Emotion Detection Using EEG Signals Based on Machine Learning

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Abstract:
Emotions describe what an individual feels and can be interpreted through various methods like voice, facial expressions and physiological signals. In this, Electroencephalogram signals are used to detect the human emotions. Electroencephalogram (EEG) measures brain signals (brain waves) using a headset placed on the scalp. By using EEG signals plays an important role in Human-Computer Interaction (HCI). EEG signals are typically divided into different frequency bands such as delta, alpha, beta, and gamma. Machine learning models combine features from different frequency bands to make the accurate predictions. In this research, a publicly available dataset, titled '**EEG brainwave Dataset: feeling emotions'** is used. Support Vector Machine (SVM) classifier is used, which gave the accuracy of 89%.

Keywords: Emotion Recognition, EEG signals, Human-Computer Interaction, Machine learning, Support Vector Machine (SVM)

1. Introduction:

Human emotion detection plays a crucial role in the development of human- technology interaction. Emotions are the feelings that humans experience such as happiness, anger, sadness, fear, excitement. These emotions affect the actions and decision-making in life in different aspects. Human emotion recognition is a widely growing field in research to interpret the human emotions. Emotion detection can be predicted through facial expressions, tone of voice. However, the facial expression and vocals can be manipulated, which makes the interpretations the emotions difficult and less reliable.

There are Physiological signals such as electroencephalogram (EEG), electrocardiogram (ECG), and electromyogram (EMG), as they are highly secure because they are difficult to fake or hide. In this study, The Electroencephalogram (EEG) signals are used for emotion detection. EEG signals have different frequency bands: delta, theta, alpha, beta and gamma which indicate the different brain activity (Table 1). These signals are collected with the help of headset device with electrodes placed using the international standard system. The process of detecting the emotions involves various steps such as data collection, preprocessing, feature extraction and at last classifying them using machine learning. Machine learning is used for EEG based emotion detection. In This study, Support vector machine (SVM) is used for classifying the emotions.

TABLE 1: The frequency range of EEG signals	
Signal	**Range**
Delta (δ)	0-3 Hz
Theta (θ)	4-7 Hz
Alpha (α)	8-13 Hz
Beta (β)	14-30 Hz
Gamma (γ)	30-100

2. LITERATURE REVIEW

Electroencephalography (EEG)-based emotion recognition has emerged as a key area within affective computing due to its ability to capture natural brain activity, offering a more dependable way to measure emotional states compared to external indicators like facial expressions or speech. Early research conducted by Oude Bos [1] explored how visual and auditory stimuli influence emotion recognition and showed that EEG signals can be used to classify emotions based on their valence and arousal levels. However, this study faced limitations due to a small sample size and the use of a limited number of electrodes, which reduced the generalizability of the findings.

Later studies aimed to improve the accuracy of emotion classification by refining feature extraction methods and incorporating machine learning techniques.

Rahman et al. [4] introduced a feature-level fusion method combined with an ensemble classifier to enhance the performance of emotion recognition systems. Similarly, George et al. [5] used time-frequency analysis paired with a Support Vector Machine (SVM) classifier to extract meaningful features from EEG signals. Ang et al. [10] applied discrete wavelet transform (DWT) features along with artificial neural networks (ANN), emphasizing the value of time-frequency features for achieving better classification results.

With the development of more advanced computational tools, deep learning approaches have gained popularity in EEG-based emotion recognition.

Fernandes et al. [6] utilized deep learning models to automatically extract both spatial and temporal features from EEG data, reducing the reliance on manual feature engineering. Fang et al. [8] proposed a multi-feature deep forest model that achieved comparable performance with lower computational demands than deep neural networks. Zhu et al. [7] introduced a multi-frequency band collaborative method that used optimal projection and shared dictionary learning to identify complex patterns across different EEG frequency bands.

In recent years, hybrid and advanced learning techniques have been explored to further boost system performance.

Nobari Azar et al. [13] developed a modified convolutional fuzzy neural network that combined convolutional layers with fuzzy logic to manage uncertainty in EEG signals, leading to improved accuracy. Zhang and Cui [9] introduced a self-supervised learning method to lessen the dependence on labeled data, which is typically costly and time-consuming to obtain.

Beyond model development, several studies have contributed through comprehensive reviews and the enhancement of datasets.

Hamzah and Abdalla [3] provided an overview of EEG-based emotion recognition systems, highlighting major challenges and research trends. Ma et al. [11] conducted a detailed review of deep learning techniques, discussing their advantages and drawbacks. Chen et al. [12] introduced the FACED dataset, which includes a larger number of participants and more detailed emotion categories, addressing the shortcomings of earlier datasets.

S.No	Author(s) & Year	Dataset Used	Model Used	Accuracy	Emotions	Contribution	Research Gaps
1	Danny Oude Bos, 2010	IAPS + IADS	Fisher Discriminant Analysis (FDA)	60-90%	Valence, Arousal	Studied effect of visual & auditory stimuli	Small dataset, limited electrodes, no personalization
2	Haruhiko Kaiya et al., 2017	Not specific (SLR)	Systematic Review	NA	NA	Review of software traceability systems	Not EEG-focused, lacks experimental validation
3	Hussein Ali Hamzah et al. 2021	Multiple datasets	Comparative ML/DL models	NA	Multi-class	Comprehensive study of EEG emotion systems	Lacks unified benchmark comparison
4	Md. Mahbubur Rahman et al. 2020	DEAP	Feature Fusion + Ensemble Classifier	90%	Valence, Arousal	Combined multiple features for improved accuracy	High complexity, feature dependency
5	Fabian Parsia George et al. , 2019	DEAP	Time-Frequency + SVM	85–90%	Valence, Arousal	Used time-frequency analysis for classification	Limited to SVM, lacks deep learning comparison
6	João Vitor Fernandes et al. 2022	DEAP	Deep Learning (CNN/LSTM)	90%	Multi-class	Applied DL models for emotion detection	Requires large data, computationally expensive
7	Jiaqun Zhu et al. 2021	SEED / DEAP	Dictionary Learning + Projection	90%	Multi-class	Multi-frequency band feature learning	Complex model, hard to implement
8	Yinfeng Fang et al. 2022	DEAP	Deep Forest Model	90%	Multi-class	Introduced deep forest for EEG classification	Less explored, needs more validation
9	Min Zhang & YanLi Cui	Physiological signals	Self-Supervised Learning	NA	Multi-class	Reduced dependency on labeled data	Still developing, lower interpretability

S.No	Author(s) & Year	Dataset Used	Model Used	Accuracy	Emotions	Contribution	Research Gaps
	2023						
10	Adrian Ang et al. 2018	DEAP	DWT + ANN	85–90%	Valence, Arousal	Combined wavelet features with ANN	Limited feature diversity
11	Weizhi Ma et al. 2023	Multiple datasets	Deep Learning Review	NA	Multi-class	Comprehensive DL survey in EEG	No experimental validation
12	Jingjing Chen et al. 2023	FACED	ML + Contrastive Learning	High	9 emotions	Large-scale fine-grained dataset	Cross-subject issues remain
13	Nobari Azar et al. 2024	DEAP	CNN + Fuzzy Neural Network (CFNN)	98%	Valence, Arousal	High accuracy hybrid model	High complexity, not real-time

3. RESEARCH GAPS

- **Limited Dataset and Poor Generalization:** The already existing studies rely on small and controlled datasets with a limited number of subjects. As a result, the models often fail to generalize effectively across diverse populations and real-world scenarios.
- **Subject Dependency of EEG Signals:** EEG signals exhibit high variability across individuals due to differences in brain activity patterns. Many approaches are subject-specific, requiring separate training for each user, which limits scalability and practical usability.
- **Inadequate Feature Extraction Methods:** A large number of studies focus primarily on basic frequency-domain features such as alpha and beta bands. These features are insufficient to fully capture the complex and nonlinear nature of emotional states.
- **Noise And Artifact Interference:** EEG signals are highly susceptible to various types of noise, including eye movement (EOG), muscle activity (EMG), and environmental interference. Insufficient preprocessing and artifact removal techniques significantly affect classification performance.
- **Lack of real-time and Efficient Systems:** Most research is conducted in offline environments using pre-recorded data. Additionally, many models are computationally intensive, making them unsuitable for real-time emotion recognition applications.

4. Problem Statement

The already existing emotion recognition systems based on EEG signals face a few key challenges in the real - time applications: (1) The high computational complexity that demands excessive resources, (2) The lack of standard preprocessing of the data that leads to inconsistent results, and (3) the lack of focus on basic emotional states like Calm, Stress, and Excitement.

5. Objective

- To develop the system for detecting the basic human emotions (such as calm, stress, happy) based on EEG signals.
- To preprocess the raw EEG signals and extract the relevant features from different frequency bands (such as alpha, beta and gamma).
- To develop a lightweight and interpretable model suitable for real-time emotion detection and evaluate its performance using standard metrics

6. METHODOLOGY

The methodology includes stages such as data acquisition, preprocessing, feature extraction, classification, and performance evaluation.

- **Data Acquisition:** EEG signals are recorded using scalp electrodes placed according to the standard 10–20 electrode placement system. During the recording process, participants are exposed to different stimuli that help in generating emotional states. These signals represent the brain's electrical activity associated with various emotions**.**
- **Preprocessing:** The raw EEG signals usually contain noise due to eye movements, muscle activity, and other external factors. Distorted parts of the signal are removed, and normalization is performed to maintain consistency across all recordings. Filtering techniques are applied to keep only the important frequency components.
- **Feature Extraction :** In this step, useful information is extracted from different EEG frequency bands such as delta, theta, alpha, beta, and gamma. Statistical features like mean, variance, and standard deviation are calculated along with frequency-based features like band power.\
- **Emotion Classification:** The extracted features are used as input to a machine learning model for emotion classification. This model is capable of handling complex and high-dimensional data effectively. The dataset is divided into two sets - training and testing sets to evaluate the model's performance. The model is trained to identify different emotional states such as calm, stress, and excitement, and its parameters are adjusted to achieve better accuracy.
- **Performance Evaluation:** The performance of the model is assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score.

7. WORKING / SYSTEM FLOW

The EEG emotion recognition system follows the below working system:

- **EEG Signal Input:** EEG signals are obtained from a publicly available dataset on Kaggle, where brain signals are recorded using scalp electrodes during emotion-eliciting tasks.
- **Preprocessing:** The raw EEG signals are pre-processed to remove noise, and artifacts. Filtering and normalization techniques are applied to improve signal quality and consistency.
- **Feature Extraction:** Important features are extracted from the pre-processed signals, including statistical features (mean, variance) and frequency-domain features from EEG bands such as alpha and beta, which help in identifying emotional patterns.
- **Feature Vector Formation:** The extracted features from all EEG channels are combined to form a single feature vector representing the emotional state.

- **Emotion Classification:** The feature vector is fed into a trained Support Vector Machine (SVM) classifier, which classifies the emotions into categories such as calm, stress, and excitement.
- **Output:** The system outputs the predicted emotional state along with performance metrics such as accuracy (89%), precision, and confusion matrix.

8. HARDWARE & SOFTWARE REQUIREMENTS

8.1 Hardware Requirements

S. No.	Component	Specification
1	Processor	Intel Core i5 / AMD Ryzen 5 or higher
2	RAM	Minimum 8 GB(16 GB recommended)
3	Storage	At least 20 GB free space
4	Input Source	EEG Dataset
5	Operating System	Windows 10/11 or Linux

8.2 Software Requirements

S. No.	Software Type	Specification
1	Programming Language	Python 3.x
2	Development Environment	Jupyter Notebook / VS Code
3	Libraries	NumPy, Pandas, SciPy
4	Machine Learning Tool	Scikit-learn
5	Visualization Tools	Matplotlib, Seaborn
6	Dataset Source	Kaggle EEG Emotion Dataset

9. Performance Evaluation

To evaluate the efficacy of the EEG emotion recognition model, a confusion matrix is utilized. This tool provides a detailed breakdown of the model's performance by comparing actual emotional states—specifically Calm, Stress, and Agitated—against those predicted by the system. This matrix allows for a granular analysis of classification errors and overall reliability. The following quantitative metrics are derived from the confusion matrix to evaluate the results:

- **Accuracy:**

This represents the proportion of total correct predictions relative to the entire dataset.

$$Accuracy = \frac{Correct\ predictions}{Total\ Predictions}$$

- **Precision:**

Precision indicates the reliability of the positive classifications by measuring the ratio of true positives to all instances predicted as positive.

$$Precison = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

- **Recall:**

Recall assesses the model's ability to correctly identify all actual positive instances within the dataset.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ negatives}$$

- **F1-Score:**

The F1-Score provides a balanced assessment of the model by calculating the harmonic mean of both Precision and Recall.

$$F1 = \frac{2(Precision * Recall)}{Precision + False\ Recall}$$

10. Result And Discussion

The model has achieved the 89% accuracy. The emotion calm shows the best performance with F1 score 0.95 while Stress shows the lower performance as its F1 score 0.84.

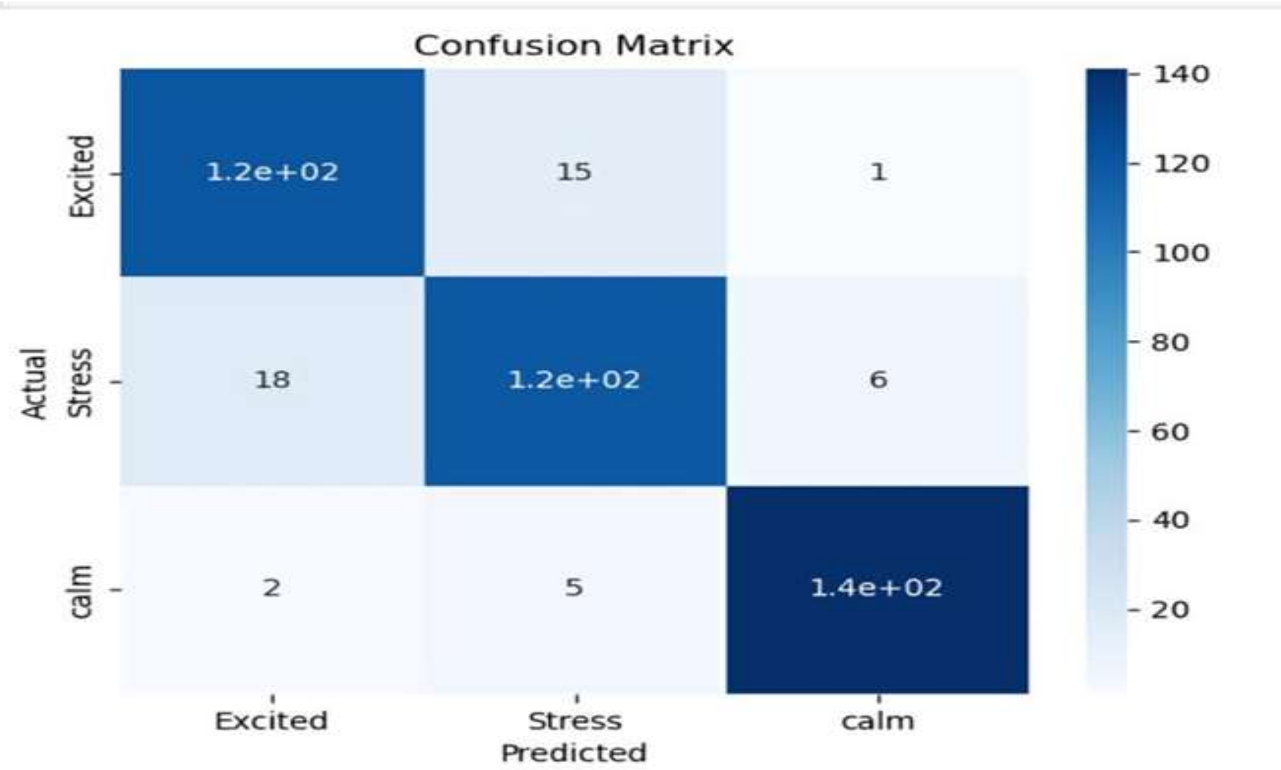

Fig 9.1 Confusion Matrix

1. **Excited:** the accurately predicted outcomes are 120 and inaccurately are 16 in which 15 were predicted as "Stress" and 1 as "Calm".
2. **Stress :** the accurately predicted outcomes are 120 and inaccurately are 24 in which 18 were predicted as "Excited" and 6 as "Calm".
3. **Calm :** the accurately predicted outcomes are 140 and inaccurately are 7 in which 2 were predicted as "Excited" and 5 as "Stress".

The model performance is evaluated using standard metrics (Table 2):

	Precision	Recall	F1-Score	Support
Excited	0.86	0.88	0.87	136
Stress	0.86	0.83	0.84	143
Calm	0.95	0.95	0.95	148
Accuracy			0.89	427
Macro Average	0.89	0.89	0.89	427
Weighted Average	0.89	0.89	0.89	427

Table 2 Emotion classification result

The confusion between Excited and Stress emotions may be due to the similar EEG patterns in high - arousal states of brain. Still the model achieved the balanced performance of all the classes (macro F1 =0.89) , making it suitable for the real time application.

11. CHALLENGES

Despite achieving good classification accuracy, several challenges remain in EEG-based emotion recognition systems:

- **Variability of EEG Signals:** EEG signals vary significantly across individuals, making it difficult to develop a generalized model that works efficiently for all users.
- **Noise and Artifacts:** EEG signals are highly sensitive to noise caused by eye movements, muscle activity, and external interference. Removing these artifacts without losing useful information is challenging**.**
- **Limited Dataset:** The dataset used is limited and may not fully represent real-world emotional variations, which affects the generalization ability of the model.
- **Similarity Between Emotions:** Some emotions, such as stress and excitement, have similar EEG patterns, leading to misclassification and reduced accuracy.
- **Real-Time Implementation Issues:** Although the model performs well in offline testing, implementing it in real-time systems requires further optimization and computational efficiency.

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