EMOTIONS CLASSIFICATION AND REORGANIZATION OF THE PERSON BY EEG USING SVM

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Abstract

Various emotions are produced by the human during interaction or communication and they vary in meaning, intensity, and complexity. Behavioral Emotions can also be expressed by human body language, voice tone, facial expression, etc. and it may be easy to understand, but when we are talking about those humans which not able to express their emotions by behavior, is very difficult to recognize the emotions in this situation brain signals can be used for that. In this paper, we classified the emotions using a signal which produces in the human brain according to their emotional state. We used EEG Eight frequency band signals for emotion detection. Expressions were discussed and recognized different emotions such as happy, sad, angry, fear, surprise, neutral, and disgust. by showing 5 minutes of these seven emotion-based Indian movies clipping and analyzing the intensity of the emotion by the brain signal and comparing it with the statement of the person. For this, we choose 50 people aged between 18-50andselected 35 Indian movie clippings based on seven emotions. For emotion detection, we applied two methods reply to the questions and another Support vector machine for the classification of brain signals to get better accuracy.

Keywords: Emotion, Eeg, Svm, Classifier.

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1. Introduction

Human awareness is an emotion, and emotion is necessary for conscious thought, perception, and intelligent human interaction. Emotion is a representation of non-physiological information, such as verbal and nonverbal body language, tone of voice, and facial and vocal emotions. Many research on the recognition of emotions based on non-physiological signals have been conducted and published recently. [1]. Due to its mobility, affordability, simplicity, and convenience of use, EEG-based emotion recognition has recently attracted interest from all over the world. The very subtle emotional changes that are preserved in recorded EEG signals with excellent time resolution show the link between emotional state and brain activity. Interaction between humans and computers is used to satisfiy user requirement and also ehnace their productivity. Emotions and interactions have a significant role in several needs for a perceptive human being. In their statement, Picard and Klein write, "Recognising effect should greatly facilitate the ability of computers to heed the rules of human communication" [2]. The conscious perception of a feeling (emotion), its physiological arousal, and its behavioural expression (affect) are all formally separated in psychology. Due to the increased interest in brain-computer interaction (BCI), electroencephalograms (EEGs) have been examined. The EEG shows a physiological response or also reveals the mental emotion being experienced.[3]
EEG is used to record such physiological activities and is reliable for emotion recognition due to its relatively objective evaluation of emotion compared to non-physiological.In this paper, we use an Electroencephalogram (EEG), which is one kind of test. Brain signals are measured by EEG. EEG is a reliable and cost-effective technology. Multiple steps are involved in detecting emotion using EEG signals. [418]

The signals captured by the EEG are categorised using SVM. Because there are just a few electrodes available in our instance, it's crucial to note that these signals are divided into seven emotional valences and arousal, which the primary EEG features are found during a variety of emotional stimuli.

•**Valence:** When compared to negative emotions, cheerful, positive emotions increase right parietal beta power and frontal alpha coherence.
•**Arousal:** Excitation showed decreased alpha activity and greater beta power and coherence in the parietal lobe.
•**Dominance:** The degree of an action's force, which is typically represented in the EEG by an increase in the frontal lobe's beta/alpha activity ratio as well as an increase in the parietal lobe's beta activity.[5,17] Through years of studying emotions, psychologist proposed that there are seven primary emotions that serve as the foundation for all others: happy, sadness, disgust, fear, anger, surprise, and neutral.
Section 2 gives the information related to this research in the literature review, and Section 3- describes the methodology. Results and analysis are shown in section 4 and the last section 5 is the Conclusion.

Relate Work
Physiological signals like the electroencephalogram (EEG), skin temperature (SKT), and electrocardiogram (ECG) have been the subject of extensive research in recent decades. Compared to physiological cues, behavioural reactions like voice and facial expression offer less accurate and suitable information about emotional states. Fdez etal.(2021) introduced stratified normalisation, a new participant-based feature for training deep

neural networks in the task of cross-subject emotion categorization from EEG signals, was introduced by Fdez et al. in the year 2021. The technique proved successful in removing participant variability while preserving the emotional content of the data. They used the SEED dataset, which includes 62-channel EEG recordings taken from 15 subjects as they watched film snippets, to conduct our research. The classification accuracy for two emotion categories (positive and negative) and three emotion categories (positive and negative) was 91.6% and 79.6%, respectively, for networks extracted from EEG features using the multitaper method, respectively. Results showed that networks trained with stratified normalisation significantly outperformed standard training with batch normalisation (also neutral).[6] Pandey et al.(2020) discussed the multimodal biometrics system with its applications, different levels of fusion and methods of fusion .They discussed on an automatic recognition of a person based on her behavioral and/or physiological characteristics also referred by Biometrics This paper helped to security researchers some useful insight whilst designing better multimodal biometric systems.[7]

Ding et al.(2019). Ding et al. (2019) demonstrated the efficacy of their approach on a new dataset. They demonstrated that both our suggested model and current state-of-the-art models are affected by the level of physical activity in terms of performance. The P300 signal was evoked with individuals on a stationary bike under three circumstances of physical activity: rest, low-intensity exercise, and high-intensity exercise. Their suggested model performs noticeably better for the physical activity situations once nonscalp electrode signals are added. The results indicated the possibility for ubiquitous BCI by suggesting that the addition of new modalities linked to eye movements and muscle activity may enhance the effectiveness of mobile EEG-based BCI systems. [8] Bhatt et al.(2019) focused on the dataset of EEG using an SVM classifier with the external library LibSVM (3.23).They achieved fantastic improvement in the accuracy and performance by classifying the EEG SEED dataset. Different approaches are listed and explained toimprovising the performance and accuracy of the dataset. Various classifiers - SVM with KNN, ELM, SVM with SEED dataset, and SVM used with DEAP dataset.[9] DamaševiIius et al.(2018) performed a security study and displayed the method's security properties using their own dataset of electroencephalography (EEG) data gathered from 42 participants, they assessed a biometric cryptosystem. A biometric authentication approach based on the discrete logarithm problem and Bose-Chaudhuri-Hocquenghem (BCH) codes. The trial outcomes demonstrated the viability of the presented biometric user authentication system, with an Equal Error Rate (ERR) of 0.024. [10] Meriemetal (2017) reviewed EEG Biometrics. In this study, they evaluated and addressed current contributions to the field of research as well as the difficulties of developing an EEG-based person recognition system. They outlined what they expected from the EEG-based biometrics in terms of improved performance. [11] Polat et al. (2017) categoriesd the EEG associated with various emotions. These audiovisual stimuli that are based on emotions have channel selection preprocessing. They talked about audiovisual stimuli, the channel selection preprocessing utilised in emotion recognition, and they examined features collected from the alpha, beta, and gamma bands as well as the tetra band from EEG data in the detection process of emotion EEG signals. The outcomes demonstrated that a recognizer system can be accurate when employing acceptable learners like Artificial Neural Networks (ANN) and adequate characteristics for extracting emotional state, such as Discrete Wavelet Transform (DWT). [12]

YongruiHuang et al. (2017) researched on emotional recognition where, the input signal was the electroencephalogram- and facial expression-produced record of brain activity. The neural classifier detects facial expression, while the Support Vector Machine detects EEG (SVM). Their shortcomings as a single information source are made up for by the integration of facial expression and EEG data for emotion identification. [13]

Barde et.al. (2014) proposed work is an implementation of person identification fusing face and ear biometric modalities. PCA (Principle Component Analysis) based neural network classifier for feature extraction from the images is used. Person Identification was made using Eigen faces, Eigen ears and their features. Reorganization accuracy is improved [14]

Barde (2015) is used two modalities face and foot for calculating matching score using different approaches like PCA based neural network classifier for face and modified sequential harr transform for foot.When multiple biometric modalities are combined using different fusion methods have been achieved optimal result[15]

Pandey et al (2023) discussed Brain signals have allowed us to identify persons' emotional states. Distinct emotional movie clips have been shown to each individual in a number of experiments, and it has been found that this causes distinct signals in their brains depending on the emotional movie clips they have encountered. [16]

Pandey et al. (2023) recognized emotional state of human by extracting facial expression. Several Experiments has been done by showing different emotional movie clips to each subject and it reflects as expression on subject’s face according to movie clips which he had experienced. [17]

2. Methodology

Emotion is feeling which an important factor of communication is. Through emotion one can communicate their feeling verbally or nonverbally. Actually, expressions acts like interfaces where one can understand their mind and feeling. In other words emotions are a natural aspect of human communication, usually in the form of non-verbal indicators. Until In recent times, human-computer interfaces have not integrated affective communication. [18] In this research, we proposed an EEG emotion database using Indian movie clips and verify the created database. EEG signals are recorded by the subject under the emotional stimulus. Support Vector Machines is a supervised machine learning algorithm which used to classify different emotional states such as happiness, sadness, anger, sadness, neutral, disgust and fear, from the emotional database of humans. A series of preprocessing operations were performed on the EEG-created database in order to extract features for the verification database. The feature explores the emotion-related channel set and corresponds to emotion retrieved from the preprocessed EEG database. Using statistical analysis, it looks at where the brain activates in relation to emotional processing. [19]

Design of working modal

Expressions play a vital role in non-verbal communication processing. They are mediums which makes able to communicate to each and another, just like the tone of voice, body language, facial movement, etc. We have designed a modal to identify and recognize of emotions of people, for this, we have done the work in two phases. The working modal is shown in figure 2.

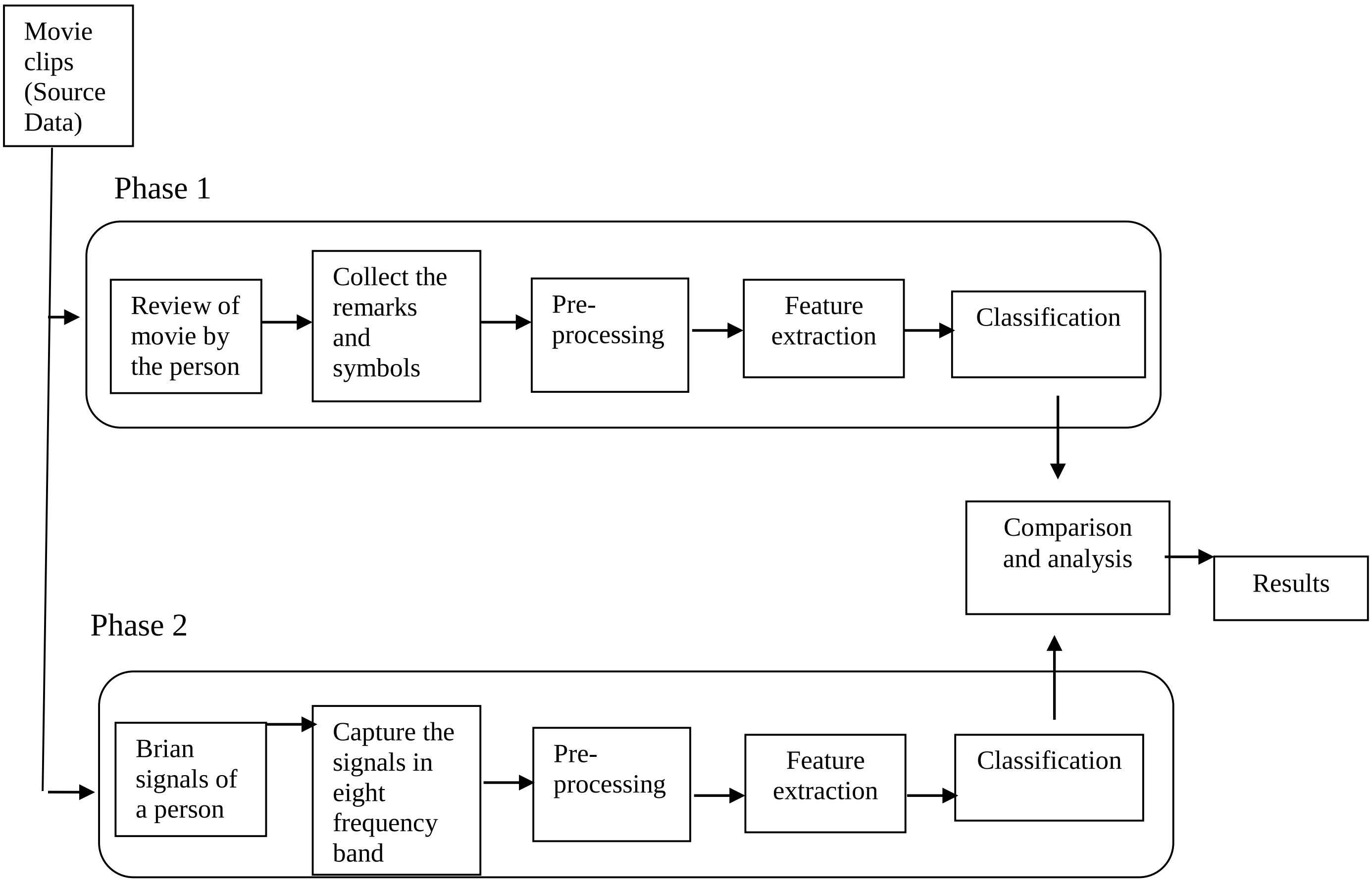


Fig.2 Different stages of processing

Indian Movie Clips (Source Data)

Human feeling can be record through various methods verified by the pictures, and video clips and also use storytelling techniques to produce emotions and record their brain activity. In this paper, we selected Indian movie clips of specific scenes containing any one emotion of the seven emotions.Table1 shows the movie clip that has different emotions.

Table 1: The different emotions scenes of the movie clips

Angry		
		
Fear		

Surprise

Disgust

Happy

Sad

Process of Phase I

The Selection of Emotional Stimuli. 35 movies from the Indian film industry were chosen. All "A" grade films. The questionnaire was used to conduct two surveys. 100 people took part in the survey (70 participated in the first survey and 30 participation in the second survey, age range from 18 to 50). Table 2 displays the detailed paper questionnaire for the first and second surveys. After watching the movie clips, 30 other participants who weren't involved in first survey, participated in the second survey are requested to complete a questionnaire. 35 movie clips are prepared of 5minutes for the second survey's rating using the first survey's dimension model. The criteria for choosing movie clips to elicit the participant's emotional states are as follows: (1) the movie clip should not induce many emotions, (2) it should be comprehended by participants without explanation, and (3) it should elicit a single targeted emotion.

Table 2: The entire survey questionnaire for selecting emotional stimuli

First Survey (Posters)	Question 1	Have you ever seena movie clip?
	Question 2	How did you feel about this clip?
	Question 3	What emotion can you feel through the movie?
	Question 4	Evaluate movie clips for Happy, Angry, Sad, disgust, fear, surprise, and neutral using emojis.
Second Survey (Movie clip)	Question 1	Have you ever seen a movie clip?
	Question 2	How did you feel about this clip?
	Question 3	What emotion can you feel through the movie?
	Question 4	Evaluate movie clips for Happy, Angry, Sad, disgust, fear, surprise, and neutral using emojis.

70 participants were asked to answer a questionnaire that evaluates the feeling generated by movie's clips, which are filled out only when they have never seen it before in the first survey only saw the poster at that time. The evaluation criteria are used by the Self-Assessment Report (SAR) shown in Figure 3.

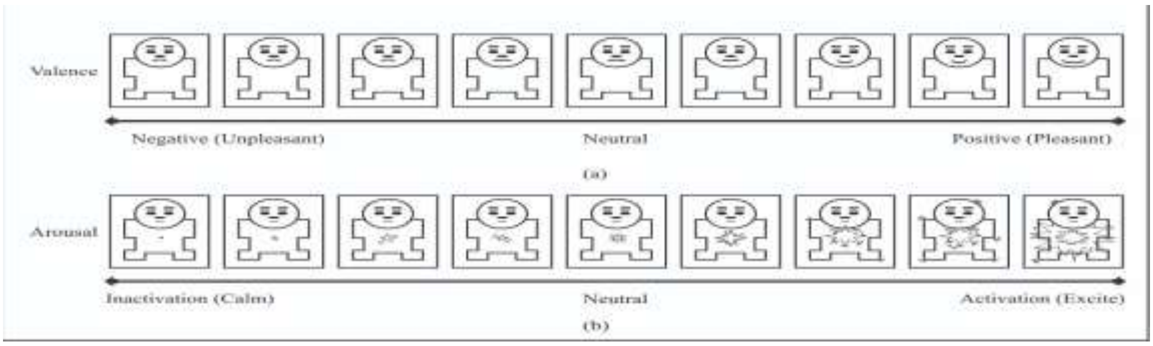
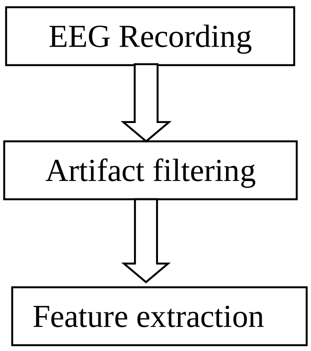


Fig.3: self-assessment manikin (SAM) measures valence (a), and arousal (b) on a discrete scale of 1 to 9 (1: very low, 5: neutral, 9: very high).

Process of Phase II
EEG Recording process

EEG Sensor: Brain signals are an invisible activity generated in the human brain EEG signal detectors are designed and fed into the detection procedure to recognize the emotional state.Figure4 shows the process of recognizing the different emotions[20].



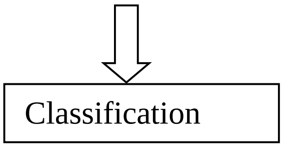


Fig.4 Process to recognize different emotion

EEG Pre-processing and Feature Extraction

Two progressive stages preprocessing and feature extraction used in EEG detection where feature extraction is based on PSD. Eight frequency bands, including delta (1-3 Hz), theta (4-7 Hz), alpha1 (8-10 Hz), alpha2 (11-13 Hz), beta1 (14-20 Hz), beta2 (21-30 Hz), gamma1 (31-40 Hz), and gamma2 are used to band pass filter the EEG data (41–50 Hz). Table 3 illustrates EEG signals for the eight aforementioned frequency ranges. By using the Short-Time Fourier Transform (STFT).

Table 3:The Eight Frequency Bands

Frequency	**Range(Hz)**	**Mental activity**
Delta	1-3	Slow
Theta	4-7	Slow and dreaming
Alpha1	8-10	Relax
Alpha2	11-13	Relax and yet aware
Beta1	14-20	Alert and thinking
Beta2	21-30	Alert thinking, an active state of mind
Gamma1	31-40	Active brain
Gamma2	41-50	Hyper brain activity

Emotion Classification using Support Vector Machine (SVM)

The first classifier is used to categorise emotional states, while the second classifier is used to categorise emotional intensities. It's a linear SVM classifier for both. In order to classify samples (xi, yi) and (xi, yj), where xi stands for the feature vectors corresponding to the seven emotion states or the three emotion intensity levels, respectively, are trained. The power density spectrum for the eight frequency bands is represented by the symbols Xi=DELTA, THETA, ALPHA1, ALPHA2, BETA1, BETA2,GAMMA1, and GAMMA2. Yi is the name given to the six emotional states. Seven scores—denoted by the numbers s2i I = 1,..., 7—are obtained when the feature vectors are subjected to the first trained SVM classifier. The six emotion states (happy, surprise, neutral, sorrow, disgust, anger, and fear) that the EEG classifier identified are represented by thatWe normalize the seven scores by mapping them to the range [0, 1].

Xi= DELTA,THETA, ALFA1,ALFA2
BETA1, BETA2, GAMMA1, GAMM2

$$Y_i \left\{ \begin{array}{l} \text{1. Happy} \\ \text{2. Neutral} \\ \text{3. Sad} \\ \text{4. Disgust} \\ \text{5. Angry} \\ \text{6. Fear} \end{array} \right. \qquad Y_j \left\{ \begin{array}{l} \text{-1 weak} \\ \text{0 moderate} \\ \text{1 Strong} \end{array} \right.$$

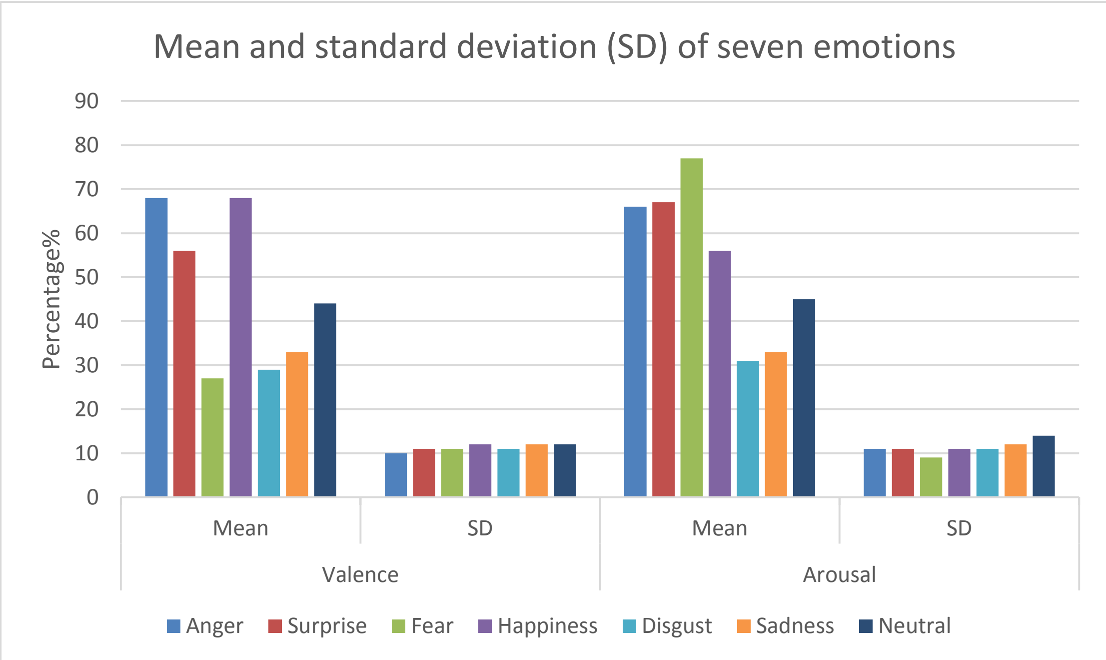
3. Experimental Results And Analysis

Statistical Data Analysis and Results: Phase I and Phase II of this study's studies were conducted. Each subject was instructed to refrain from making any movements, including blinking their eyes, while they were each comfortably situated on a chair. The data collection included twenty trials. At the conclusion of the trial, after 5 minutes of movie clips depicting various emotional states have been shown, participants are required to complete the questionnaire for each movie clip. The result is based on the Self-Assessment ratings for Valence and arousal(scale ranges from 1-to-9)during the experiment shown in table 4 in terms of mean value and standard deviation and its graphical representation is shown in figure5. We found that the happiness valence level (mean=6.8 and SD=1.11) is higher than the arousal level(mean=5.6 and SD=1.12). Fear arousal level is the highest (mean=7.7 and 0.90) and valence level is low (mean=2.7 and SD= 1.14) among the emotions.

Table4: Mean and standard deviation (SD)by dimension model

Emotion	**Valence**		**Arousal**	
	Mean	**SD**	**Mean**	**SD**
Anger	6.8	1.01	6.6	1.15
Surprise	5.6	1.16	6.7	1.11
Fear	2.7	1.14	7.7	0.90
Happiness	6.8	1.11	5.6	1.12
Disgust	2.9	1.10	3.1	1.13
Sadness	3.3	1.13	3.3	1.14
Neutral	4.4	1.15	4.5	1.43

Fig.5 Mean and standard deviation (SD) of seven emotions



EEG Dataset

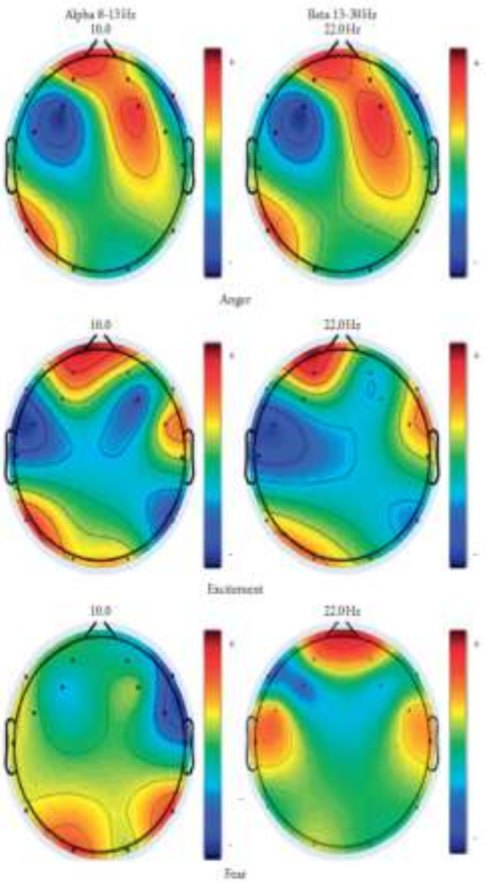
One sample with a length of 510 samples (4 seconds) was used to create an EEG signal feature vector, generating a step of 124 samples (1 second). Since pre-processing of EEG signals is done to remove artefacts, the data size for emotions varies from 422 to 544 samples. Table5 details the sample data size.

Table 5: The sample data size

Emotion	Training	Test	Total
Happiness	425	100	525
Fear	386	96	482
Surprise	452	112	564
Anger	510	124	634
Sadness	340	82	422
Neutral	428	104	532
Disgust	368	95	463

Brain Mapping Topography Analysis

In phase II, a similar approach was used for every trial. The emotional state was recorded at the conclusion of each movie clip using an EEG detector. According to Figure 6, where the band that corresponds to various emotional states.) I.e., isobar colour conveys the degree.



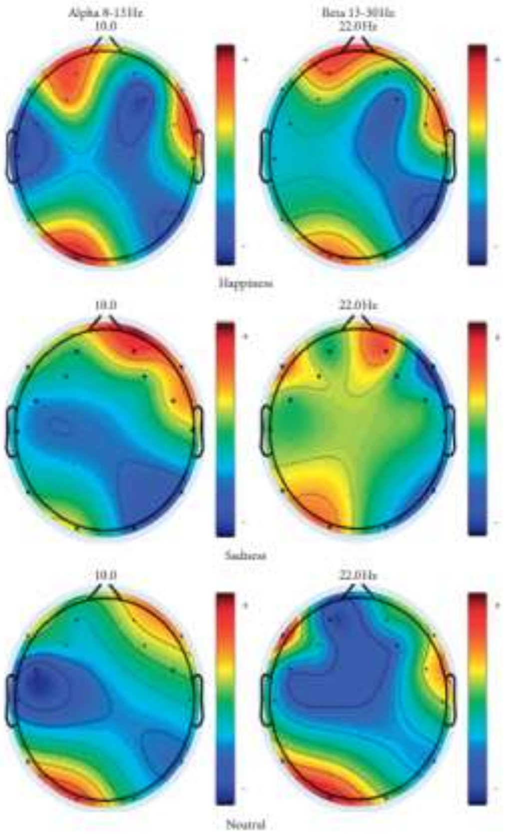


Fig.6 Brain mapping topography of the correlation coefficients between the specific band and emotional state

Emotion-Related Channels Selection

EEG feature vector that was generated in eight different types of frequency bands.We obtained the spectral power and experimental conditions are:

Frequency bands: all (1-50 Hz) bands versus alpha/beta (8-30 Hz) bands. We propose the emotion-related eight channels: DELTA, THETA, ALPHA1, ALPHA2, BETA1, BETA2,GAMMA1, and GAMMA2 mentioned as C1 to C8.

Seven feelings (anger, disgust, fear, surprise, sadness, happiness, and neutral), as normalized to three intensities (Strong, Moderate, weak) from [0 to 1], make up the emotion category.

Channels: Selected channels vs. All channels (14 channels) (7 channels).

The results of the statistical data analysis are shown in table 6. We extracted the emotion-related EEG features in order to verify the resulting EEG database. We analyzed data statistically. (ANOVA (analysis of variance) with repeated measures) in according to a topographical analysis of brain mapping. We the repeated-measures procedure (mixed design) ANOVA using the factors of emotional states and frequency bands and channel locations; importance level. The cutoff point for all statistical analyses was 0.05 ($p < 0.05$). It was carried out utilizing the statistical software tool SPSS (25.0 version).

Table 6: The results of paired t-test: the mean values about spectral power in the emotions, is significant ($p < 0.05$), ∗<0.01, ∗∗<0.001)

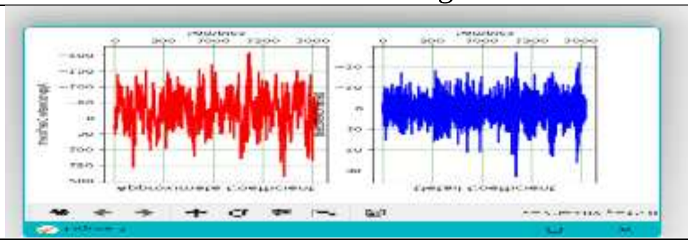
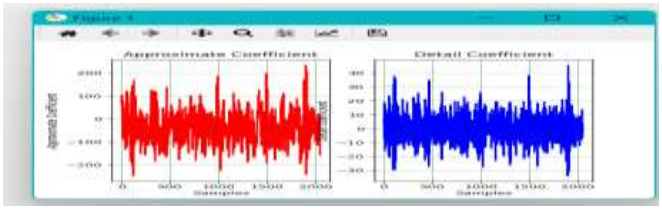
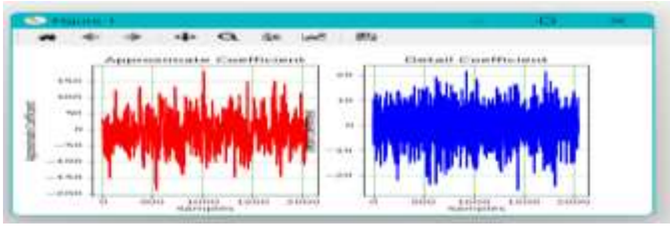
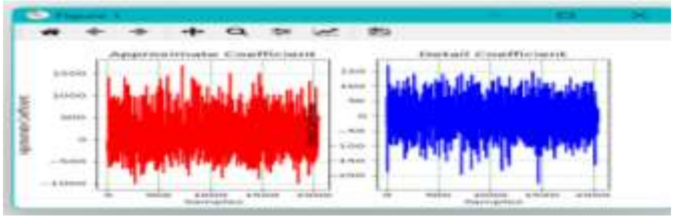
S.No.	Channel	Anger	Disgust	Fear	Surprise	Sadness	Happiness	Neutral
		M/SD	M/SD	M/SD	M/SD	M/SD	M/SD	M/SD
1	Alpha_C1	7.53	7.44∗	8.23	7.44∗∗	13.89	20.14	4.22
		4.30	3.67	0.78	4.62	5.80	6.92	0.16
2	Alpha_C2	10.10	12.79∗∗	11.65	14.70	11.65	12.57	4.22
		7.21	6.32	4.50	3.23	3.21	7.54	1.36
3	Alpha_C3	10.39	11.59	10.75	27.32	17.56	31.68	7.56
		9.38	4.52	6.78	5.43	2.67	8.21	2.18
4	Alpha_C4	25.75	14.01	19.75	20.25	19.79	27.21	6.25
		8.10	5.32	3.21	9.21	5.89	11.23	2.53
5	Alpha_C5	17.21	15.68	18.59	24.41	10.59	44.41	4.41
		9.41	7.04	6.50	11.41	4.39	13.65	6.23
6	Alpha_C6	14.94	7.21	25.20	12.21	15.76	35.76	10.59
		8.80	11.42	5.72	7.20	14.38	12.65	4.59
7	Alpha_C7	9.75	16.21	14.84	19.25	13.59	39.75	9.59
		4.03	5.61	11.40	6.54	5.03	7.32	3.01
8	Alpha_C8	18.75	15.21	13.84	18.25	15.59	49.75	10.59
		12.50	9.30	4.67	7.29	11.32	16.74	4.98
9	Beta_C1	14.65	29.24	18.35	15.59	14.41	46.59	7.21
		9.58	6,79	9.04	11.40	7.28	13.49	8.76
10	Beta_C2	14.39	10.25	17.00	15.75	25.30	29.59	9.75
		9.75	10.35	7.49	12.83	15.92	11.28	9.49
11	Beta_C3	17.56	22.75	14.68	29.75	13.68	47.21	19.50
		10.88	7.35	9.39	11.60	8.34	13.55	9.05
12	Beta_C4	19.59	19.50	19.21	19.50	17.34	45.75	15.75

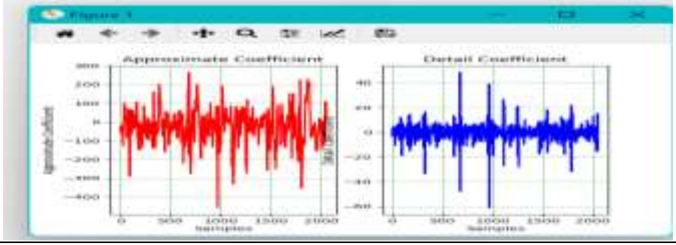
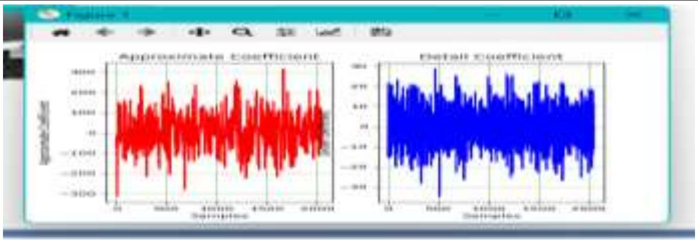
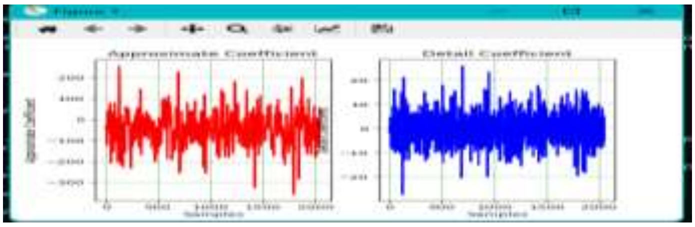
		13.07	6.39	6.45	7.54	6.67	11.02	3.42
13	Beta_C5	14.41	29.25	9.59	13.68	11.21	59.50	19.68
		10.55	34.30	10.40	9.47	7.91	9.42	11.61
14	Beta_C6	35.76	27.56	17.56	27.65	19.50	60.25	17.31
		9.30	12.49	16.31	12.70	9.87	15.40	9.02
15	Beta_C7	44.72	35.62	31.76	30.76	9.75	67.56	25.76
		21.67	21.89	13.87	9.34	10.20	24.85	13.56
16	Beta_C8	39.59	19.85	28.21	27.50	19.34	45.25	14.75
		31	28.23	12.42	8.96	13.52	15.32	8.91

Emotion Classification using Support Vector Machine (SVM)

Figure 7 shows a screenshot of a brain signal which is recorded in EEG. Basic seven states of emotion (anger, fear, disgust, Surprise, sadness, happiness, and neutral) and three emotion intensities (weak, moderate, and strong) were evaluated.

Fig. 7 Screenshot of brain signals

Emotion	Picture Captured	EEG Recording
Anger		
Fear		
Disgust		
Surprise		

Sad		
Happy		
Neutral		

The self-reported emotion states and EEG signal intensity levels were utilised to train an SVM classifier using the gride search method in order to validate the classification of EEG emotions. In order to handle nonlinear issues, input feature vectors are transformed into a dimensional feature space that may be linearly separated. 5-fold cross-validation is used in this study.) i.e., the dataset is partitioned into five subsets at random (equal or approximately). The calculations for the outcomes are as follows. True Positive(TP): Values that are actually positive and predicted positive. False Positives (FP): Values that were anticipated to be positive but are really negative.False Negative (FN): Values that are projected to be negative but are actually positive. Values that are both genuinely negative and expected to be negative are referred to as True Negatives (TN).[21,22]

In a confusion matrix, rate is a metric. The four types of it are TPR, FPR, TNR, and FNR.

True Positive Rate (TPR) is equal to True Positive (TP) / Positive.

Negative / False Positive (FP) = False Positive Rate (FPR)

FNR (False Negative Rate) = FN (False Negative) / P

Negative minus True Negative (TN) = True Negative Rate (TNR).The precision (PPV), and false discovery rate (FDR) are the expected proportion of type I errors the calculation is shown in Table 7.

Table 7: Rate for seven emotions based on the movie clip

Emotions	**TPR**	**FPR**	**TNR**	**FNR**	**PPV**	**F1-SCORE**	**FDR**
Anger	0.717948	0.03333	0.94761	0.31428	0.8	0.75675	0.2
Fear	0.65476	0.03571	0.93095	0.41428	0.78571	0.71428	0.21428
Disgust	0.68831	0.04047	0.942857	0.34285	0.75714	0.72108	0.24285

Surprise	0.72003	0.03809	0.95	0.3	0.77142	0.74482	0.228571429
Sad	0.73654	0.03333	0.94761	0.314285714	0.8	0.75675	0.2
Happy	0.65476	0.035714	0.93095	0.41428	0.78571	0.714285	0.21428
Natural	0.68831	0.04047	0.94285	0.34285	0.75714	0.72108	0.24285

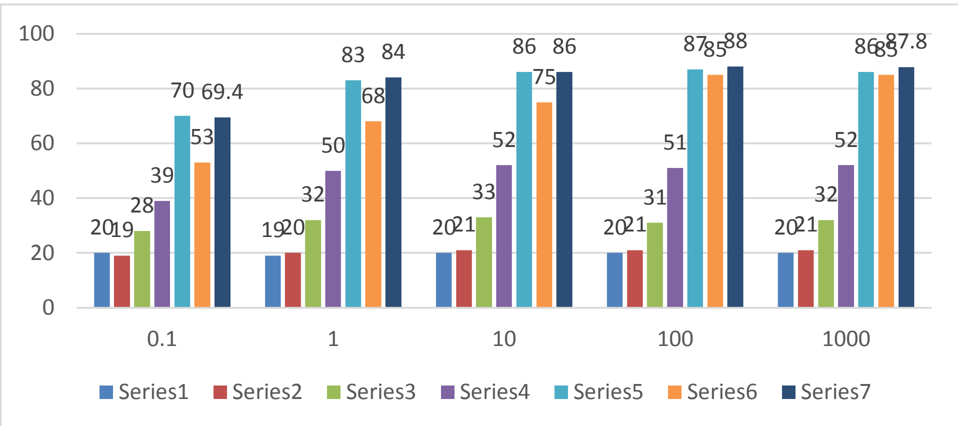
The confusion matrix is used to evaluate how effectively the classification model is working. When we have unbalanced data, it can be misleading to measure the performance of our models by accuracy. The tools used to evaluate categorization models are performance measures.

We were able to confirm that there was a highly significant (p > 0.001) correlation between the frequency ranges, channels, and emotions.

Figure 8 shows the seven emotions' accuracy at approximation coefficients and detailed coefficients, and Figure 9 shows confusion metrics for the seven emotions utilising suggested channels with alpha and beta frequency bands (8-30 Hz) (A: Anger, F: Fear, D: Disgust, Su: Surprise, S: Sadness H: Happiness, N: Neutral,).

Fig. 8: Calculated accuracy of seven emotions emotion at approximation and detailed coefficients

(a)



(b)

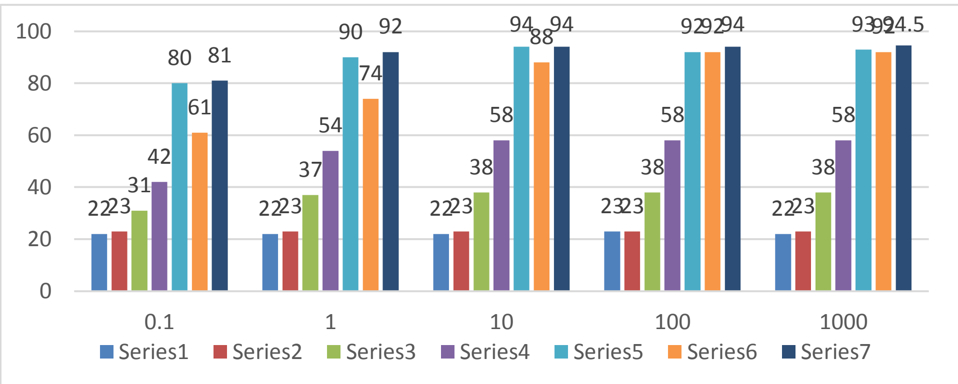


Fig. 9 The confusion metricsfor seven emotions (A: Anger, F: Fear, D: Disgust, Su: Surprise, S: Sadness H: Happiness, N: Neutral,)using eight channels with alpha and beta frequency bands (8–30 Hz)

	A	F	D	Su	S	H	N
A	98.78	0.02	0.07	0.04	0,23	0.09	0.05
F	0.12	95.47	2.07	3.76	1.79	0.48	11.50
D	0.10	7.20	92.83	0.45	1.67	5.76	3.48
Su	1.27	1.82	1.96	96.44	0.83	2.61	0.08
S	1.29	9.84	0.57	2.75	83.67	1.98	1.42
H	0.23	1.97	0.94	1.24	1.42	93.95	0.12
N	1.14	15.54	10.23	2.56	3.64	0.17	74.96

4. Conclusion

The EEG-based Indian emotion database was introduced in this study, and the created database was verified using emotion classification. We describe a novel continuous EEG-based emotional database created after 50 individuals observed emotional stimuli intended to elicit specific emotions. The eight channels—DELTA, THETA, ALPHA1, ALPHA2, BETA1, BETA2, GAMMA1, and GAMMA2—that were triggered by diverse emotions could be distinguished. In addition, we employed a Support Vector Machine (SVM) to validate the efficacy of the proposed emotion-related channels. A variety of channel, frequency band, and emotion configurations are used during the categorization performance. The best accuracy was 94.57% when seven emotions were used, together with alpha and beta bands. As a conclusion, this paper describes the Indian EEG emotion database for EEG-based emotion identification] and validates the effectiveness of the proposed EEG emotion-related channels. As a result of these findings, the Benchmark database will be made accessible for use in interdisciplinary research for behavioural and emotional analysis. Additionally, depending on our recommended emotion-related channels, it will help in emotion classification using machine learning approaches. It also provides a means of determining whether a work is suitable in light of a person's emotional intensity levels.

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