Emotion Recognition Using Machine Learning Models on EEG Signals

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Abstract: This study proposes an emotion recognition model based on EEG signals. The performance of the proposed model was compared with that of various machine learning models. After preprocessing the raw EEG data, Principal Component Analysis (PCA) was applied for dimension reduction. Emotion classification was performed using various classifiers such as LSTM, SVM, DNN, GRU, RNN, XGBoost, Logistic Regression, and Random Forest using the obtained features. As a result of the studies, GRU achieved the most successful result with an accuracy rate of 97.89%. LSTM achieved 96.25%, DNN 97.81%, Random Forest 95.78%, Logistic Regression 94.61%, SVM 95.55%, XGBoost 96.72%, and RNN 95.55% accuracy rates. These results show that emotional states can be classified with high accuracy by effectively processing EEG signals using PCA.

1 INTRODUCTION

Emotion is a complex physiological behaviour in all human beings, representing a physiological and behavioural response to both internal and external stimuli. The purpose of recognizing human emotions is to identify them through various methods, including body language, physiological indicators, and audio-visual indicators. Emotion is crucial in human-to-human communication and interaction. Emotion is the outcome of the mental processes that people undergo and can be described as a response of their psychophysiological state (Chatterje and Byun, 2022).

Over the past few years, there has been a great deal of research on engineering methods for automatic emotion recognition. These can be grouped into three broad categories. The first category analyzes speech, body language, and facial expressions. These audiovisual methods allow emotion recognation without physical contact. The second group mainly focuses on peripheral physiological signals. Studies have demonstrated that different emotional states modulates peripheral physiological signals. In the third group, the focus is on brain signals originating from the central nervous system, captured using devices that measure brain wave activity, including electroencephalography (EEG) and electrocorticography (ECoG). Among these brain signals, EEG signals have been shown to possess informative properties in response to emotional states. Davidson et al. suggest that the experience of two emotions is associated with electrical activity in the frontal lobe; which are positive and negative emotions (Davidson and Fox, 1982). According to these studies, there has been much debate about the connection between EEG asymmetry and the emotions.

The electrocardiogram (ECG) signals provide information that is useful for recognizing emotional distress in people. Over the years, numerous studies have been conducted on emotional distress, particularly in the field of psychology. Mental health conditions such as depression, anxiety, and bipolar disorder are strongly influenced by emotional distress. In the field of affective research, emotions are commonly classified into two primary categories: positive (happiness and surprise) and negative (sadness, anger, fear, and disgust). EEG offers high temporal resolution in capturing the brain's electrical

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activity. In this work, three emotional states (positive, negative, and neutral) are classified. Acknowledging that brain activity is individual-specific and that emotional responses vary across different brain regions among individuals is crucial for understanding how emotions can be identified through neural signal. This study examines the effectiveness of machine learning (ML) models in the classification of human emotional states using EEG data (Chatterje and Byun, 2022).

Determining what specific brain activity patterns correspond to momentary mental experiences is a significant challenge in applications involving brain-machine interfaces. The sheer amount of information necessary to represent the complex, nonlinear, and unpredictable nature of EEG signals accurately is one of the most critical challenges in EEG signal classification. In this study, a variety of machine learning (ML) models have been employed to categorize different emotional states, including GRU (Gated Recurrent Unit), LSTM (Long Short-Term Memory), XGBoost (Extreme Gradient Boosting), RF (Random Forest), DNN (Deep Neural Network), SVM (Support Vector Machine), and RNN (Recurrent Neural Network).

2 LITERATURE REVIEW

This literature review extensively examines the field of EEG-based emotion recognition. This review examines various aspects of the subject, including signal processing, feature extraction, classification techniques and areas of application. Our review highlights the progress made in EEG based emotion recognition while also emphasizing the emerging challenges and potential directions within this interdisciplinary area. New techniques have been developed by researchers to make EEG-based emotion recognition systems more sensitive, applicable and usable.

In recent years, research on detecting emotions using EEG signals has gained significant momentum. In particular, the availability of low-cost EEG devices and the sharing of open data sets among researchers have accelerated work on this subject. In this context, the “EEG Brainwave Dataset: Feeling Emotions” published on Kaggle, which we also used in this study, has been one of the sources frequently referred to in research. The relevant dataset consists of four-channel (TP9, AF7, AF8, TP10) EEG signals obtained with the Muse EEG device in positive, neutral, and negative emotional states.

Earlier studies on EEG-based emotion detection focused on determining if emotional data could be obtained from brain waves. Numerous studies have examined the link between emotional experiences and brain activity, with a particular focus on the frontal regions. Within this context, frontal alpha asymmetry has been explored as it reflects variations in alpha brainwave activity of the frontal cortex, which are connected to different emotional states. In their work, Allen and Reznik identified frontal EEG asymmetry as a potential marker for vulnerability to depression. Although frontal asymmetry may help detect individuals at greater risk for depression, large scale longitudinal studies are still required to confirm this finding (Allen and Reznik, 2015).

Frontal alpha asymmetry neurofeedback was investigated by Mennella et al. as a strategy for mitigating symptoms of anxiety and negative affect. In their study, neurofeedback training was employed to examine discrete changes in positive and negative affect, anxiety, and depression, as well as variations in alpha power across the left and right hemispheres. These pioneering studies established a scientific foundation for subsequent research into the neural correlates of emotions using EEG (Mennella, Patron and Palomba, 2017).

From the acquired EEG signals, J. J. Bird et al. extracted statistical features across the alpha, beta, theta, delta, and gamma bands, followed by feature selection using techniques including OneR, Information Gain, Bayesian Network, and Symmetrical Uncertainty. The dataset, consisting of 2,548 features, was reduced using 63 features selected by Information Gain, and ensemble classifiers such as Random Forest trained on these features achieved approximately 97.89% accuracy. The Deep Neural Network (DNN) achieved 94.89% accuracy (Bird, Faria, Manso, Ekárt and Buckingham, 2019).

Joshi and Joshi evaluated the performance of RNN and KNN (K-Nearest Neighbour) algorithms in classifying human emotions using EEG signals. In the study, EEG signals corresponding to positive, neutral, and negative emotions were analyzed. During the preprocessing stage, channel selection was performed, and discrete wavelet transform (DWT) was used for feature extraction. The obtained features were fed as input to the RNN and KNN algorithms. The experiments showed that the RNN algorithm achieved 94.84% accuracy, while the KNN algorithm achieved 93.43% accuracy. These results demonstrate that both algorithms performed well in the EEG-based emotion recognition task. In particular, the RNN's ability to model dependencies in time series data provided an advantage in the emotion recognition task (Joshi and Joshi, 2022).

Mridha et al. aimed to recognize emotions from EEG signals using deep learning algorithms and compared DNN, LSTM, and GRU models. The first model was a DNN with 98.44% accuracy, the second was an LSTM with 97.5% accuracy, and the third was a GRU with 97.18% accuracy. The GRU model has achieved up to 96% accuracy in identifying negative emotions. This result shows that different model configurations can exhibit varying levels of success depending on the type of emotion (Mridha, Sarker, Zaman, Shukla, Ghosh and Shaw, 2023).

Dhara et al. developed hybrid structure that combines machine learning and deep learning techniques for recognizing emotions using EEG signals. In the study, various classifiers were tested after feature extraction from raw EEG signals, and it was noted that models with early-stage filtering performed better. Specifically, using the hybrid CNN-LSTM model, accuracy rates of 96.87% and 97.31% were achieved for valence and arousal dimensions, respectively. These results demonstrate that hybrid deep learning models can perform well in EEG-based emotion recognition tasks (Dhara and Singh, 2023).

In their study using various machine learning models, Rachini et al. achieved high success rates with accuracy rates of 99% for Random Forest, 98% for SVM, and 94% for KNN (Rachini, Hassn, El Ahmar and Attar, 2024).

Another study in this field was published by Prakash and Poulose. In this study, the performance of eight different supervised machine learning algorithms was evaluated using the “EEG Brainwave Dataset: Feeling Emotions” dataset. The models used included Logistic Regression, Decision Trees, Random Forest, Gaussian Naive Bayes (GNB), AdaBoost, SVM, LightGBM, XGBoost, and CatBoost algorithms. Additionally, PCA, t-SNE, and LDA techniques were applied for dimension reduction. Experiments conducted with five-fold cross-validation revealed that the XGBoost algorithm achieved the highest performance with an accuracy rate of 92.79%. This was followed by CatBoost (92.05%) and LightGBM (91.79%). On the other hand, the Gaussian Naive Bayes algorithm had the lowest accuracy rate at 72.83%. However, it has been observed that the GNB model shows an approximately 10% increase in accuracy after PCA is applied. These results demonstrate that data preprocessing and dimension reduction significantly impact success, particularly for low performance algorithms (Prakash and Poulose, 2025).

3 MATERIALS AND METHODS

3.1 Dataset

EEG Brain Wave Data Set: The Feeling Emotions dataset was employed in this study to classify distinct emotions. As presented in Table 1, participants in this dataset were exposed to a series of video clips designed to elicit three distinct emotional states: positive, negative and neutral. For each condition, 6 minutes of brain wave activity data were recorded from two adult subjects, one male and one female, aged 20 and 22, to produce 36 minutes of brain wave activity data (Bird, Faria, Manso, Ekárt and Buckingham, 2019).

Table 1: The movies and scenes watched by the participants.

Movie	Scene	Emotion
Marley and Me	Death Scene	Negative
Up	Death Scene	Negative
My Girl	Funeral Scene	Negative
La La Land	Musical Scene	Positive

Data were collected using the Muse headset from extracranial electrodes positioned at TP9, AF7, AF8, and TP10. Human emotions were elicited through visual stimuli, and EEG recordings were obtained according to the 10-20 electrode placement system. The electrode configuration of the EEG setup is illustrated in Figure 1. This study focused on classifying three emotional states: positive, negative, and neutral. The corresponding emotion graph indicates that the signal patterns differ across these emotional states, suggesting that variations in EEG signal characteristics can serve as a fundamental basis for emotion classification. (Bird, Ekart, Buckingham and Faria, 2019).

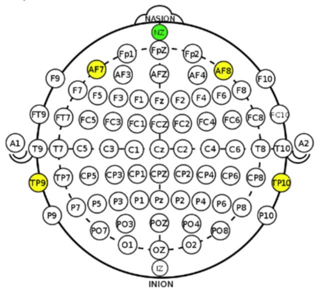

Figure 1: EEG sensors on the Muse headband in the international standard EEG placement system: TP9, AF7, AF8, and TP10 (Bird, Ekart, Buckingham and Faria, 2019).

When the EEG data samples in the dataset were arranged equally, no problem related to class imbalance was encountered during the model training and testing processes of the proposed system. Given that the dataset contained 2558 features, we performed feature dimension reduction in our study. For this purpose, we used the Principal Component Analysis (PCA) model. Principal Component Analysis (PCA) is a technique that projects high dimensional data onto a lower dimensional space while maximizing the captured variance. For a given set of points, PCA identifies the 'best fit line' that minimizes the average distance to all points in the dataset (Prakash and Poulose, 2025).

The use of this public dataset highlights the unique qualities relevant to the objectives of our study. Despite its frequent application, this dataset provides distinctive opportunities to analyze EEG derived emotional responses within a controlled experimental framework. Data collected from multi-electrode regions with the Muse headset yield a comprehensive set of temporal statistical features, including mean and variance, alongside frequency domain characteristics derived via FFT (Fast Fourier Transform). Such features offer a detailed representation of brain wave activity, supporting an in-depth evaluation of ML approaches for emotion classification. The structure of the dataset is well suited to our research focus, facilitating a thorough assessment and generalization of ML methods in EEG based emotion classification.

3.2 Models Used

In this study, various machine learning algorithms were used to recognize the emotional states of individuals based on EEG signals. The dataset used is the "EEG Brain Wave Dataset: Feeling Emotions," a dataset publicly available on the Kaggle platform that contains EEG recordings corresponding to different emotional states.

In the "EEG Brain Wave Dataset: Feeling Emotions" dataset, several preprocessing steps were applied to prepare the data for machine learning models. First, categorical labels corresponding to emotional states were converted into numerical values using a Label Encoder to ensure compatibility with the algorithms. Next, normalization was performed to scale the features to a uniform range, thereby reducing bias caused by varying magnitudes and improving model convergence. Finally, Principal Component Analysis (PCA) was applied for dimension reduction. This helped minimize redundancies, highlight the most informative features, and improve computational efficiency. After undergoing preprocessing phase, the dataset was employed for training with various machine learning algorithms. The general architecture of the proposed model is shown in the block diagram in Figure 2.

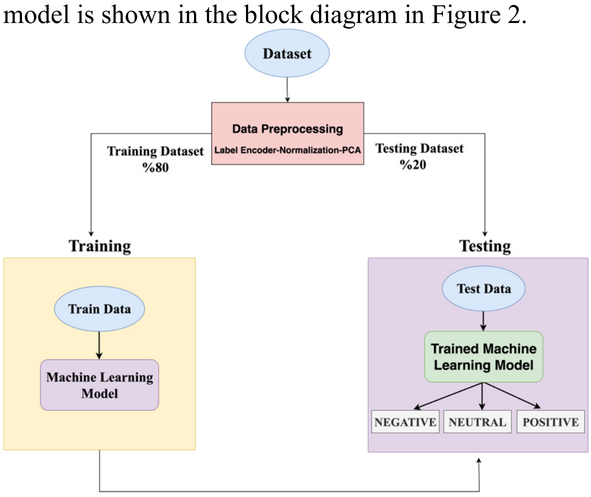

Figure 2: Block diagram of the model presented in this study.

LSTM is a type of RNN known for its ability to learn long term dependencies in time series data. Through the integration of memory cells and gating mechanisms, LSTMs effectively overcome the vanishing gradient problem, rendering them particularly well suited for tasks involving sequential data, such as speech recognition, natural language processing, and EEG signal analysis. In this study, the GRU network was applied alongside LSTM in order to assess its sensitivity to the temporal patterns of emotional states. DNN, composed of multiple layers of artificial neurons, is capable of learning high-dimensional and abstract representations from complex data. After normalization, EEG features were provided as input to the DNN, and multilayer architectures employing Rectified Linear Unit (ReLU) activation functions were systematically evaluated. The learning capacity of the DNN shows strong performance, particularly when combined with carefully selected features, highlighting its potential in capturing nonlinear relationships within EEG signals (Mridha, Sarker, Zaman, Shukla, Ghosh and Shaw, 2023). SVM, a traditional yet robust machine learning algorithm, has proven effective in scenarios with limited sample sizes and high dimensional data, owing to its ability to maximize the decision margin and generalize well in such contexts (Rachini, Hassn, El Ahmar and Attar, 2024).

XGBoost is a powerful ensemble learning technique based on gradient boosted decision trees and it typically achieves high accuracy values by balancing both model complexity and learning time. In this study, the XGBoost model trained with features extracted from EEG data has drawn attention, particularly for its robustness against overfitting. Logistic Regression, despite being a simple and interpretable algorithm known for producing linear decision boundaries, has achieved satisfactory results on well preprocessed EEG data. Random Forest, on the other hand, is an ensemble learning technique that classifies by combining the outputs of multiple decision trees; it has shown successful performance on EEG data due to its resilience to noise in the data and its lack of tendency toward overfitting (Prakash and Poulose, 2025).

Various experiments were conducted on the dataset using the mentioned models. The results obtained from these experiments are explained under the section titled Experimental Results.

4 EXPERIMENTAL RESULTS

In this study, the performance of various machine learning algorithms (Logistic Regression, Random Forest, SVM, XGBoost, RNN, GRU, and LSTM) was compared for emotion classification using FFT based features that were reduced in dimensionality through PCA. Table 2 shows the applied machine learning models and their respective performance metrics.

Table 2: Machine learning models used and their performance metrics.

Model	Accuracy	Precision	Recall	F1-Score
LSTM	0,9625	0,9626	0,9625	0,9626
GRU	0,9789	0,9794	0,9789	0,9789
DNN	0,9781	0,9781	0,9781	0,9781
Random Forest	0,9578	0,9589	0,9578	0,9579
Logistic Regression	0,9461	0,9492	0,9461	0,9458
SVM	0,9555	0,9560	0,9555	0,9554
XGBoost	0,9672	0,9676	0,9672	0,9671
RNN	0,9555	0,9569	0,9555	0,9552

Among the models examined in this study, GRU demonstrated the highest classification accuracy. This result indicates that GRU exhibits an outstanding performance with signal-based data due to its ability to effectively learn time dependent patterns. Specifically, the GRU's ability to learn similarly to deep structures such as LSTM with fewer parameters optimizes training time while also improving classification performance. In this context, we conclude that the GRU offers an effective and efficient alternative model for applications such as sentiment analysis working with high dimensional data containing time series features.

Looking at Table 3, we can observe that the GRU, XGBoost, and RNN models achieve better results than the studies in the literature, while the other models achieve similar results to the studies in the literature.

Table 3: Comparison of literature results and proposed model performance.

Model	Accuracy	Authors
LSTM	0,9750 0,9625	Mridha et al. (2023) Proposed Model
GRU	0,9789 0,9718	Proposed Model Mridha et al. (2023)
DNN	0,9489 0,9781 0,9844	J.J. Bird et al. (2019) Proposed Model Mridha et al. (2023)
Random Forest	0,9789 0,9900 0,9578	J.J. Bird et al. (2019) Rachini et al. (2024) Proposed Model
SVM	0,9800 0,9555	Rachini et al. (2024) Proposed Model
XGBoost	0,9672 0,9279	Proposed Model Prakash et al. (2025)
RNN	0,9484 0,9555	Joshi et al. (2022) Proposed Model

5 CONCLUSIONS

In this study, experimental research was conducted to perform emotion recognition based on EEG signals using machine learning models. Current studies in the literature were reviewed and compared with the results obtained from the experimental research.

Thus, machine learning models show promising results in classifying emotional states with high accuracy rates, even with low-cost EEG devices. However, the nature of signals being prone to noise, individual differences, and the challenges encountered in real time applications are among the significant problems awaiting further research in this field.

In our future work, the focus will be on developing more flexible and reliable systems through multi-modal approaches, more advanced and personalized models, and the integration of explainable artificial intelligence (XAI).

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