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EEG-BASED EMOTION CLASSIFICATION FOR MOVIE CLIPS WITH SUPPORT VECTOR MACHINE

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Abstract

During engagement or communication, the human body produces a range of emotions that differ in complexity, intensity, and meaning. It may be simple to interpret behavioral emotions communicated through body language, voice tonality, and facial expressions, but when it comes to those who are unable to express their feelings through behavior, emotions can still be detected by a person's brain signal. In this study, we used a signal that the human brain generates based on emotional state to categorize emotions. For emotion detection, we employed EEG signals from the eight frequency bands. Different emotions, including joyful, sad, angry, fearful, astonished, and neutral expressions, were recognized. by displaying various emotional video clips, measuring the intensity of the emotion using brain signals, and contrasting it with the subject's own words. We have prepared a dataset of 100 people's brain signals as well as 40 different emotion-based movie clippings. Apply For the purpose of calculating and comparing results, support vector machines and deep learning networking were used.

Keywords-Emotion, EEG, SVM, Classifier, expression.

1. Introduction

Human awareness is an emotion, and emotion is essential for intelligent human interaction, perception, decision-making, and consciousness. Emotion is a representation of non-physiological data, including voice tone, words, expressions on the face, and body language. In recent decades, numerous studies on emotion recognition based on non-physiological signals have been done and published. Recently, EEG-based emotion identification has drawn attention from all around the world due to its portability, affordability, simplicity, and ease of use. The relationship between emotional state and brain activity can be seen in the very subtle emotional changes that are captured in recorded EEG signals with great time resolution.

Human-computer interaction (HCI) is emotional computing that satisfies user demands and increases user productivity. Many requirements for a perceptive human being are tied to emotions and interactions.

"Recognising effect should greatly facilitate the ability of computers to heed the rules of human communication," write Picard and Klein. In psychology, there is a formal division between the cognitive experience of a feeling (emotion), its physiological arousal, and its behavioural expression (affect). Electroencephalograms (EEGs) have been studied due to the growing interest in brain-computer interaction (BCI). The EEG displays a physical reaction, or it also sheds light on the feeling that's being felt psychologically.

Due to the availability of a finite number of electrodes, the EEG is used to record brain signals and neural networks classifying them into seven emotional valences and arousal. What's significant for our case are the prominent EEG features detected during different emotional stimuli, which are represented in figure 1.

•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.

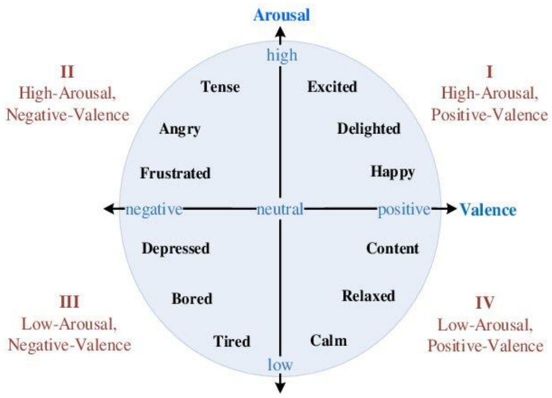

Fig.1: Valence-arousal dimensional model

2. RELATED WORK

Bhatt et al. (2019) employed an SVM classifier with the third-party library LibSVM to focus on the EEG dataset. They classified the EEG SEED dataset, and the accuracy and performance saw a remarkable improvement. The performance and accuracy of the dataset can be improved using a variety of strategies, which are outlined and explained. Different classifiers were utilised, including SVM with KNN, ELM, SVM with the SEED dataset, and SVM with the DEAP dataset.[2]

Pre-processing, feature extraction, and selection, followed by emotion recognition using IKNN, were the three processes that Doye et al. (2019) examined. They created an algorithm to measure performance in the SEED platform of the Matlab simulation programme using five factors. The accuracy, precision, recall, and mean square error of this classification method were the best. With their results, they provided a thorough summary of the various classification strategies.[3]

EEG biometrics were reviewed by Meriemet al. (2017). 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.[2]

The EEG waves associated with various emotions were categorised by Polat et al. (2017). These audiovisual stimuli that are based on emotions have channel selection preprocessing. They talked about the preprocessing of channel selection utilised in emotion recognition, talked about audiovisual stimuli, and looked at characteristics extracted from the alpha, beta, and gamma bands as well as the tetra band from EEG signals in the detection process.[3]

Houshmand et al.'s (2017) analysis of emotion feature extraction and categorization. They investigated the best way to categorise the six emotional states: fear, happiness, sadness, pleasure, and satisfaction.[4]

3. METHODOLOGY

Humans have a crucial characteristic called emotion, which allows us to express our feelings either verbally or nonverbally. Actually, facial expressions serve as interfaces via which one can perceive what is happening in one's head and how one is feeling. Human emotion is a broad phrase for a complicated collection of emotions involving interactions between different goals. Neural and hormonal systems that are mediated by subjective factors are able to:

1. Produce perceptual events like pleasure or discomfort, and feelings of arousal;

2. Emotionally relevant perceptual effects, appraisals, labeling processes, etc. produced by cognitive processes;

3. Although there have been changes in behavior, they have not always been expressive, goal-directed, or adaptive.

3.1 Working modal design

The process of non-verbal communication is significantly influenced by facial expressions. Similar to body language, facial expressions, voice inflection, and other communication tools, expressions are a means through which we can convey information to others. We have created a modality to categorize and classify people's emotions, and we worked on it in two stages. In Figure 2, the working modal is displayed.

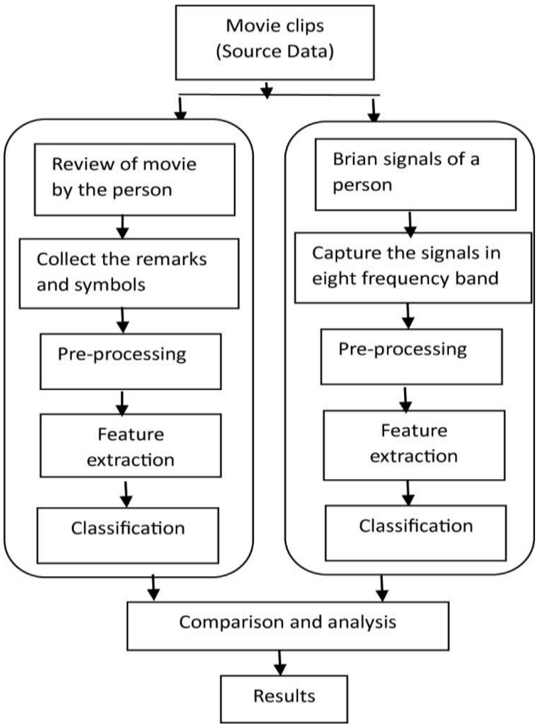

Fig.2 The steps are working modal

3.2 Data gathering

There are several ways to capture human emotions and have them validated by images and video clips. You can also employ storytelling techniques to evoke emotions and capture brain activity. Phase one data from a variety of emotionally charged movie clippings was gathered for this paper's review of three sources. One is the use of different emotional movie clippings to record different brain signals in accordance with the clipping.[9] When the patient watched the movie snippets, we measured the signals that came from their brains. Figure 3 displays the video clip with the various emotions.

Fig.3 Movie clip shows a different emotion

3.3 Phase I's operation

Emojis can be used to express seven different emotions in a sequential manner, as seen in joyful, furious, scared, neutral, surprised, sad, and disgusted. The purpose of this study is to categorize these seven fundamental emotions using brain signals.

3.4 Phase II process

Figure 4 depicts the process for identifying a person's various moods.

fig.4 Process to recognize different emotion

EEG Sensor:

EEG sensor: The brain produces unseen activity known as brain signals. Phase II involves designing EEG signal detectors and feeding the EEG signal into the detection process so that the EEG sensor can identify the emotional state.

Preprocessing and feature extraction, both sequential processes employed in the detection of EEG, are based on PSD.

The eight frequency bands that the EEG data are bandpass filtered over are 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 (41-50 Hz).We compute the conventional PSD characteristics with two windows: a 1-s window and no overlapping Henning window, using the Short-Time Fourier Transform (STFT).

One is used to classify emotion states, and the other is used to classify emotion intensities. Both are linear SVM classifiers. To classify the samples (xi, yi) and (xi, yj), we train them.

DELTA, THETA, ALFA1, ALFA2

Xi=

BETA1, BETA2, GAMMA1, GAMM2

Yi =	1. Happy
	2. neutral
	3. sorrow
	4. disgust
	5. anger
	6. fear

Yi=	+1
	0
	-1

Yi stands for the label of the six emotion states, Yj is the label of the three emotion intensity levels, and xi represents the feature vectors corresponding to the six emotion states or the three emotion intensity levels. Where Xi=DELTA, THETA, ALPHA1, ALPHA2, BETA1, BETA2, GAMMA1, and GAMMA2 represent the power density spectrum corresponding to the eight frequency bands.

When the first trained SVM classifier is applied to the feature vectors, we get six scores, which are represented by the letters s2i (i = 1,..., 6). The six emotion states (happy, neutral, sorrow, disgust, anger, and fear) that the EEG classifier observed are represented by that. By mapping the six scores to the range [0, 1], we normalize the scores.

For the purpose of identifying human emotion using neural networks, the subsequent procedures are used:

- Various traditional methods are researched and examined for recognizing human emotions.
- Python 3.9 is used to analyze and recognize human emotion using a developed simulator.
- Achieve Results are compared to the program's execution and earlier outputs.
- Language needed: Python 3.9

Python is a high-level, all-purpose programming language that is interpreted. Python's design philosophy places a strong emphasis on code readability through the use of noticeable indentation. Its language constructs and object-oriented methodology are intended to aid programmers in creating logical, understandable code for both little and big projects. [10]

4. RESULTS AND ANALYSIS

The studies for this study were undertaken in phases I and II. Each subject was advised to perform this while comfortably seated in a chair without moving their bodies, including blinking their eyes. Twenty trials were included in the data collection. Participants are asked to select yes or no and an emoji for each of the two-minute video snippets that illustrate different emotional states on a questionnaire at the end of the study. The knowledge they acquired through the experiment depicted in Table 1 will decide the outcome.

On a mobile device, 200 sets of EEG readings were used in each experiment. Throughout the self-evaluation, valence and arousal scores were recorded. The basic seven emotional states—happy, neutral, sad, angry, disgusted, and frightened—as well as four emotion intensities—low, low, middle, average, and high—were evaluated. EEG emotion classification was confirmed using the self-reported emotion states and intensity levels that were provided. The emotional states that accompanied the EEG readings were used to train an SVM classifier. Two classifiers—a neural network classifier and an SVM—that were personalized for each person were employed in Experiment 2 to categorize different emotional states.

TABLE1: Rate for each movie clip given by subject

Accuracy	Sensitivity (Tpr,Recall)	Specificity (Tnr,Selectivity)	Precision (Ppv)	False Discovery Rate(Fdr)	F1-Score	FAR	FNR
0.9265	0.71794	0.94761	0.8	0.2	0.7523	0.0333	0.3142
0.9102	0.65476	0.9309	0.78571	0.2142	0.7142	0.0357	0.4142
0.9163	0.68831	0.94285	0.75714	0.2428	0.7210	0.0404	0.3428
0.9244	0.72	0.95	0.77142	0.2285	0.7448	0.0380	0.3

In this study's Experiment 1, 40 movie clips are evaluated over the course of 30 trials for each participant. In Experiment 2, all trials were conducted using the same methodology. An EEG detector was used to create the emotional state at the conclusion of each movie clip. If the detection result was correct, there was cheering for four seconds to indicate that. There were no more remarks made. The online accuracy for performance evaluation was calculated as the ratio of the number of accurate predictions to the total number of trials that were displayed. Screenshots from Experiment 2's face movies and a brain signal captured by an EEG shows in Figure 5.

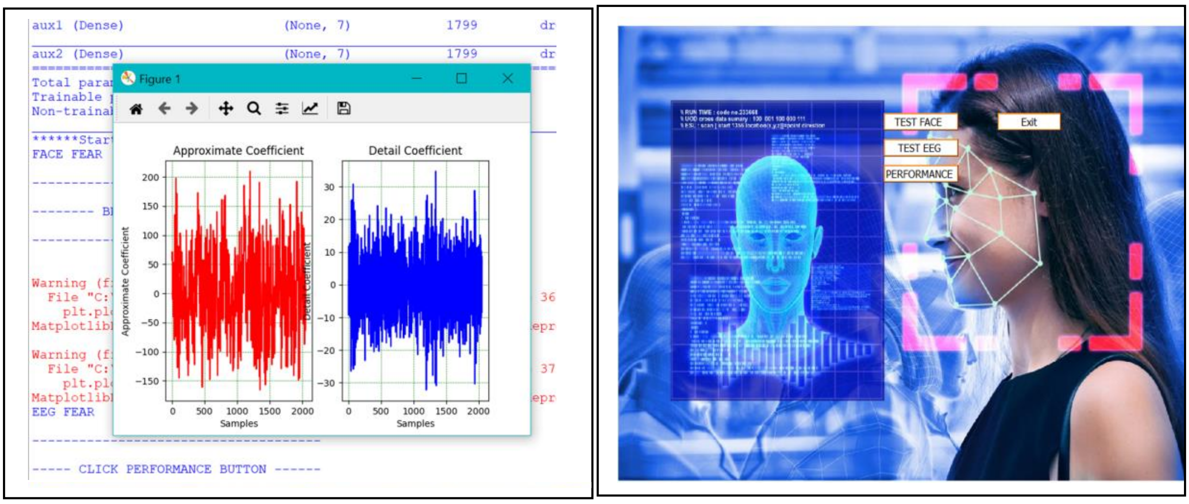

Figure 5: Example screenshot of EEG signals from Experiment 2

(Offline) data analysis. For the Experiment 1 data set, we used emotion states to train an SVM classifier. For the Experiment 2 data set, we employed the detector based to determine the emotional state and estimated the associated offline accuracy rates shown in Table 2. And its graphical representation shows in Figure 6.

Table 2 : Six emotions reading of a persons

PERSON	ANGRY	FEAR	HAPPY	DISGUST	NEUTRAL	SAD
P1	0.95653	0.9102	0.97612	0.90449	0.85428	0.934694
P2	0.95643	0.9102	0.97232	0.90359	0.84429	0.933493
P3	0.96553	0.91022	0.97633	0.90438	0.85428	0.937691
P4	0.95493	0.9102	0.97632	0.90449	0.85428	0.939654
P5	0.96153	0.9102	0.97632	0.90459	0.8529	0.935693
P6	0.96652	0.91022	0.97633	0.90438	0.85382	0.934491
P7	0.95633	0.9102	0.97632	0.90449	0.84486	0.934694
P8	0.96622	0.9102	0.97632	0.90459	0.8542	0.937193
P9	0.95652	0.91022	0.97633	0.90438	0.84482	0.930791
P10	0.96653	0.9102	0.97632	0.90449	0.83486	0.932594

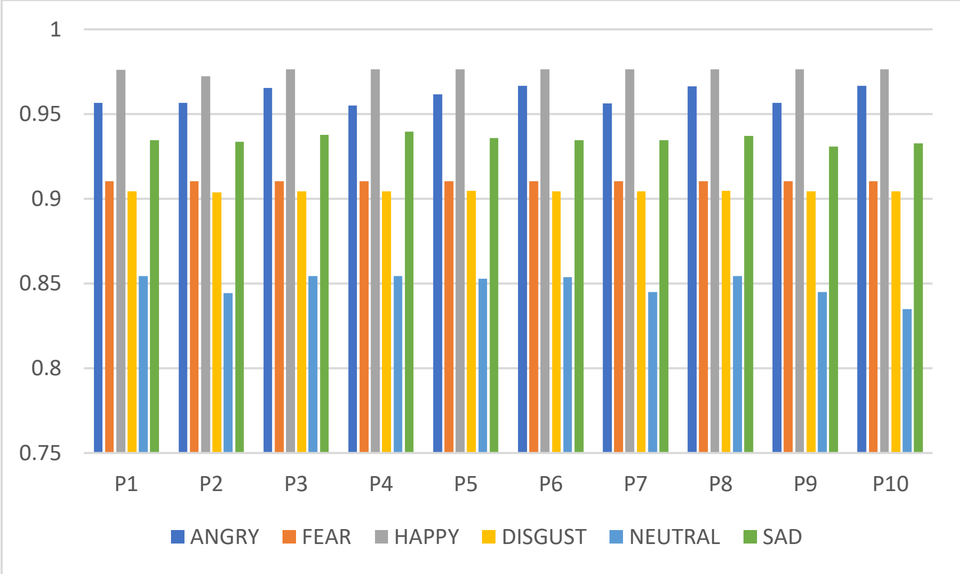

Fig.6: Six emotions of persons

5. CONCLUSION

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.

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