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Analysis of EEG Based Emotion Detection of DEAP and SEED-IV Databases using SVM

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***Abstract:** The Affective computing is one of the fast-growing areas which has inspired research in the field of emotion detection for many applications. This paper briefs out the related work on EEG based emotion detection using publicly available data and a proposed method to detect inner emotion-states. A supervised machine learning algorithm is developed to recognize human inner emotion states in two-dimensional model. The electroencephalography signals from DEAP and SEED-IV database are considered for emotion detection. Discrete Wavelet Transforms are applied on preprocessed signals to extract the desired 5 frequency bands. Some features like Power, energy, differential entropy and time domain are extracted. Channel wise SVM classifier is developed and channel combiner is done to detect the appropriate emotion state. The classification rate for four classes are 74%, 86% ,72% & 84% for DEAP database and 79%, 76%,77% & 74% for SEED-IV database.*

***Index Terms:** BCI, DEAP, DWT, EEG, SEED-IV, SVM.*

I. INTRODUCTION

Brain computer Interface is an emerging research field since past few years. BCI systems involves in analysis of Electro-Encephalogram signals from brain. The concept of BCI began as assisting individuals with physical and physiological disorders over a decade. [1][2] Now the research in BCI has extended in various fields including normal people. Some of such applications are classification of abnormal brain activity, epilepsy detection, emotion detection etc. Emotion detection is one among the growing areas in the field of affective-computing in which the interaction between machines and individuals can be improved through the change in individual's inner states. [3] This motivated many researchers to develop real time emotion detection for clinical, entertainment, marketing etc. [4]

Emotions have a major effect on the social skills of a person and their perception of the world. Human emotion can be detected by a plethora of factors like expressions, speech and physiological signals. In [5], emotion detection using EEG signals is advantageous than other methods.

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EEG tracks and records electrical impulses of the neurons in the brain. EEG was primarily used for medical diagnosis but since the introduction of more portable and cost-effective BCI headsets, the possibility of application in the entertainment industry has increased. Emotion states are interpreted through dimensional model as shown in Fig-1 as well as discrete model. In dimensional model, the discrete basic emotion states are spatially represented across valance and arousal.

In this paper, a review on emotion detection using EEG-signals data sets available online is carried out and a method is proposed on two databases. In the proposed system, a machine learning algorithm is developed to identify emotion states based on dimensional model for the available database. Time domain features, wavelet features and entropy features are identified and classified using SVM classifier. This paper is organized as stated below: Introduction of BCI, emotion detection is described in section I. In section II, literature review of similar work is discussed. Methodology, results and discussion are elaborated in section III and IVand conclusion in section V.

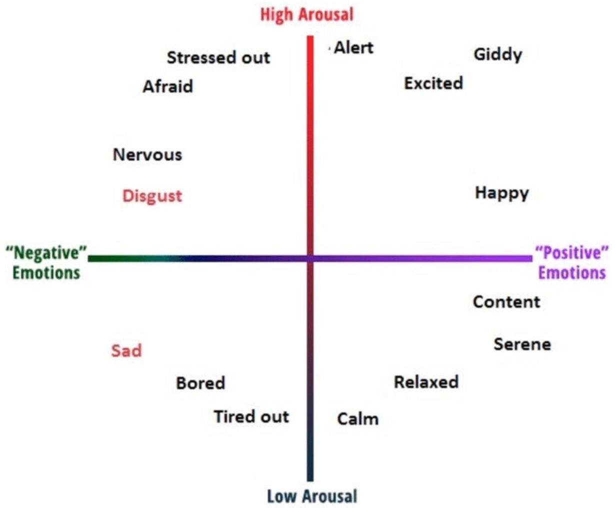

Fig 1: Dimensional model

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II. LITERATURE REVIEW

The following authors used DEAP Data-set for analyzing emotion states. Hongpei et al. [6], explains the effect of detecting emotion states accuracy of brain signal with different bands of frequencies and number of channels.

The classifier used is the K-nearest neighbor Classifier. Better accuracy of about 95% is obtained in gamma frequency bands and accuracy was increased when number of channels were increased from 10,18, 18 and 32. Zamanian et al. [7], extracted Gabor and IMF along with time-domain features and using multiclass SVM as classifier, they obtained an accuracy of 93% for 3 and 7 channels. Chao et al. [8] explored deep learning framework achieving a rate of 75.92% for arousal and 76.83% for valence states. Liu et al. [9], classified the data using time and frequency domain features and obtained 70.3% and 72.6%, using SVM. Mohammadi et al. [10], used Entropy and energy of each frequency band to classify using KNN and achieved an accuracy of 84.05 % for arousal and 86.75 % for valence. Xian et al. [11] used MCF with accuracy of 83.78 % and 80.72% for valence and arousal respectively with statistical, frequency and nonlinear dynamic features. Alhagry et al. [12] proposed a LSTM Recurrent Neural Network and the average accuracy for arousal, valence, and liking classes was 85.65%, 85.45%, and 87.99%. Maria et al. [13] investigated power features based on Russell's Circumplex Model and applied to SVM with performance of 88.4% for Valence and 74% for Arousal.

Singh et al. [14] used SVM classifier to classify emotions into four quadrants through ERP and latency features. The accuracy rate was 62.5% to 83.3% for single trail and for multi subject trails, they obtained 55% classification rate for 24 subjects. Ang et al. [15] proposed an algorithm using wavelet transform and time-frequency features with ANN classifier. A classification rate of 81.8% for mean and 72.7% standard deviation y for happy emotion was obtained. For sad emotions, performance of frequency domain features was 72.7%. Krishna et al. [16] used Tunable-Q wavelet transform to get sub-bands of EEG signals which is acquired from 24 electrodes by watching 30 video clips. They obtained higher classification accuracy of 84.79%.

From the survey it is seen that researchers have developed many ML algorithms using different features and have obtained an accuracy of 74 to 90 %. In this proposed method, a machine learning algorithm is developed to classify the emotion states in to 4 classes using channel fusion method for data available from DEAP and SEED-IV data base separately.

III. METHODOLOGY

It is observed from the survey that the models developed for detecting emotion states are preferably supervised algorithms. The preprocessed SEED-IV and DEAP data are analyzed using different features in frequency and time domain. A supervised machine learning model is developed to identify the emotion states into 4 classes. The proposed method is shown in Fig-2.

A. Data Acquisition

The first and one of the most important things to start is with data acquisition. The EEG signals are obtained by use of very high-performance systems at various sampling rate based on the capacity of the system used. The sampling rate of the device used must be more than 150hz as the EEG signals range from 5hz to 70hz. To analyze emotion states using EEG signals, the data from 2 different online available databases namely DEEP and SEED-IV are used.

In DEAP database [17], the brain signals for 32 subjects is acquired from a 32-channel EEG device at a sampling rate of 500hz, by showing 40 video trails of each 1 min duration to all subjects. Two different devices namely Twente and Geneva were used for data acquisition. The data which is available online is pre-labelled based on the emotion wheel. The protocol followed for the process of data acquisition is shown in Fig-3.

In SEED-IV database, EEG data is acquired from a 64-channel device by showing 2 mins videos for 15 subjects at a sampling rate of 1000hz.For each subject 3 sessions were performed on different days.So, it makes a total of 45 subjects.

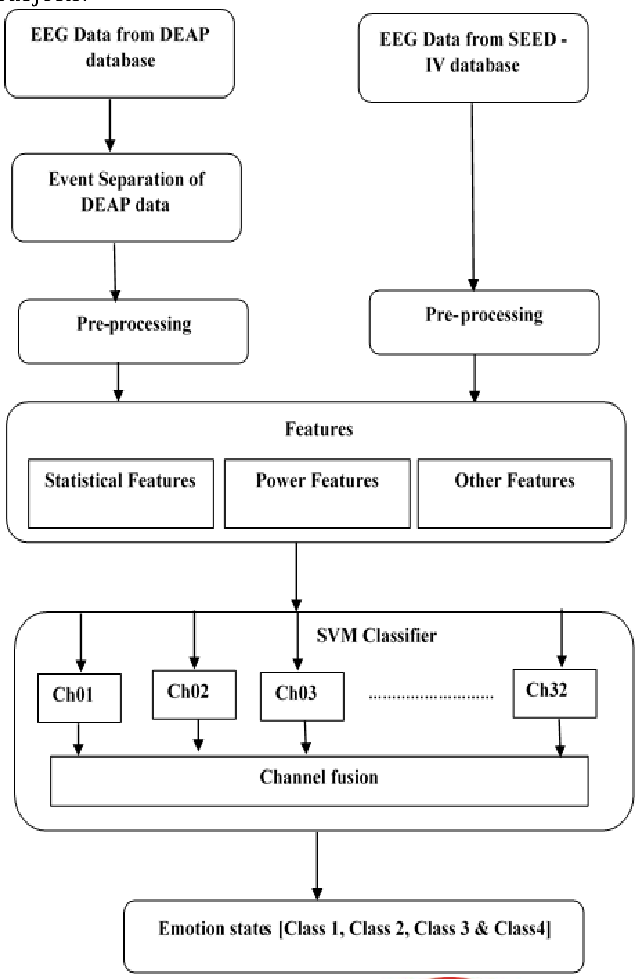

Fig 2: Proposed Methodology

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B. Event Separation

The duration of events varies based on the length of the video shown and the number of events in a trial depends on the number of videos shown in each trial during data acquisition. The duration of each event and number of events per trial could be different in different databases based on the protocol followed for data acquisition. The raw data obtained by DEAP database is converted to mat files after separating each event from the continuous data, based on the protocol followed during the data acquisition. The data obtained from SEED-IV are mat files which has events pre-separated based on the protocol followed. The same channels were considered for both the databases.

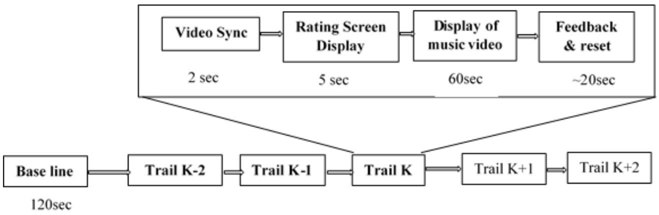

Fig 3: DEAP data protocol

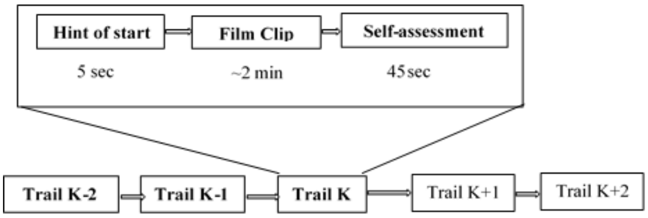

Fig 4: SEED-IV data protocol

C. Pre-Processing

For pre-processing the raw EEG signals, the signals are passed through 3 different filters removing different types of artifacts from the raw signals at each filter. First the signals are passed through 50hz/60hz notch filter to remove the line frequency artifacts added into the raw data during data acquisition. As we use 50hz, 230V AC power supply, we used a 50hz notch filter. Before analysis the data is converted from fixed or common reference to average reference since the electrodes are spread across the scalp, moving average re-referencing method is used to re-reference the data. The signals are then given to a 1-D 10th order median filter. This removes the impulsive noises present in the data. Hence, a smooth signal is obtained without spikes or impulsive noises present in it. This filter is implemented using "medfilt" function in MATLAB. Finally, the signals are passed through a band pass filter. A bandpass filter of order 20, with lower and upper cut-off frequencies 0.1 and 60 respectively is implemented using "filtfilt" function in MATLAB. This filter band limits the acquired signal's frequencies in the EEG signal range.

D. Feature extraction

It is the process of extracting meaningful features out of the pre-processed data to implement robust classification. There are many features that can be extracted from an EEG signal. The two-main category of features that can be extracted are in time domain, frequency domain [18] [19],the features used in this paper for analyzing EEG signals are given below in Table-1. 8-level DWT decomposition "db8" is carried out on the pre-processed signal to obtain 5 frequency bands: delta (1-3Hz), theta (4-7Hz), alpha (8-13 Hz), beta (14-30Hz), gamma (31-60Hz) [20]. For both the databases, channel wise feature vector is computed for each channel and stored, in-order to feed them respectively to the 32 channel wise classifiers used.

E. Classification

Support Vector Machine (SVM) is used to classify the emotions into 4 classes based on the extracted features. SVM is a supervised machine learning algorithm. The features extracted are given to SVM classifier. In each database, 70% of the data is used for training, the remaining 30% is used for testing. Labelled training data is given as the input to the algorithm, the output obtained is an optimized hyperplane which is used to categorize new examples. The SVM algorithm used has various parameters like regularization, gamma and kernel etc., by choosing the correct parameters based on the nature of available data we have achieved considerable nonlinear classification. In this paper, 32 classifiers, one for each channel, is developed to classify the emotions into four states. To predict the final emotion state, a channel fusion method is employed. The SVM algorithm is implemented in python. Separate SVM classifier is developed for both databases.

Table 1: Extracted Features

Feature Type	Feature Name
Time domain (Statistical Features)	Mean, Root mean square, Std-deviation, First difference, Normalized first difference, Second difference, Normalized second difference, Kurtosis, Skewness, Variance, Mobility and Complexity (Hjorth Parameters)
Wavelet or Frequency Domain features of 5 band	Band energy, Power spectral density, Differential entropy, Average band power
Other features	Hurst exponential and Permutation entropy

DEAP database has signals acquired from 32 subjects. Out of 32, the data of 22 subjects are used for training while the remaining 10 subjects' data are used for testing the trained model. The feature vector used for training each channel wise classifier is

880*34 in size, which comprises the data of 34 features extracted from 40 events present in all 22 subjects' data.

SEED-IV database has down sampled data of 45 subjects. Out of the data of 45 subjects, the data of 32 subjects are considered for training while the remaining 13 subjects' data is used for testing. A 742*34 feature vector is fed to each channel wise classifier. The feature vector comprises the dataof 34 features extracted from 24 events present in all 32 subjects' data.

IV. RESULTS

In DEEP database, 22 subject's data are used for training. Each subject has 40 events and 34 extracted features, so 880*34 feature vector is fed to each of the 32-channel based SVM classifiers. In SEED-IV database, 32 subject's data are used for training. A feature vector of 742*34 is applied for each of the 32-channel based SVM classifiers. The trained network is tested on remaining 30% data for both the models. The training model is designed to predict 4 classes, class1: HAHV, class 2: HALV, class 3: LALV and Class 4: LAHV.

The classification accuracy for DEAP database is 74 %, 86%, 72% and 84% for class1, class 2, class 3 and Class 4 respectively.

The performance rate for SEED-IV database is 79%, 76%,77% and 74% for class 1, 2, 3, and 4 respectively. The overall performance of trained SVM model for both databases is shown in Table 2. The accuracy rate of the classifier is shown in Fig-5.

Table 2: Overall Performance

Class	SVM- Classifier performance	
	DEAP data	SEED-IV data
1. HAHV	74%	79%
2. HALV	86%	76%
3. LALV	72%	77%
4. LAHV	84%	74%

It was observed that among 34 features extracted, Hurst exponential, differential entropy and average power of all bands, and a few time domain features like kurtosis, RMS, skewness, second and first normalized difference were predominant for all the classes.

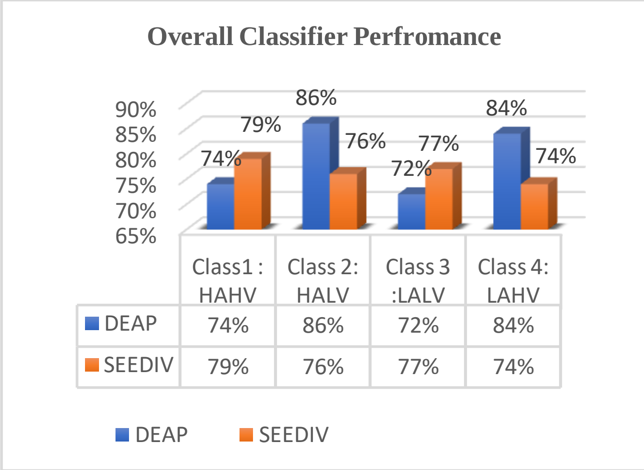

Figure 5: SVM Classifier performance for two databases

IV. CONCLUSION

In this paper, highlight on the work done for available databases like SEED-IV and DEAP were discussed. The Statistical features, frequency domain features, Hurst exponential and Permutation entropy were extracted for both the databases: SEED-IV and DEAP separately. Power features, Hurst exponential and a few time domain features played an important role in distinguishing the emotion states. The average performance of the SVM classifier is 79% and 76.5% for DEAP and SEED-IV database respectively. The overall classification rate for 4 emotion classes of DEAP database is 74%, 86%, 72%, 84% respectively and for the SEED-IV database it is 79%, 76%,77% and 74% respectively.

The channel fusion method employed with channel wise SVM classifier seems to perform better for DEAP data than for SEED-IV data. A model is developed to obtain the performance of the signals acquired.The same model developed can be used in future to compare performance of real time signals acquired [18] [20]. Further some more features can be added to increase the classifier rate. A robust model can be developed to classify inner emotions for different databases.

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