture is presented. Accordingly, further testing is required to comprehend the effect of attention, mood, and mental illnesses on the interpretation of emotional inputs. You can tell if someone is feeling happy or sad by their arousal and valence levels.The feed forward method achieves excellent precision. Many different feature extraction methods are compared to the accuracy of a feed forward network.

ISSN NO: 9726-001X
Volume 08 Issue3 July2020

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