Machine learning-based hybrid emotions recognition model using electroencephalogram signals

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ABSTRACT

This paper uses Hindi video clips to propose an electroencephalogram (EEG) signal-based hybrid system for emotion identification. EEG signals cannot be altered, unlike other forms of expressiveness-like voice and facial emotion. The suggested approach uses a self-created dataset under the control environments. Accuracy is the main objective of the proposed model. This study used a self-created constructed using an 8-channel unicorn black hybrid EEG machine on 30 participants while they viewed Hindi movie video clips mimicking emotions: happy, fearful, sad, and neutral. The proposed model used a two-hybrid classifier support vector machine (SVM) and k-nearest neighbor (KNN), implemented using MATLAB R2017a. In the proposed implementation, the four emotion classification categories (happy, sad, fear, and neutral) observed an average accuracy of 60.832%. The results of the presented study were compared with two recent systems. It was found that the proposed system observed better accuracy for the category of NHP five classes and the category of HP Five Classes.

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1. INTRODUCTION

Electroencephalogram (EEG) measures the activity in the brain by electrical signals. An analysis of such signals involves the frequency bands namely Delta, Theta, Alpha, Beta, and Gamma. Most basic emotions such as happiness, fear, sadness, and neutrality have been classified through the extraction of features from these signals, for instance, using band power and entropy. These characteristics allude to arousal and valence; a pattern such as increased Beta activity depicts fear or anxiety and is associated with calmness or neutrality with Alpha waves. For recognition of these patterns, machine learning techniques can use EEG signals effectively for emotion recognition and advance applications in neurofeedback, mental health, Parkinson's disease, and human-computer interaction [1], [2].

Most of the research on EEG-based emotion identification in healthy individuals has shown positive findings. Using a hearing loss simulator and the vocal morphing approach, emotion detection studies were performed on both elderly and young normal hearing (YNH) subjects [1]–[3]. Speech sounds were altered to symbolize feelings between all possible combinations of joy, sorrow, and rage and have looked at populations like those with hearing impairments [4], [5]. Some specialists claim that because of their hearing loss, persons with hearing impairments have difficulties in understanding accurate information from the outside world as compared to persons with normal hearing [6], [7]. Zhu *et al.* [8] proposed a theory on image-stimulated emotion identification for subjects with hearing impairments using EEG data signals. They used three different classifications namely neutral, positive, and negative; and also five different classifications namely neutral, happy, sad, angry, and fearful to test emotion recognition accuracy. The results of their experiments presented that the multi-feature fusion helped hearing-impaired and non-hearing-impaired people, and the recommended strategy is better than the traditional feature technique. The average classification accuracy [9] was observed as 72.05% (three-classifications) and 51.53% (five-classifications) for hearing-impaired individuals and 50.15% (three-classifications) for non-hearing-impaired subjects, respectively.

Jin *et al*. proposed a theory based on face-affective photostimulation. For this purpose, they used an emotional self-created EEG dataset of 15 hearing-impaired and 15 normal people. The dataset created by Jin *et al.* [10] included five different emotion types (happy, neutral, sorrow, fear, and rage). Preprocessing filters and eliminates artifacts from the gathered EEG signals. After extracting traits including power spectral density (PSD), differential entropy (DE), and wavelet entropy (WE), it was shown that the linear support vector machine was the most effective classifier for a 10-fold cross-validation for emotion classification. As per their findings, the DE characteristic observed the highest accuracy in identifying emotions among respondents with hearing impairments (40.8%) and normal subjects (45.5%). Yang *et al.* [11] examined the emotional recognition pattern of deaf persons. They used a deep belief network in conjunction with the EEG and facial expressions to distinguish three types of emotions. A total of 15 deaf participants' signals were captured as they viewed the movie clips.

In this study, a hybrid system is proposed for emotion classification and tested using a self-created dataset [12]. The model is based on Hindi movie videos with voice, mute, and deaf-based movie clips [13]. The further sections in the paper are organized as follows: The proposed method for emotion classification is demonstrated in section 2, along with the specifications and description of the proposed model. The results and discussion are presented in section 3, and the concluding remarks with future scope are described in section 4.

2. METHOD FOR EMOTION CLASSIFICATION

By employing the right method, emotion recognition may become more successful. In order to ensure accuracy, consistency, and accuracy, the section on experiments/methods provides a summary and explanation of the methods, tools, processes, and data analysis used in this research. Using the Unicorn Black 8-channel EEG program, 30 people aged between 18 and 56 participated in the self-created dataset. The participants were shown in separate Hindi video clip scenes, in which fears, tears, joys, and neutral emotions were reflected. To ensure uniformity of data collection, this procedure was performed sequentially for each participant. The domain parameters were selected based on what previous research has shown to be useful in differentiating the emotions present. In order to exploit the unique advantages of each classifier with improved accuracy and robustness, a hybrid classification strategy was used in the study, which combined support vector machine (SVM) and k-nearest neighbor (KNN) classifiers. Given the relatively small size of the dataset, leave-one-out cross-validation (LOOCV) was used as a validation method to ensure reliable model estimation and maximize the use of available data. Pre-defined signal-to-noise ratio and visual assessment criteria were used to reject trials with high noise or poor signal quality. Raw EEG data were pre-processed using conventional filtering methods to remove noise and artifacts. Section 2.1 provides the detailed parameters of the EEG equipment, such as electrode location, channel setting, and sampling rate, as well as the synchronization procedure for emotion labeling and stimulus presentation. Figure 1 presents the steps for the proposed emotion recognition model and the connections between the different processes. A detailed discussion of each step is presented in the subsequent sub-sections.

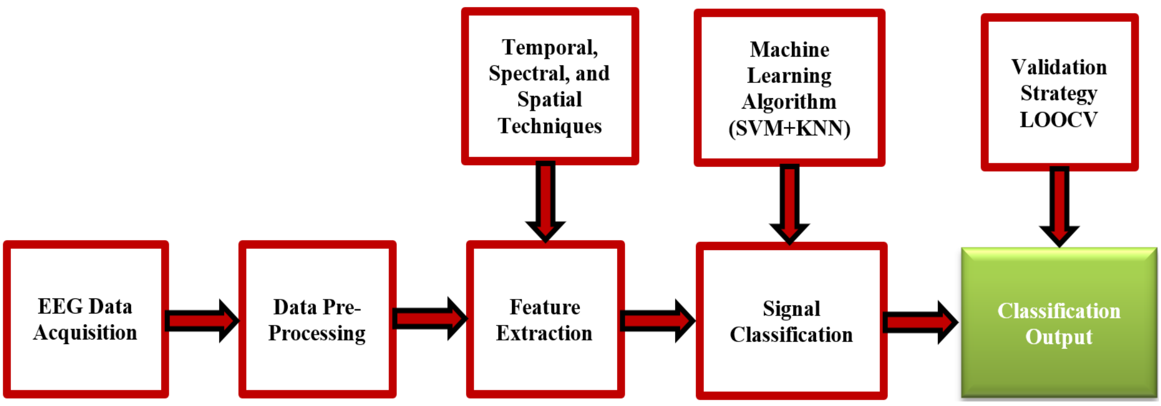

Figure 1. Proposed emotion recognition model

2.1. EEG data acquisition

EEG signals are captured from a hybrid Unicorn Black 8-channel EEG equipment to record participants' brain activity as they watch particular video stimuli to generate an EEG dataset for emotion detection. Low spatial resolution necessitates appropriate validation on a varied setup with regard to diversity in different devices or populations, but the enhanced 8-channel Unicorn Black hybrid EEG machine makes the implementation truly portable and simple enough for real-world applications. Thirty participants, ranging in age from eighteen to fifty-six, viewed Hindi videos intended to elicit four different emotions: fear, sad, happy, and neutral. Three distinct stages were included in each recording session, each including a variety of stimuli to allow for a thorough examination of the emotional reactions. The parameters of the self-created [12] dataset are presented in Table 1.

Table 1. Self-created dataset description

Parameter	Details
Participants	20 Male, 10 Female
Channels Number	08
Type of Signals	EEG
Number of videos (for each participant)	12
Sample rate frequency (after pre-processing)	250Hz
The number of classifications for the dataset	4
Classification Name	Happy, Fear, Sad, and Neutral
Quantity of information (.csv file)	360
Numerical data	12 videos×8 channels×30 Participants.

2.1.1. EEG equipment and channels

The Unicorn Black EEG 8-channel device is a high-performance wearable BCI device designed for the real-time recording of EEG data from the scalp using non-invasive electrodes. Analyzing mental states, including emotional reactions, requires signals indicating electrical activity produced by the neurons of the brain. Eight electrodes were placed on specific scalp sites according to the standard 10-20 system for electrode placement in EEG recording [5]. Electrodes were placed normally across the frontal, temporal, and parietal regions of the brain areas sensitive to emotional inputs. Each electrode recorded various brainwave frequency bands with different variants applied to measure shifts in different states of emotions. Figure 2 provides the position of the eight channels applied for signal recording that include Fp1, Fp2, C3, C4, P3, P4, O1, and O2.

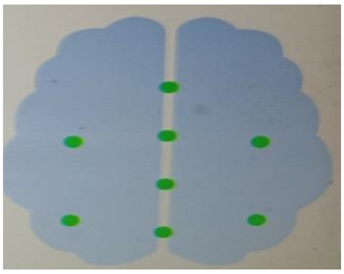

Figure 2. First Author with Unicorn black EEG device with 10/20 system

2.1.2. Procedure for gathering data

The study is divided into three phases: Phase 1 is the listening support while watching Hindi video clips, Phase 2 is hearing-impaired or deaf-mute persons watching Hindi video clips, and Phase 3 is a silent watching by participants of original Hindi clips without sound support.

Phase 1: Sound-assisted Hindi video clips

Phase 1 of the data collection process involves watching sound-assisted Hindi movie video clips (as shown in Figure 3). Participants in the first phase saw four Hindi movie video clips, each of which represented one of the four target emotions: Happy, Fear, Sad, and Neutral. Because the audio in these films was normal, viewers could see the visual material in addition to hearing it. The EEG gadget monitored the brain activity in response to these multimodal inputs (auditory and visual) during this phase. The file of this phase was stored as 1.csv, 2.csv, 3.csv, and 4.csv, which stand for the feelings of happiness, fear, sadness, and neutrality, respectively. This stage attempted to record the participants' authentic emotional reactions during their complete immersion in the visual and aural elements of the video clips, as both visual and auditory stimuli might affect brainwave patterns.

Figure 3. Normal Hindi movie clips

Phase 2: Hearing-impaired or deaf-mute individuals viewing Hindi video clips

During this stage, each participant was shown four distinct Hindi video segments (as shown in Figure 4). Since these were made for deaf or deaf-mute people, it is likely that the video material relied less on aural input and was mostly visual, potentially with subtitles or more expressive visual clues. During this phase, the individuals' EEG waves were gathered in order to examine the differences in emotional reactions when the audio component was either minimal or missing. EEG recordings of this phase were stored as 5.csv, 6.csv, 7.csv, and 8.csv, which are more correlated to the four emotions: Happy, Fear, Sad, and Neutral. The extent to which auditory input plays a role in the emotional processing of these video clips by contrasting the outcomes of this phase with Phase 1 was established.

Figure 4. Hindi movie clip based on deaf person

Phase 3: Muted/silently watching the original Hindi clips

Participants rewatched the first batch of Hindi movie video clips from Phase 1 in the final phase, but this time with the sound muted (as shown in Figure 5). With just visual stimuli available in this session, participants may decipher the emotions shown in the movies by concentrating on body language, facial expressions, and other non-auditory clues. This stage offered important information on how the brain's emotional response was impacted by the lack of auditory input. This stage helps investigate how effectively the brain can retain and understand emotional signals only through visual material because the participants had already seen these films with sound. This phase's EEG data was stored as 9.csv, 10.csv, 11.csv, and 12.csv files.

Figure 5. Hindi movie clip based on muted

2.1.3. Digital organization

The EEG signals in digitized form were kept for each participant in a folder structure arranged as S01 through S30, with one folder for each participant. Twelve .csv files, one for each of the three phases' various emotional states, are contained within each folder. Files 1.csv to 4.csv correspond to the initial phase (audio-visual standard with sound), files 5.csv to 8.csv represent the second phase (videos for deaf or deaf-mute individuals), and files 9.csv to 12.csv correspond to the third phase (original videos with muted audio).

2.1.4. Interpretation and understanding

Brain activities vary as participants experience emotions through distinct sensory channels (audio-visual, visual-only for deaf or mute, and visual-only following exposure to the audio-visual) and examine the EEG data from these three stages. EEG data from each condition may be compared to extract properties, such as brainwave patterns or frequency bands, which are unique to a certain emotional state. To create reliable emotion detection models based on EEG data, these characteristics may further be analysed and classified.

2.1.5. Challenges

Figure 6 demonstrates the experimental setup for the self-created EEG dataset. Maintaining consistent data quality among participants, reducing artifacts (including eye blinks and muscle movements), and managing inter-subject variability were the challenges with the self-created EEG datasets. To guarantee reliability, stringent procedures were followed during the EEG signal recording process such as uniform stimulus presentation and regulated ambient conditions. Preprocessing methods for improving signal quality were quite reliable. Cross-validating emotion labels with participant feedback preserved inter-rater reliability. In order to ensure that the model is generalizable across participants and sessions, robustness is achieved by feature extraction that captures a range of signal characteristics and LOOCV cross-validation.

Figure 6. A participant in EEG signal recording

2.2. Data pre-processing

Since each individual has a unique impedance on the electrodes and a distinct signal strength, normalization falls within the pre-processing step and must be done first. Additionally, there are variations in the signal between acquisition days for the same person. Before categorization, all data should be standardized or normalized. Three major normalization techniques are Z-score normalization, Minimum-Maximum normalization, and decimal scaling normalization. These three approaches are identical to one another. The Z-score Normalization technique was applied in this study. The standard deviation and mean were used to standardize the data. For all data, the standard deviation is one and the mean is 0. To determine the Z-score of each variable, subtraction of the mean was made from each data point and then divided by the standard deviation.

2.3. Feature extraction

After EEG signals data preprocessing, feature extraction is the next step. Frequency-domain properties are very important for understanding the patterns of brain activity related to different emotions during EEG emotion detection. The band power ratios play an important role in the brain-computer interface or it depends on mental states. By computing ratios between different frequency bands by analysing power distribution across these bands, several emotional states can be detected [14], [15]. These ratios help to distinguish states like happiness, fear, sadness, and neutrality as they indicate how varying the amplitude of brainwaves for different emotions. This methodology increases the reliability of identifying emotion as more importance is given to subtle variations between frequency domains in brainwave activity. Delta activity predominates in deep sleep, theta band appears in a very relaxed, contemplative, drowsy, or meditative state.

People who are awake and paying very calm, passive attention are known to exhibit the alpha band that is more pronounced when their eyes are opened. When focused or thinking actively, the beta band is visible. The beta band is visible when anxiety is predominant, active, and relaxed. Concentration may be found in the gamma band [16], [17]. High delta power indicates that the brain is in a very relaxed state or the recovery phase in deep sleep. Higher theta power indicates reduced alertness, perhaps in a state of daydreaming or light sleep. Increased alpha power is accompanied by a calm, relaxed, but awake state, such as closing the eyes in a quiet room. Beta power increases with increased mental activity, attention, or focus. It might be associated with anxiety or stress in extreme cases. High gamma power was often seen to accompany high levels of concentration, learning, or processing. EEG data was analysed for the first Hindi movie clips for participant S01. After processing the EEG data from 01.csv in MATLAB R2017b, the values of various band powers for each channel are displayed in Figure. 7. The X-axis represents the channel in Graphical representation and the Y-axis represents the power.

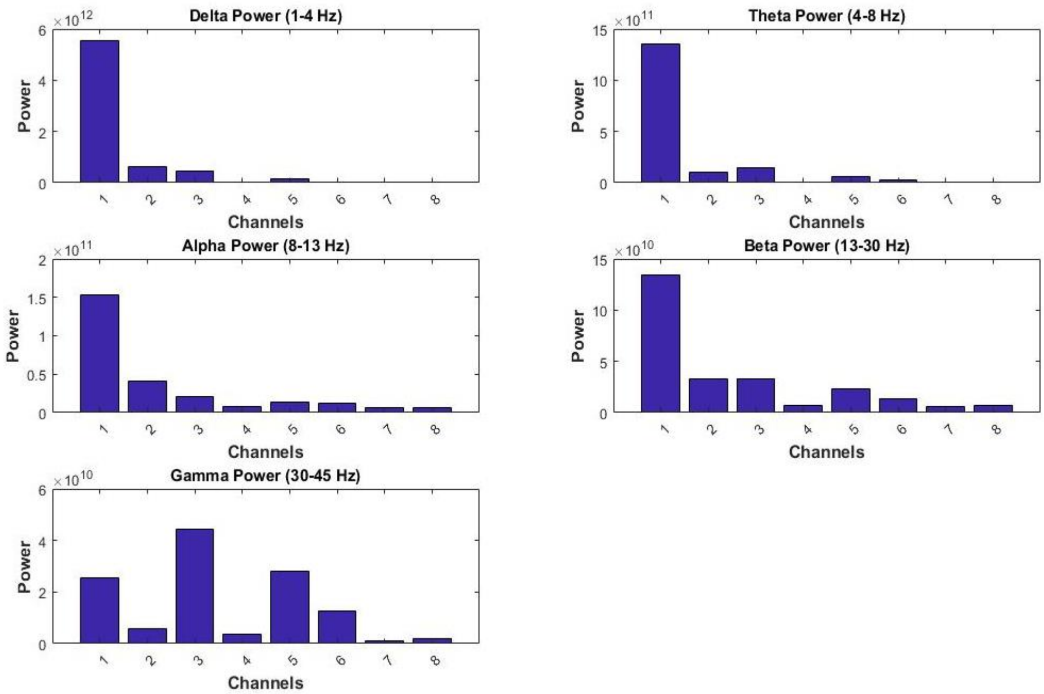

Figure 7. EEG band power for each channel for S01

2.4. Signal classification

After the completion of feature extraction for each participant, the procedure of classification comes under consideration. The same process as mentioned in Figure 7 needs to be applied for s02 to s30 participants and frequencies of EEG like alpha, beta, theta, delta, and power; the procedure of classification begins. Various classifiers are employed in the research based on how well they function in EEG applications, and their efficacy is assessed to direct the optimization procedure suggested, like artificial neural networks, KNN, linear SVM, SVM with radial basis functions, decision trees, linear discriminant analysis, and naive Bayes [18].

This study offers a fusion of SVM and KNN, two distinct categorization techniques. SVM and KNN, two hybrid classifiers, were chosen due to their complementary advantages in EEG-based emotion classification. While KNN successfully captures local patterns, SVM is adept at handling high-dimensional data with strong global decision limits. Grid search with LOOCV was used to optimize the hyperparameters for KNN and SVM in order to guarantee generalization. The hybrid model, which was adjusted for balanced contributions, integrated their outputs by weighted voting. The SVM-KNN hybrid model outperformed previous combinations, according to empirical evaluations, providing strong accuracy and F1-scores across emotions (happy, fear, sad, and neutral) and successfully handling participant and session variability.

Every individual was exposed to four different kinds of emotional stimuli. Once the raw EEG data was pre-processed, feature extraction was used to retrieve information from every channel at every epoch. Due to their complementary characteristics, SVM and KNN classifiers are often hybridized for emotion identification using EEG data. SVM can identify the ideal hyperplane that divides different class boundaries. On the other hand, KNN is an instance-based learning algorithm that does not depend on any specific statistical distribution of the input space. Moreover, being non-parametric, it adapts to local patterns and tends to do well with noisy data. As both the SVM and KNN classifiers complement each other well, they are ideal for the classification of emotions from EEG data. SVM performs rather well in high-dimensional environments because the identification of best decision boundaries yields stable separation between emotional states. It also makes good use of kernel functions to manage non-linear interactions. Although KNN is intuitive and adapts well to local patterns, even noisy or overlapping data, since it makes decisions based on neighbouring examples, its hybrid strategy, when combined, improves classification accuracy for the many intricate patterns present in EEG data to find the balance between global decision-making and local adaptation.

2.4.1. Approach to hybrid classifiers

The extracted feature set of EEG data can be represented as (1),

$$X = \{x_1, x_2, \dots x_n\} \tag{1}$$

x_i represents the feature vector of the i^{th} sample and $Y = \{y_1, y_2, \dots y_n\}$ is the collection of labels for all the related emotions.

The SVM seeks to identify the hyperplane or decision border that maximally divides two classes, where $w.\varkappa + b = 0$. The following is the SVM objective function:

$$min \frac{1}{2} \|\omega\|^2 \quad \text{subject to } y_i(w \cdot x_i + b) \geq 1 \forall\, I \tag{2}$$

when the label is y_i the weight vector is w, the input feature vector is x_i and the bias term is b. The decision boundary needed for classification is provided by the optimization problem's solution.

KNN uses the KNN approach to classify an input instance x_i. The metric of distance $d(x_i, x_j)$ is utilized to determine these neighbors, and it is often Euclidean distance. The following factors are used to assign the label $y_{i.}$

$$y_i = argmax \sum_{k \in N(xi)} I(y_k = y_j) \tag{3}$$

where the indicator function is denoted by $I(\cdot)$ and the collection of KNN is represented by $N(x_i)$.

2.4.2. The strategy of hybridization

In the hybrid model, KNN classifies instances close to the decision border, where SVM could have trouble, to refine the initial classification made by the SVM. This combination improves accuracy for EEG-based emotion identification tasks by combining the global decision-making power of SVM with the local flexibility of KNN. To improve classification accuracy, this hybrid classification method applied SVM and KNN using the majority voting method.

2.5. Classification output

In general, EEG datasets are usually modest in size but highly dimensional. Techniques like leave-one-out cross-validation are quite effective in the evaluation of the performance of the models for emotion identification based on EEG signals. LOOCV ensures that each sample of the EEG signal has been used once as a test point and also as a training set, which completes an exhaustive assessment of generalizability for the model.

Why Use LOOCV to recognize emotions?

EEG datasets usually have fewer trials and subject samples, especially in the case of emotion detection. This is vital in small datasets as LOOCV [14] allows the model to be trained on n-1 samples, using all the datasets both for training and validation**.** The emotional states in EEG signals are faint and overlapping; thus, finding them is not an easy task. Compared to previous k-fold approaches, LOOCV guarantees that each sample is evaluated, giving a more thorough and precise estimation of the classifier's performance. LOOCV minimizes the danger of overfitting, particularly in situations where emotion-specific EEG signals differ between people or sessions, by training on almost the whole dataset for each iteration.

Hybrid classifiers, such as SVM-KNN in conjunction with LOOCV, provide accurate insights about the potential of the model to generalize to new, unseen data for emotion recognition. Such models can generalize emotion recognition to fresh and untested data. After every iteration of the final performance measures, which include the F1-score, accuracy, and precision, are averaged, and an objective assessment of the classifier's capacity to identify emotions from EEG data is provided [19]–[22].

2.6. Performance metric

The accuracy of the classifier in the presented study was determined by assessing its capacity to accurately detect emotions from EEG data (4). The percentage of properly categorized cases across all samples will be calculated. This accuracy metric aids in measuring how well the proposed system recognizes emotions [23].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

The model that correctly classifies as positive is called true positive (TP). Information that the model accurately identifies as negative is called true negative (TN). The model that incorrectly classifies from the negative category as positive is known as false positive (FP). False negative (FN) data is produced by the model when it erroneously classifies positive category data as negative [15].

3. RESULTS AND DISCUSSION

The researchers developed a hybrid emotion-identification system based on K-Nearest Neighbours and SVM classifiers using EEG data. For the sake of experimentation, the developed system was applied to EEG data acquired from thirty subjects at twelve trials intended to evoke four distinct emotional conditions: fear, sadness, happiness, and neutrality. The Proposed model worked with the eight channels of the EEG recordings and applied LOOCV for the assessment of the hybrid classifier. From normalized EEG data, we obtained frequency-domain characteristics. The four predominant frequency bands for which we computed the band power are delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), and beta (12-30 Hz) [24], [25]. These frequency bands are related to various states of cognitive and emotional changes, they are well-known in EEG research. Band power in these frequency bands was calculated for each trial and channel that made the feature set to be used for classification. By using the dataset of EEG, the hybrid classifier is tested in the MATLAB code. EEG data of all participants is read from corresponding .csv files, pre-processing, and extraction of characteristics. The accuracy of the system was assessed using leave-one-out cross-validation (LOOCV). Each dataset sample was utilized once as a test sample in LOOCV, with the remaining data being used for training. Because it makes the most use of the available data, this validation approach is especially helpful for tiny datasets. The model was trained using the hybrid SVM-KNN method for every LOOCV iteration. Both classifiers were used to predict emotion accuracy, and a majority vote was used to make the final choice. After the cross-validation procedure, accuracy was determined. The DEAP [5], DREAMER [19], MAHNOB-HCI [26], SEED [27], and AMIGOS [28] datasets served as inspiration for the recording and processing of an EEG dataset for emotion identification. Emotions such as happiness, sadness, fear, and neutrality were evoked by Hindi video clips. The Unicorn Black 8-channel device was used to record EEG data. In MATLAB R2017a, all the steps are performed to pre-process the EEG data, extract features, and classify the emotional states with algorithms such as SVM and KNN involved. Then, accuracy is computed by equation 4. EEG signals were acquired with a device with 64 channels from 40 individuals in [8] and

EEG data was recorded from 30 participants in [10] during the data-gathering process. The comparison of the proposed approach with other algorithms is shown in Table 2.

Table 2. Comparison of proposed model

Contribution	Dataset	Physiological signals	Average accuracy	Model	Emotion classify
Zhu *et al.* [8]	Own datasets	EEG	70.2%	HP Three Classes	positive, neutral, negative
			50.15%	HP Five Classes	happy, neutral, sad, angry, fearful
			72.05%	NHP Three Classes	positive, neutral, negative
			51.53%	NHP Five Classes	happy, neutral, sad, angry, fearful
Jin *et al.* [10]	Own datasets	EEG	40.8%	HP Five Classes	happiness, neutral, sadness, fear and anger
Proposed work	Self-created dataset	EEG	60.832%	NHP Four Classes	happy, fear, sad, and neutral

*HP stands for hearing-impaired participants.
*NHP stands for Non-hearing-impaired participants.

4. CONCLUSION

The emotional-video clip-induced EEG emotion recognition technique was presented in this study. Thirty volunteers' EEG signals were recorded as they watched the various Hindi video clips. With frequency-domain feature extraction, a hybrid SVM-KNN classifier, and Z-score normalization for preprocessing, the suggested method proved successful in identifying emotions, with LOOCV guaranteeing an accurate accuracy estimate. Table 2 displays the proposed model findings, which indicate an accuracy of 60.832% on average for the four emotional classes-happiness, sadness, fear, and neutral. Based on EEG data and band power ratios, this accuracy suggests a modest performance level in differentiating between emotions. Although the outcomes show that the method can distinguish between distinct emotional states well, there is still space for development. Further research endeavors may optimize feature extraction techniques, investigate more intricate categorization schemes, or integrate supplementary information to augment emotion identification’s general precision and resilience. The plan in the future should be to increase the size of our dataset with other language video clips and focus on hybrid feature extraction approaches and classification techniques for people with and without hearing problems in subsequent studies or based on video clips, which are based on other local languages. Proposed datasets, like several standard datasets DREAMER, AMIGOS, SEED, and MAHNOB-HCI, may be made publicly available for research reasons, especially if cutting-edge methods are used.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Ram Chandra Singh	✓	✓	✓		✓	✓	✓		✓			✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Mendeley at doi: 10.17632/58rydc6vwc.1.

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