International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com ǁ PP.05-12

An Algorithm to Detect Emotion States and Stress Levels Using EEG Signals

Thejaswini S[1], Dr. K M Ravi Kumar[2], Abijith Vijayendra[1], Rupali Shyam[1], Preethi D Anchan[1], Ekanth Gowda[1]
[1] *Department of Telecommunication Engineering,*
B M S Institute of Technology and Management, Bengaluru, India
[2] *S J C Institute of Technology, Chickballapur, India*

Abstract: Emotions are an essential part of the human mental and physical state. Hence it is vital to understand it especially in the case of individuals who cannot express it verbally. Similarly prolonged feeling of negative emotions may lead to stress which can further lead to a number of mental health issues. With the increasing number of people undergoing stress it is vital to be able to detect it at an early stage and help people realize and rectify it before much damage is done. In this paper, a detailed survey of the various methods used in emotion and stress detection using EEG signals are presented. Also, a sample algorithm is proposed to discuss the various stages of the emotion recognition and stress analysis process. The publicly available SEED (SJTU Emotion EEG Dataset) and DEAP (Database for Emotion Analysis using Physiological signals) is used to extract features in time domain and time-frequency domain using discrete wavelet transform(DWT). The features then extracted are reduced using a feature selection process. These selected features are classified into three different states (positive, neutral and negative) using Artificial Neural Networks (ANN) classifier to obtain an accuracy of about 84%. Further the stress levels are computed based on the arousal and valence scores of each of these emotional states. The stress levels are quantified and identified as high, medium and low.
Keywords: Brain Computer Interface, Electroencephalogram, Artificial Neural Networks, Emotions, Stress

1. INTRODUCTION

Brain computer interface (BCI) facilitates a connection between the human brain and an external device such as a computer, mobile phone, etc. and it has been vital in assisting the physically disabled and impaired people. The goal of a BCI system is to allow the user to interact with the device using electro-encephalogram signals(EEG) and other such bio-signals. The interaction is enabled through a variety of intermediary functional components, control signals, and feedback loops as detailed in fig 1. The various processing stages focus on understanding the intentions of the brain signals and converting them into actions. The feedback is also used to inform the system about the state of the other components [1]. A popular physiological signal that is highly adopted for human emotion assessment is the EEG signal.The electroencephalogram (EEG) is signals representing the cortical electrical activity of the brain. EEG is measured from the human scalp and are relatively small, in the range of nano to microvolts.It is divided into different frequency bands as Delta(.5-3Hz), Theta(3-8Hz), Alpha(8-12Hz), Beta(12-38Hz) and Gamma(38-42Hz).

The BCI system can be used for analysis and classification of EEG signals corresponding to different emotions, including self-report, startle response, behavioural response, autonomic measurement, and neurophysiologic measurement.

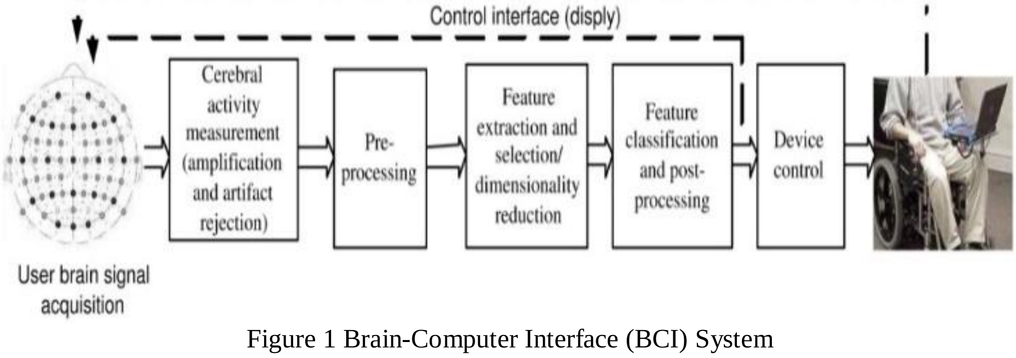

Figure 1 Brain-Computer Interface (BCI) System

The EEG signals can play an important role in detecting the emotional states for developing the BCI based analysis and classification of emotions. Since the BCI based on emotion detection can be useful in many areas like entertainment, education, health care, neuro-marketing etc.

EEG is the best way to monitor physiological signals from the central and parietal cortex regions of the brain. The recorded waveforms can be interpreted to indicate the emotional states or stress levels of an individual. The brain signals are quite small and lie in the range of 0 to 100Hz. The advantage of using EEG for emotion and stress analysis is that it is a non-invasive technique with good temporal and acceptable spatial resolution and it can be collected and analysed in real time, at the level of milliseconds (thousandths of a second). One of the drawbacks of EEG is that it's hard to figure out from which region of the brain, the electrical activity is coming from and also its small amplitude can be corrupted with various artefacts which makes pre-processing an essential step.

It must be considered that emotions are subjective to an individual i.e. each subject may experience a different emotion in response to the same stimuli. Thus emotions can be classified as two different models- Discrete model and Dimensional model. The discrete model includes basic emotions such as happiness, sadness, fear, disgust, anger, surprise, and mixed emotions such as Motivation (thirst, hanger, pain, mood), Self-awareness (shame, disgrace, guilt), etc. The Dimensional model is expressed in terms of two emotions Valence (disgust, pleasure) and Arousal (calm, excitement). The various emotions experienced by a human can represented through the Plutchik wheel of emotion as shown in Fig 2. Emotion detection plays a vital role in acquiring non-verbal information in response to certain events which help in understanding the emotional impact of that particular event on the individual [2].

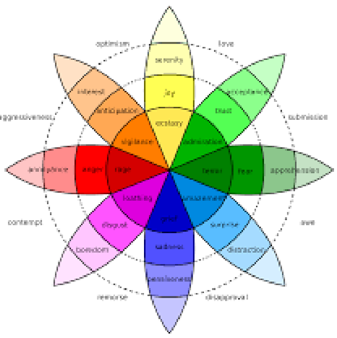

Figure 2 Plutchik's wheel of emotions

The rest of the work in this paper is organised in the following manner: Section II discusses the related work, Section III describes a proposed methodology for the detection of emotions and stress levels, Section IV gives the results obtained from the model and finally Section V discusses the conclusion and future scope of the work.

2. RELATED WORK:

The literature survey shows that, for the process of emotion recognition using EEG signals, very complex methods of signal processing are required.

In Jingxin Liu et.al. [3],different machine learning methods are discussed to study the relationship between the associated emotions states and their respective EEG recordings, in the publicly available dataset DEAP (Database for Emotional Analysis using Physiological Signals). They proposed an algorithm for feature extraction in time domain, frequency domain, time-frequency domain and multi-electrodes to capture different information from different domains. In the Time Domain, features such as Statistical Features (STA), Higher Order Crossings (HOC), Fractal Dimension (FD), Non-stationery Index (NSI) and Hjorth feature are calculated. Statistical features such as power, mean, standard deviation, first difference, normalised first difference, second difference and normalised second difference are calculated for all 32 channels. Power Spectral Density (PSD) is calculated in the Frequency Domain. In Time-Frequency domain, Discrete Wavelet transform is used to calculate three separate feature vectors-Recursive Energy Efficiency, Root Mean Square and entropy features. Finally, in the Multi Electrode features such as Differential Asymmetry, Rational Asymmetry, Magnitude Squared Coherence Estimate (MSCE) has been calculated. Maximum Relevance Minimum Redundancy (mRMR), feature selection method for the entire feature set to reduce its dimensionality. For classification K-Nearest Neighbour (KNN) and Random Forest methods have been used to find the accuracies of each feature. In this paper they address the binary classification problem that results after they threshold the self-assessments. The affective label will be set to high if the rating is above 5. If the rating is equal or lower than 5, the corresponding affective label will be set to low. Thus for each trial, two labels were generated. HV (high valence) or LV (low valence) was to describe the affective level in valence space, and HA (high arousal) or LA (low arousal) was to describe the affective level in arousal space. Identification of valence and arousal levels are addressed as two independent tasks in this paper. It should be mentioned here that the work is based on 10-folds Cross Validation and 32 participants. The best performance of all features is Magnitude squared coherence estimate. From the result we can see that after mRMR selection both arousal and valence reach the highest performance of 71.23% and 69.97% respectively.

In John Atkinsona et.al. [2], an EEG feature-based emotion recognition method was proposed combining the feature-selection methods (mRMR) and SVM classifiers using RBF kernels, yield significant improvements in accuracy for two dimensional emotion model (i.e., Valence and Arousal). This approach deals with a higher number of emotion classes (i.e., 8) on a standard DEAP dataset, which makes the problem more realistic but at the same time, the training task becomes more demanding. It combines feature selection and kernel classifiers and uses multi-label classifiers to simultaneously recognize a wider set of emotion classes based on a dimensional emotion model. For both dimensions, this method reduced the number of relevant features required to produce an average accuracy of 63%. Furthermore, the method is promising when considering a higher number of classes per dimension (i.e. 3 and 5). This also showed our method recognizes a higher number of emotion classes without using additional emotions classifiers. This method requires less work to classify based on a smaller set of selected so as to achieve higher accuracy than other techniques.

In Adnan MehmoodBhatti et.al.[4], a new dataset of EEG signal in response to audio music tracks is created using single channel EEG headset (Neurosky), which is easy to wear and computationally efficient. A hybrid feature selection approach from the time, frequency and wavelet domains is proposed to enhance the emotion recognition accuracy. Human behaviour of different age groups in response to different genres of music is analysed. Single channel Neurosky headset with a sampling rate of 512 Hz was used for the recording of non-invasive EEG signals. Thirty audio music tracks are used as an external stimulus for EEG based emotion recognition experiment. Raw EEG signals were decimated from 512 samples/sec to 300 samples/sec. For noise reduction band pass filter with a pass band from 1.0 Hz to 50 Hz was used. Thirteen features belonging to three different domains - time, frequency and time-frequency were extracted from pre-processed EEG data. The classifier used were Artificial Neural Networks (ANN), K-nearest neighbour classifier (K-NN) and Support vector machine (SVM). Using audio music is that it allows emotion recognition of visually disabled persons. Thirteen features from three different domains are extracted, which are then classified into four different emotions (happy, sad, love and anger) using the three different types of classifiers. MLP gives the best accuracy rate compared to the SVM and K-NN classifiers,happy and sad emotions are easiest to classify irrespective of the classifiers used; on the other hand, love and anger emotions are difficult to recognize. Furthermore, it is established that rock and hip-hop music genres evoke happy and sad emotions respectively in majority of the subjects considered, and rap and metal music genres evoke sad and angry emotions in subjects under study. Finally, it is identified that brain signals of age group (26-35) years give the best emotion recognition accuracy in accordance with self-reported emotions.

In PawełTarnowski et.al. [5], a method for classification of emotions in EEG signals for the use in neuromarketing research. Emotions were evoked by presenting images on a computer screen. In a session 45 images were shown and each picture was displayed for 5 seconds. EEG signal was registered by two bipolar channels with the use of only 4 electrodes. Classification was carried out for 1 second windows of EEG signal using k - nearest neighbour algorithm (k-NN). Fast Fourier Transform (FFT), in bandwidth 1-40Hz, for two channels of EEG signal. In this process a sliding time window was used. Thus for each second 80 features were generated. No method of feature selection was implemented. The average result of classification accuracy, for pairs of emotions (one vs. another), is equal 84%. In particular, the accuracy of the classification of unpleasant emotions vs. neutral is 87%, pleasant vs. neutral 83% and pleasant vs. unpleasant 82%. The result of classification accuracy for all emotions is 74%. In the paper they have presented an original method of emotions classification based on recording of EEG signal with a simple electroencephalograph and relatively simple methods of signal analysis. The use of EEG signal allows detecting subconscious response to the presented stimuli, what is very important in neuromarketing studies.

In Giorgos et.al.[6], DEAP database is used to detect Stress as an emotion that is characterized by negative valence and positive arousal. The following features have been used. Frontal asymmetry within the alpha band is inversely related to stress. For the frontal asymmetry the F3-F4 pair was considered more appropriate as Fp1-Fp2 could be contaminated with eye related artefacts. Coherence is calculated among two signals x, y and it is the fraction of square cross-spectral density between x and y, divided by the product between spectral density of signal x over spectral density of signal y. Brain load index defining the overall external or internal load is calculated from parietal and frontal lobe using θ and α bands. Spectral centroid frequency was estimated using time-frequency representation of signal and calculating spectral information within overlapping sliding windows. Hjorth parameters, namely activity, mobility and complexity, are time domain parameters useful for the quantitative evaluation of EEG. Correlation Dimension is a nonlinear measure based on the correlation integral which has been used as a feature for stress detection. Feature selection was performed using sequential forward selection (SFS) and sequential backward selection (SBS) methods.

In Guo Jun et.al. [7],the Stroop colour-word test and mental arithmetic test are used as stressors to induce low level and high level of stress respectively. Power band features from EEG signals are analysed and using the relative difference of beta and alpha power as feature along with Support Vector Machine as classifier, three-levels of stress can be recognized with an accuracy of 75%. For two-level stress analysis, accuracy of 88% and 96% are achieved for Stroop colour-word test and mental arithmetic test respectively.

3. METHODOLOGY

The main emphasis of this paper is to explain the procedure used to develop an algorithm to detect the emotional states based on the most relevant work that has been done in the field. Hence, a simple prediction model has been designed using limited features and classifiers to produce the most accurate results possible. In this paper, publically available dataset SEED and DEAP have been used. This pre-processed data undergoes a feature extraction process in the time and time-frequency domain. The extracted features form a feature vector. A portion of the feature vector is used to train the model using a neural networks classifier and the remaining data is used for testing to provide the output emotions. These output emotional states are further classified into stress levels based on the arousal and valence values of the emotions. An overview of the proposed methodology is shown in Fig 3.

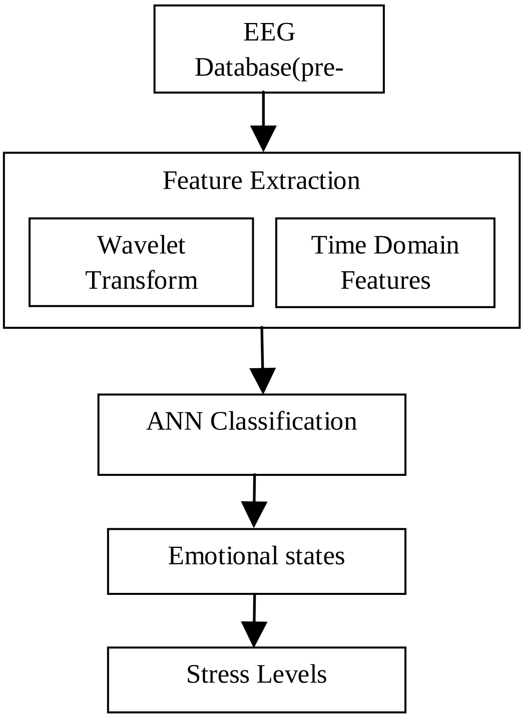

Figure3 Proposed Methodology

3.1 SEED DATASET

The publicly available SEED dataset consists of EEG data acquired from 15 subjects in response to watching 15 emotional video clips. A feedback was taken from each subject reporting their emotional reactions to the clips by filling a questionnaire immediately after watching each film clip. For the feedback, participants were told to report their emotional reactions to each film clip by completing the questionnaire immediately after watching each clip. Each film clip has duration of about 4 minutes and each of the subjects perform the trials for three sessions with an interval of a week to monitor the neural signatures and stability of the pattern across sessions and individuals. Hence a total of 45 experiments are available along with the labels of their corresponding emotional labels (-1 for negative, 0 for neutral and +1 for positive) for each trial. EEG signals were recorded using an ESI Neuro-Scan System at a sampling rate of 1000 Hz from the 62-channel active silver-chloride electrode cap according to the conventional international 10-20 system [8].

The raw data is pre-processed by down sampling to 200Hz and band passing the filter through a range of 0 to 75Hz. The resultant 45 experiments are stores in .mat files each containing 15 arrays one for each trial and one array for the labels.

3.2 DEAP DATASET

The DEAP (Database for Emotion Analysis using Physiological signals) is a publically available benchmarked dataset which has been validate by several researchers. The database is acquired from 32 subjects as each watched 40 one-minute long excerpts of music videos. EEG and physiological signals were recorded and each participant also rated the videos based on arousal, valence and dominance using SAM mannequins on a discrete 9-point scale. The original data recordings contain 32 subjects data recorded with 48 channels (out of which 32 are EEG) at 512Hz. This raw data is down-sampled to 128Hz with each subject's data stored in a 3D (trial x channel x timeslot) vector.

3.3 FEATURE EXTRACTION

From the available pre-processed data the features are extracted in the time domain and in time-frequency domain. In the time-frequency domain, discrete wavelet transform (DWT) is used to obtain both time and frequency components of the data. From the survey, it can be concluded that DWT provides better resolution compared to short term Fourier transform (STFT) and FFT. Wavelet transform filters the frequencies into two ranges using a high pass filter and a low pas filter. The high pass component (also called the detail component) is left as it is and the low pass component (also called the approximation) is further divided. This process continues until we obtain the desired frequency bands. For the given range of data, 4 levels of decomposition is done to obtain signals in the delta (1-3Hz), theta (4-7Hz), alpha (8-13 Hz), beta (14-30Hz), gamma (31-50Hz) bands as shown in Fig 4.

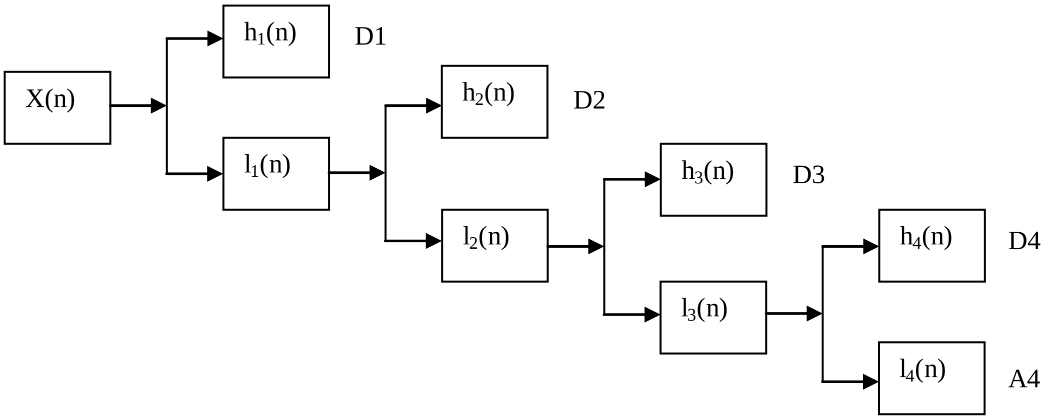

Figure 4 The corresponding frequency bands for Alpha, Beta, Gamma, Theta and Delta.

Using DWT, energy spectrum for each of the channels is computed in each band. Hence a total of 62x5 features are computed. Simultaneously in the time domain statistical parameter related features are obtained .Thus the final feature vector includes a combination from both the domains which comes upto a total of 394 features.

3.4 CLASSIFICATION

The features are then applied to a neural networks classifier. Inspired by biological neural networks, Artificial Neural Networks are parallel computing systems consisting of a very large number of simple processors with many interconnections. ANN models attempt to use some "organizational" principles believed to be used in the human brain. One type of network sees the nodes as 'artificial neurons'. These are called artificial neural networks (ANNs). An artificial neuron is a computational model inspired in the natural neurons. Since the function of ANNs is to processinformation, they are used mainly in fields related with it. There are a wide variety of ANNs that are used to model real neural networks, and study behaviour and control in animals and machines, but also there are ANNs which are used for engineering purposes, such as pattern recognition, forecasting, and data compression. These basically consist of inputs (like synapses), which are multiplied by weights. These weights are then computed by a mathematical function which determines the activation of the neuron [9].

For this model the flowchart show in fig 5 is implemented using the neural networks tool box available in Matlab. A part of the feature vector is used to train the data. The remaining features are used to test the data. Five-fold cross validation is performed to increase the accuracy of the data. The accuracy of the model can be calculated by developing the confusion matrix.

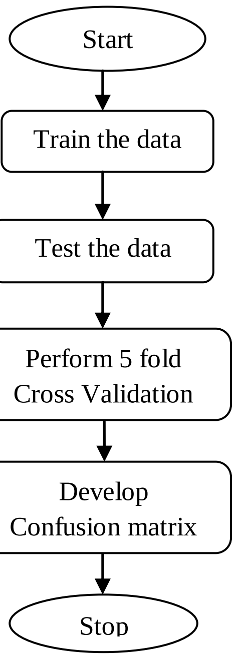

Figure5 Flowchart for classification process

The Neural Pattern Recognition toolbox(shown in fig 6) is used in Matlab to select data, create and train a network, and evaluates its performance using cross-entropy and confusion matrices.The network is trained with scaled conjugate gradient back-propagation using 10 hidden layers. The input is a 394 features vector which gives three output classes (positive, neutral and negative). The model randomly selects 70% of the data for training, 15% for testing and the remaining 15% for validation.

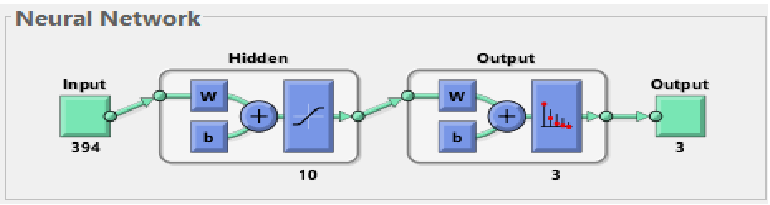

Figure 6 Neural network toolbox

Cross-validation is the processes of assessing how the results of a statistical analysis can be generalized to an independent data set. Different combinations of training and testing data are used to improve the accuracy of the model. For prediction problems, a model is usually given a dataset of known data on which training is run (training dataset), and a dataset of unknown data against which the model is tested (testing dataset). For a generalised k-fold cross-validation, the original sample is randomly partitioned into k equal sized subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining k − 1subsamples are used as training data. The cross-validation process is then repeated k times (the folds), with each of the k subsamples used exactly once as the validation data.

3.5 CONFUSION MATRIX

The confusion matrix is developed by comparing the output labels with the target labels. To obtain the best results the diagonal elements should be higher than the surrounding elements. Fig 7 shows the confusion matrix for the given model. The diagonal elements also give the distribution of accuracies for each of the emotional states. Hence the accuracies are distributed as- 33.3% for positive emotions, 26.7% for neutral emotions and 33.3% for negative emotions resulting in an overall accuracy of 93.3%(as shown in the bottom-right corner element) for one subject.

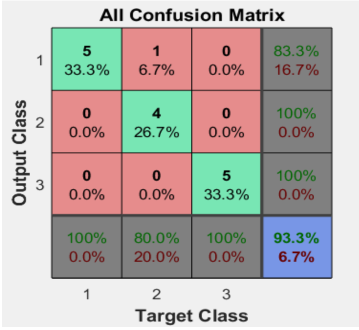

Figure 7 Confusion matrix for three states using neural network

3.6 STRESS DETECTION

The stress levels are calculated based on the valence and arousal values of the emotional states. The valence parameter gives the degree of pleasantness of the induced emotion and arousal is the instensity of the emotion. In the DEAP dataset valence, arousal and dominance are provided by each subject through self-assessment on a scale of 1 to 9 with 1 being the lowest and 9 the highest. Figure 6 shows the valence-arousal model indicating the valence along the x-axis and arousal along the y-axisa. A threshold point in chosen to divide them into 4 categories – low arousal high valence, high arousal high valence, low arousal low valence and high arousal low valence as shown below.

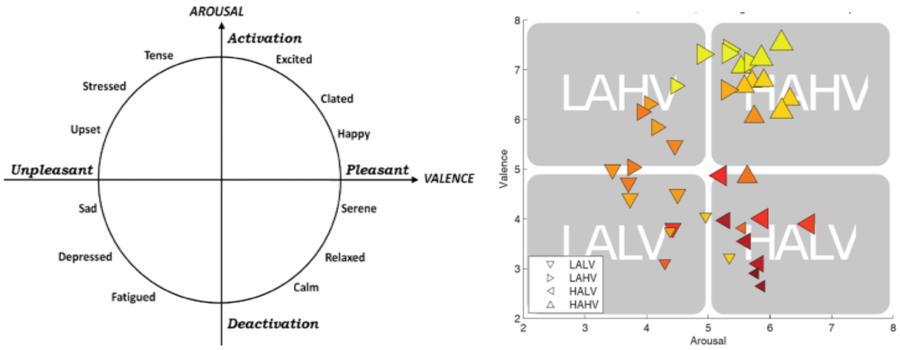

Figure8 Valence-arousal model

4. RESULTS

The results of the proposed model are derived from the accuracies given in the confusion matrix. The overall accuracy for all 45 subjects is seen to be 84%. Table 1 shows the accuracy of each emotional states as well as the overall accuracy for 5 random subjects. Table 2 shows the stress levels induced based on the valence and arousal values for another 5 subjects. Fig 8 shows the overall classification accuracy for different emotional states. It is also seen that stress levels have been predicted with optimal results.

Table 1

Subject	Positive	Neutral	Negative	Total
1	100	80	100	93.3
2	60	80	80	73.3
3	40	100	100	80
4	80	100	80	86.7
5	100	60	100	86.7

Table 2

Trial	Arousal	Valence	Stress level	Stress States
1.	7.71	7.6	1	Low
2.	8.1	7.31	1	Low
3.	8.58	7.54	1	Low
4.	4.94	6.01	3	High
5.	6.96	3.92	2	Medium

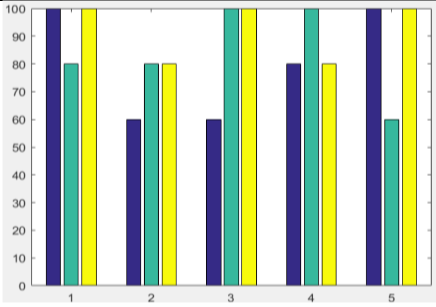

Figure 9 Accuracy of the emotion-state classification for five samples

5. CONCLUSION

In this paper, we focus on providing a simple machine learning based emotion recognition model which has been developed from an in depth survey of the various techniques and algorithms that can be applied using EEG signals. The SEED and DEAP dataset have been used extract features such as mean and standard deviation in time domain. DWT is performed to compute in energy spectrum in each band along with few multi-electrode features in the time-frequency domain. Artificial neural networks are used to classify the data and an accuracy of up to 84% is obtained.

This model works well for the downloaded datasets and the in-built ANN pattern recognition model. Hence in the future a more elaborate model consisting of a wide spectrum of features can beused on data acquired based on a certain decided protocol. The training and testing algorithms can be separately written and various classifiers can be tested to obtain the most accurate results.

REFERENCE

[1] AnirudhVallabhaneni, Tao Wang, and Bin He, Brain-Computer Interface, *Neural Engineering, Springer US 2005, pages 85--121*

[2] JohnAtkinsona, and Daniel Campos, Improving BCI-Based Emotion Recognition By Combining EEG Feature Selection And Kernel Classifiers, *Expert Systems With Applications Journal 43, Elsevier, pp : 35 – 41, 2016.*

[3] Jingxin Liu, HongyingMeng, Asoke Nandi and Maozhen Li, Emotion Detection from EEG Recordings, *12th International IEEE Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD) 2016.*

[4] Adnan MehmoodBhatti, Muhammad Majid and Syed Muhammad Anwar, Human Emotion Recognition And Analysis In Response To Audio Music Using Brain Signals, *Computers in Human Behavior journal 65, Elsevier, pp : 267-275, 2016.*

[5] PawełTarnowski, MarcinKołodziej, AndrzejMajkowski and Remigiusz J. Rak, An Innovative Approach to Classification of Emotions in EEG Signal for the use in neuromarketing Research, *12th IASTED International Conference Biomedical Engineering February 15 - 16, 2016 Innsbruck, Austria.*

[6] GiorgosGiannakakis, DimitrisGrigoriadis, and ManolisTsiknakis, Detection of stress/anxiety state from EEG features during video watching, *IEEE*

[7] Guo Jun and Smitha, EEG based Stress Level Identification , *2016 IEEE International Conference on Systems, Man, and Cybernetics , 2016*

[8] Wei-Long Zheng, and Bao-Liang Lu, Investigating Critical Frequency Bands and Channels for EEG-based Emotion Recognition with Deep Neural Networks, *accepted by IEEE Transactions on Autonomous Mental Development (IEEE TAMD) 7(3): 162-175, 2015.*

[9] Neha Gupta, Artificial Neural Network, Network and Complex Systems, *International Conference on Recent Trends in Applied Sciences with Engineering Applications, Vol.3, No.1, 2013*

[10] S. Valenzi, T. Islam, P. Jurica and A. Cichocki, Individual classification of emotions using EEG, *Journal of Biomedical Science and Engineering, vol. 7, pp. 604, 2014.*

[11] Raja MajidMehmood , Hyo Jong Lee, A novel feature extraction method based on late positive potential for emotion recognition in human brain signal patterns, *Computers and Electrical Engineering journal, Elsevier.*

[12] H. Peng, F. Long and C. Ding, Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy, *Pattern Analysis and Machine Intelligence, IEEE Transactions On, vol. 27, pp. 1226-1238, 2005.*

[13] Gary Garcia Molina, TsvetomiraTsoneva and Anton Nichol, Emotional Brain computer interfaces, *IEEE 2009*

[14] Adnan MehmoodBhatti, Muhammad Majid and Syed Muhammad Anwar, Human emotion recognition and analysis in response to audio music using brain signals, *Computers in Human Behavior journal, Elsevier.*