

Existing Emotional State Detection Models: Review Paper

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Abstract

Human daily live filled with emotion as a subjective psychological and physical response to environmental events. Emotion recognition using EEG data is emerging as a multidisciplinary study area with the advancement of artificial intelligence and brain science. This study investigates emotional features extraction techniques from EEG signals and for classifying them using those features utilizing relevant scientific literature from the previous five years. Techniques for feature extraction analysis that are often utilized include time domain, frequency domain, and time-frequency domain studies. the accuracy found ranged 70.89% to 99.7%, algorithms for machine learning that use Support Vector Machines (SVM), k-nearest Neighbour (KNN), Naive Bayes (NB), Weighted cascade forest (CF), and other techniques are often utilized. Classification accuracy for the neural network (NN), Random Forest (RFC), and XGBoost-based deep learning algorithms ranges from 65.38% to 80.56%.

Key words-*k-Nearest Neighbor; Naive Bayes; Convolutional Neural Network; variational mode decomposition; Weighted cascade forest*

I. INTRODUCTION

A new era for brain technologies has been introduced by the brain-computer interface (BCI). BCI has made a unique type of communication available for controlling wheelchairs, robots, security, and alarm systems. Electroencephalography (EEG) is used to identify the signals, which are then supplied to the alarm activist. Brain signals are measured using different methods[1]. These methods are divided into invasive, semi-invasive, and non-invasive.

In the invasive; the signals are taken from the inserted electrodes into the cortex, whereas for semi-invasive the signals are taken from Dura or in the arachnoid. For the non-invasive, the signals are captured from the scalp[2]. Emotional sensing using EEG has gotten more 4 attention, especially for disabled security studies[3]. Human emotions have a significant impact on all aspects of selection, human engagement, the detection of mental diseases like depression, etc. Humans have employed body posture, gesture, and aural cues in addition to facial expressions to identify emotions.

In comparison, a machine cannot comprehend another person's emotions. Affective computing in this context strives to enhance communication between people and machines by sensing human emotions, hence increasing this interaction's accessibility, usability, and effectiveness. Physiological alterations in the body are correlated with emotional experience.

As a result, understanding each emotion's physiological response is crucial for conducting an emotion analysis. As a result, research has been done to identify emotions using physio-logical markers[4]. While we may find it straightforward to navigate our emotions, our understanding of the brain's mechanisms that govern emotional regulation is still quite limited. This gap has led to an increased emphasis on research related to emotion recognition. Recognizing emotions is crucial in various fields, including understanding emotional behaviors and enhancing human-machine interactions.

In recent studies, researchers have turned to physiological signals derived from the peripheral nervous System and brain activities as a prevalent approach for developing systems aimed at recognizing emotions. Among these signals—such as electrocardiograms and galvanic skin responses—brain signals stand out as particularly reliable since they are less affected by individual subjective perceptions. Consequently, processing electroencephalogram (EEG) signals has become an increasingly prominent topic in the realm of emotion recognition research.

Emotions play a significant role in the psychological makeup of people, and as technology for human-computer interaction advances, so too has emotional perception computing. Possessing unbiased, trustworthy, and constant emotions is one of the prerequisites for doing emotion research. To elicit emotions, researchers use a variety of emotional stimuli, including images, sounds, and movies. Researchers commonly use video resources depicting various emotions as visual and aural stimuli. It's possible that the subjects feel personally present. The DEAP, MAHNOB-HCI, and SEED EEG datasets are currently accessible to the general public and are based on emotional video stimuli[5].

The purpose of this study is to evaluate the brain signals of disabled people when they are in Rick's condition. The framework for signal detection is based on P300, focusing on the visual cortex. The system could be developed experimentally using hardware and software. Further configuring and interfacing the EEG signals could also assist the alarm system. As shown TABLE(I and II) Contributed to summarizing twenty studies related to extracting emotions from the brain through the EEG device and then discussing three studies in detail, which included their methodology, results they reached, and their limitations; finally, we presented the comparison among them.

TABLE I: Summary of emotional detection investigations and their limitations

Year	Author	Technology	Methodology	Result	Limitation
2022	Shivaditya Shivganesh et al [3].	Deep learning Network.	A dataset was assembled. Each task was preceded by some downtime. There was a 2-minute break between each activity. Each recording portrayed a distinct emotional situation. The individual was instructed to spend as much time as necessary recalling or visualizing each incident. Each electrode's location on the subject's skull was noted. The data did not eliminate the eye blink, eye movement, or muscle movement artifacts.	Using the dataset, the image pipeline was applied. TensorFlow was used for designing the neural network. They have used a relatively small network for classification.	The image generation process is resource-intensive. It took more time on a dual-core CPU.
2022	Dawoon Jung et al [6].	EEG and deep learning in the eye signals used in virtual reality.	To distinguish between emotional responses based on changes in the brain, EEG data were collected and evaluated in virtual environments to compare the psychological effects of virtual objects.	In that situation, arousal and anxiety were different. The algorithm with the best classification performance was XGBoost.	Additional validation is required.
2022	Md. Zaved Iqbal Ahmed et al [4].	Manual feature extraction method on EEG.	EEG-based emotion recognition manually extracting feature data. A mix of manual and automatic feature extraction methods has been presented. The asymmetry in the different brain areas is recorded from the differential EEG signal characteristics. Then, features are automatically extracted from these AS Maps using the CNN model.	The results indicate that the features on the gamma band give higher classification over other frequencies.	Increased window size results in lower classification accuracy.
2021	Nisha Vishnupant Kimmattkar et al [7].	Processing electroencephalography (EEG).	Electroencephalography (EEG) data can be processed to identify emotional states and examine the benefits of music therapy during meditation on calming the mind.	Gamma wave activity is often very low, almost nonexistent, for any kind of emotion. When participants were attempting to remember or recall negative memories, gamma wave activity could be seen.	A classifier is used to accurately detect emotions.
2022	Nicolina Sciaraffa et al [8].	Neuromeric EEG.	Electroencephalography (EEG) data can be processed to identify emotional states and examine the benefits of music therapy during meditation on calming the mind.	Using an average Area Under the Curve, the Neuromeric was able to distinguish between mild and high-stress levels.	This measurement is appropriate for practical use and less biased than machine learning.
2021	Javier de Echegaray et al [9].	Band Oscillations.	According to studies on animals, gamma band oscillation modulation foretells cholinergic-driven plasticity shifts in sensory cortices that affect neurons' responses to fear-relevant cues learned by Pavlovian fear training.	Between 60 and 90 ms after the beginning of the CS + during fear, the gamma band increases.	A long training period was required.
2022	Zhongyang He et al [5].	TCA strategy.	Produced an emotive EEG database depending on the Chinese Emotional Video System and unique video stimuli. A solid signal foundation for studies on emotion identification across time domains is provided by this resource.	Showed that the TCA method improved emotion recognition ability across time domains.	For emotion recognition, deep learning techniques were employed.
2021	Khodijah Hullyyah et al [10].	EEG	Analyzed the emotion recognition experiment by stimulating sentiment tones using EEG. The process of classifying emotions uses SVM. The dataset of emotional annotation was carried out manually based on four classifications, specifically: happiness, sadness, fear, and anger. The annotated dataset was tested using an Electroencephalogram (EEG).	The angry emotions showed a high number with an average value above 90% because reading with angry expressions is easier to perform.	A fusion approach was used for recognizing emotion.
2022	Wachira Lawpradit et al [11].	EEG.	A NeuroSky MindWave device to record the EEG was used. They focused on responses of true or false from 5 participants and 8 observed animal images. Increased changes in theta, alpha, and gamma signals were noticed along with statistically significant acceptance.	The wave in the alpha, theta, and gamma frequencies increased and was acceptable at the level of significance of 0.05. These waves demonstrate how humans attempt to utilize their brains to imagine the outcome of lying or speaking falsely.	Gamma wave was increased.
2021	Marvin Gaertner et al [12].	EEG and deep learning in the eye.	Investigated the effectiveness of high gamma frequencies (50-100 Hz) for emotion detection by dividing the standard EEG bandwidths into fine-grained point spectra, each with a span of 0.5 Hz. They also identify the most important high gamma frequency bands.	The emotion recognition rate of 99.79% shows the model is highly accurate and capable of reliably predicting a person's emotional state.	High-frequency range should be taken into consideration.

TABLE II: Summary of survey on BCI based on Emotional Detection

Activity	Feature Extraction Method	Classification Method	Number of Classes	Number of Participants	Classification Accuracy
Emotion Sensing [13]	DFT, FFT, CUDA	CNN	In each task, imagination of emotional states was encouraged using a set of pre-recorded verbal suggestions.	34	72.03%.
Emotional State Evoked by Virtual Environment [14]	PCA	XGBoost, SVC, LR	EEG data were gathered and examined in virtual environments to recognize emotions based on brain changes.	15	The best classification.
Emotion Detection [15]	Statistical modeling method LCT	CNN, RNN, KNN, DNN	Emotions: anger, calm, happy, and sad.	22	75%
Emotion Classification Using EEG [16]	Manual feature extraction	AsMap+CNN	Three basic human emotions: positive, negative, and neutral.	15	97.10%
Fear learning in humans [10]	FFT	Neurogenic EEG.	Fear	30	95.56%
Emotion Recognition [17]	The Librosa tool in the Python package	SVM, Random Forest, Decision Tree	Happiness, Sadness, Angry, Fear.	2	90%
Cross-Day EEG-Based Emotion Recognition [18]	TCA	SVM	Positive-negative, happy-sad, happy-angry, and happy-fright.	12*	83.03%.
The brain wave of humans lies [19]	Wave voltage powers	Statistical significant values	Photos of various animals were used to create a situation where false descriptions were given.	5	Theta, Alpha, and Gamma are associated with human lying behavior.
Multi-Class Emotion Recognition [20]	PCD	RFC	Emotions within the Valence-Arousal-Dominance model	23	99.79%
Emotion Recognition Based on EEG Signal Using Deep Learning [21]	EMD and VMD	SVM, KNN	Excited, Delighted, Calm, Content, Tired, Depressed, Frustrated, Angry, Tense, Bored, Relaxed.	28*	70.89%

II. DISCUSSED TOPIC

A. First Sub Topic 1

Emotion recognition of EEG signals based on variational mode decomposition and weighted cascade forest.

1) *Materials and methods:* Materials the data used in this study came from a publicly accessible multimodal database. The participants were 32 healthy subjects. Figure(1) shows the EEG signal channel's electrode distribution; the sampling rate was 512 HZ. Each student watched

Volume 20 for 40 minutes, Issue2, 2566–2587 of Mathematical Biosciences and Engineering in 2569. Fragments from music videos. Each video lasted for one minute. Every time, 63 seconds of EEG were recorded, comprising 60 seconds of watching 3 seconds of baseline EEG with no emotional stimulation and the music video. The 14 channels used are AF3, F3, F7, FC5, T7, P7, O1, AF4, F4, F8, FC6, T8, P8, and O2. Methods The five steps of the proposed EEG emotion identification framework are decomposition, effective com-

ponent extraction, feature extraction, variable selection, and classification. EEG's foundation for recognizing emotions. The process is as follows:

- 1) Preparation of data. The information is down-sampled. The experiment's required EEG signals were chosen.
- 2) Analyzing the EEG signal. Each precompiled EEG data series is divided into K IMFs by VMD.
- 3) Extracting components with success. Pearson's correlation value between each IMF and the noise factor, which is present in some components after the de- composition original signal is calculated. The components that have correlation values that are higher than a specific cutoff are considered to be effective. Any elements with correlation coefficients below the cutoff are removed.
- 4) Segmenting the data. A sliding window of 1 second in length is used to segment the IMF signals obtained in step 3 without overlap. One second is spent slipping.
- 5) Extracting features. For each segment of data, the properties of the PE, PSD, DE, and Horthy parameters are determined.
- 6) Several options. To make the model simpler, the retrieved characteristics' dimension is reduced. The most beneficial features are provided by using the proposed CRRAEN algorithm, which is utilized to choose the feature variables.
- 7) Figure(1) shows the SVM Classification of EEG emotions. The characteristics following dimensionality are used in the classification step.

2) *Results and analysis:* Figure(2) shows From the experimental results valence classification accuracy was 80.94 %, whereas, for arousal , the classification accuracy found was. its arousal classification accuracy is 74.77 % . It significantly raises the effectiveness of EEG emotion identification accuracy when compared to several existing ones. After VMD decomposition, the high- frequency components typically contain noise. The mathematics biosciences and engineering are determined using the Pearson's correlation coefficient method. To remove the interference of noise. Each IMF's relationship to the initial signal. The correlation is

stronger when the correlation coefficient's absolute value is higher. The IMFs with absolute correlation coefficient values larger than 0.35 are kept in this study. Each IMF's relationship to the original signal is shown depicted in Figure(3) as a coefficient. IMF1–IMF5 are finally kept, in contrast.

B. Second Sub Topic 2

Cross-Day EEG-Based Emotion Recognition Using Transfer Component Analysis

1) *Materials and methods:* The participants were divided into 8 men and 4 women, with a 1.98 age standard deviation and a mean lifespan of 22.50. Due to excessive mobility, two of the collecting sessions were unable to use the other subject's signals, and one subject's signal displayed significant drift. Following ICA decomposition, one of the remaining 12 individuals deleted two artifact components, while the other 11 subjects each removed one artifact component. To eliminate the artifacts, fast ICA was used to break the EEG study

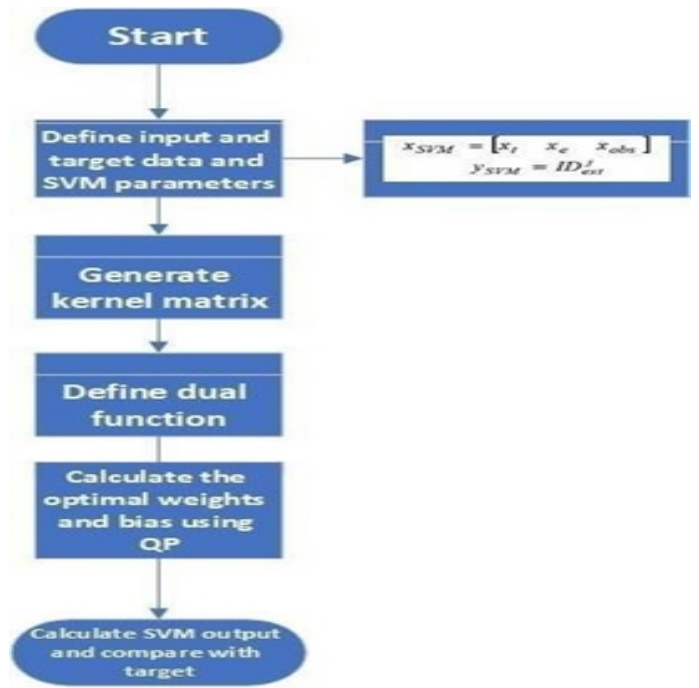


Fig. 1: SVM algorithm

Table3. Comparison of classification performance on the arousal dimension.

Method	Accuracy	Precision	Recall
CF	0.6375	0.6412	0.7277
WCF	0.6680	0.6667	0.7460
RFVS-CF	0.6633	0.6715	0.7354
mRMR-CF	0.6508	0.6530	0.7347
EN-CF	0.6234	0.6335	0.7151
AEN-CF	0.6398	0.6516	0.7201
CRRAEN-CF	0.7047	0.7192	0.7571
CRRAEN-WCF	0.7477	0.7614	0.7888

Table4. Comparison of classification performance on the valence dimension.

Method	Accuracy	Precision	Recall
CF	0.7477	0.7543	0.7795
WCF	0.7688	0.7784	0.7956
RFVS-CF	0.7648	0.7862	0.7879
mRMR-CF	0.7469	0.7735	0.7702
EN-CF	0.7375	0.7576	0.7650
AEN-CF	0.7672	0.7847	0.7913
CRRAEN-CF	0.7727	0.8325	0.7820
CRRAEN-WCF	0.8094	0.8382	0.8250

Fig. 2: Results of comparison Classification performance on the arousal dimension

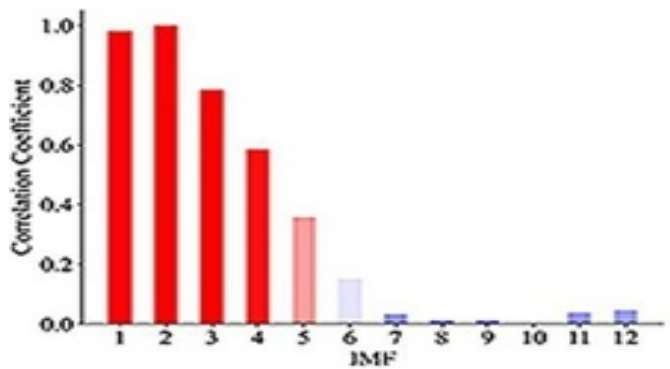


Fig. 3: Correlation coefficient between each IMF and original EEG signal

used the Fast ICA method to break the EEG signal down into its components. The EEG signal was recreated without

artifact interference after locating and eliminating the artifact components. The movie videos range in duration from 50 to 180 seconds, but the highest emotional response was felt around the end. The last 50 s of all movies were recorded for analysis to make sure the EEG signal durations were uniform across all emotion categories. By taking one sample every 2 seconds of the EEG's breadth, moving the forward signals window by one second each session, and leaving one second of overlapping between sub-sequent samples, the signal was segmented. Investigations into the identification of real-time emotions used this methodology. The 50 s-long EEG data might therefore be used to extract 49 samples.

2) *Results and analysis*: Figure(4) of this paper's attempt to identify emotions using SVM displays the overall four classification tasks' average classification performance for all subjects. The average recognition accuracy for intra-day emotions is 90.18 % for positive-negative, 86.38 % for joy-sadness, 88.12 % for joy-anger, and 85.13% for joy-fear. The accuracy of emotion Detection in the four examples significantly declines over time, showing that the patient's EEG signals would alter during the day. The mean recognition rate for positive-negative, joy-sadness, joy-anger, and joy-fear is 76.06 %, 69.23%, 68.90%, and 63.66%, respectively, with the fewest training days. The classification accuracy rates are also shown to be effectively boosted by the recognition accuracy rates, as shown in Figure(3), where the classification accuracy rates are higher when training models are created

using EEG data from various days. The average accuracy for positive-negative, joy-sadness, joy-anger, and joy-fear is 81.31%, 72.15%, 71.57%, and 72.38%, respectively, while using training data from from 4 days.

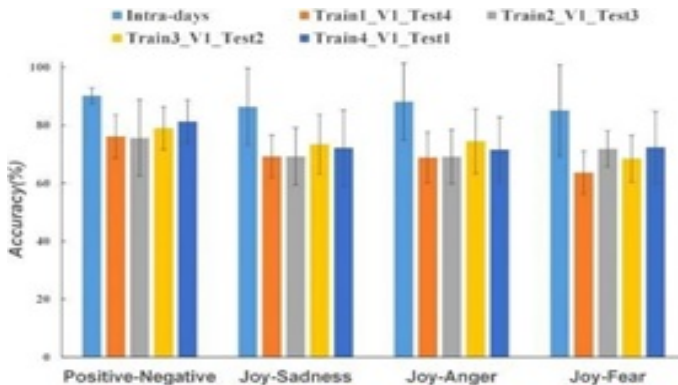


Fig. 4: The intra-day and cross-day emotion recognition performance.

C. Third Sub Topic 3

Analysis of Emotion Recognition Model Using Electroencephalogram (EEG) Signals Based on Stimuli Text

1) *Materials and methods* : The EEG instrument (EmoticE-poc+) was used to record the brain waves of two participants as they read the emotive text. Two healthy male volunteers' electroencephalogram data were captured. To ensure clarity, the text was read slowly as well as altering the intonation to match the label. Participants must fulfill the steps for

data collection before they can Eyes closed for 1 minute to evoke feelings. Step 3: Open youreyes for a full minute. Step 4 reread the paragraph with the same emotions that have been building for 4 minutes. Forthe classification of emotion, Random Forest, (SVM), andDecision Tree were used to get the best model. EEG vector characteristics were used to perform the three models, which were then split into training and tested sets of data.

2) *Results and analysis* : Figure(5 and 6) show the results of three types investigated. Decision tree techniques have a 100% accuracy rate for training data and an 87% accuracy rate for test data. Also, the Confusion Matrix reference, shows how the data generated by the ML was forecasted and used in practice. The most accurate representation of authors and readers felling with the same textis necessary because the Matrix also decides on Accuracy, Precision, Recall, and Specificity. Reader's brain waves were done manually and used to gauge how accurate it was.

III. DISCUSSION

The exploration of emotion recognition using EEG datahas achieved prominent traction in recent years, which was driven by the latest advancements in artificial intelligence and BCI technologies. The findings and methodologies of existing models in comparison to this study, provide a comprehensive understanding of the current state and future directions of emotion recognition research. Therefore, this study highlights the

Model	Emotion	Precision	Recall	F1-score
Random Forest	Angry	0.98	0.98	0.98
	Fear	0.98	0.91	0.94
	Happy	0.93	0.90	0.91
	Sadness	0.92	0.98	0.95
SVM	Angry	0.93	0.01	0.03
	Fear	0.00	0.00	0.00
	Happy	0.00	0.00	0.00
	Sadness	0.31	1.00	0.48
Decision Tree	Angry	0.93	0.94	0.94
	Fear	0.84	0.84	0.84
	Happy	0.80	0.79	0.80
	Sadness	0.90	0.89	0.90

Fig. 5: The Classification of Four Emotions of Accuracy by Three Models

importance of effective feature extraction techniques in emotion recognition. The common approaches include time domain, frequency domain, and time-frequency domain analysis, essential for capturing the nuances of EEG signals that correspond to different emotional states. Current studies, including corroborate the efficacy and emphasize the importance of selecting best-suited features depending on the type of emotion to be detected as physiological responses vary with emotional experiences. Furthermore, advanced methods like variational mode decomposition have shown promise in enhancing feature extraction, offering a refined approach to decomposing complex EEG signals into meaningful components[15]. As shown in Figure(7), The study identifies several machine learning algorithms used for classifying emotions based on EEG data, including Support Vector

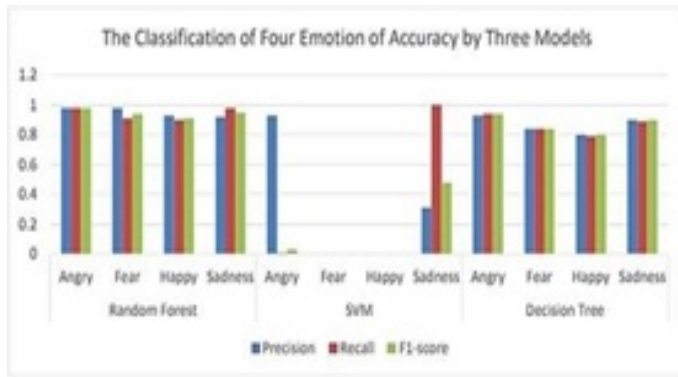


Fig. 6: Four Emotions of Accuracy are classified by Three Models.

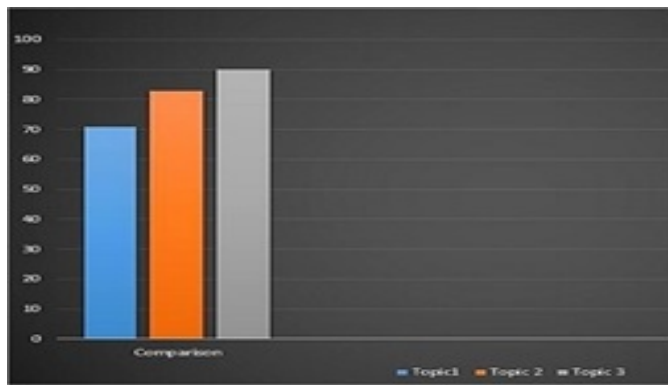


Fig. 7: Comparison of three studies for Three Models.

Machines, k-Nearest Neighbor, and Naïve Bayes, with reports accuracies ranging from 70.89% to 99.79% [20][21]. These traditional machine-learning methods have been crucial in early emotion recognition research [22]. However, recent studies have demonstrated the superiority of deep learning algorithms in handling the high dimensional and nonlinear nature of EEG data. NN, RFC, and XGBoost have been specifically important in achieving classification accuracies between 65.38% and 80.56% [6]. These findings align with those of [5], As shown in TABLE (III) Comparison between three studies for Three Models

TABLE III: COMPARISON OF THREE STUDIES FOR THREE MODELS

Study	Feature extraction method	Classification	Accuracy%
The first topic	EMD and VMD	SVM, CF	70.89
The second topic	TCA	SVM	83.03
Third topic	The Libras tool in the Python package	SVM, Random Forest, Decision Tree	90

IV. CONCLUSION

This study focuses on current literature that suggests a novel method for separating and classifying emotional components from EEG signals. Our examination of these studies demonstrates the scientific rigor of the EEG signal-based emotion classification study. This study discusses experimental and conventional emotional datasets, electrode distribution, EEG signal acquisition technology, and EEG analysis methods. In this study, we analyzed research that used an emotions EEG database to more precisely identify the feelings of joy, sorrow, rage, and fear. We also verified the efficacy of an approach for enhancing emotion detection ability across time domains. Further application of deep learning techniques for emotion recognition in future studies.

V. STATEMENTS OF DECLARATION

Conflict of interest The authors declare no conflict of interest

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