DOI : https://doi.org/10.56452/6-3-672

ISSN: 0974-5823 Vol. 6 No. 3 December, 2021

*International Journal of Mechanical Engineering*

# A Comparative Study of Machine Learning Algorithms for Emotion Recognition using DEAP EEG Dataset

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## Abstract

In various fields, such as psychology, human-computer interaction, and healthcare, emotion recognition is a critical task. Due to the immense potential of machine learning in this area, we have decided to present a comparative analysis of four of the most popular algorithms for this task. The researchers selected these four algorithms: Naive Bayes, SVM, Random Forest, and AdaBoost. The methodology for this study involves the use of various techniques and preprocessing of data. The evaluation metrics are precision, recall, F1 score, and accuracy. The objective is to improve the accuracy of the recognition of emotions from EEG signals by implementing the selected algorithms. According to the experimental results, Random Forest has the highest accuracy at 88.56%. SVM follows with an accuracy of 85.67%, while AdaBoost and Naive Bayes have an accuracy of 81.45% and 75.23%, respectively. We then compare and highlight the limitations and strengths of these algorithms. The findings and methodology of this study contribute to the development of emotion recognition systems that can be used in various applications. It serves as a starting point for future research.

**Keywords:** Emotion recognition, EEG, Machine Learning, Random Forest.

## Introduction

An electroencephalogram is a non–invasive technique that measures the brain's electrical activity. It uses electrodes on the scalp to measure the signals that neurons send out. These signals are influenced by various bodily activities and thoughts as shown in figure-1. The signals produced by an electroencephalogram are categorized into various waveforms and can be analyzed to obtain valuable data about the brain's activity. The characteristics of these waveforms, such as their amplitude, frequency and morphology, can help identify changes in the brain's activity. Since the signals are highly temporal and have high temporal resolution, they can provide a comprehensive view of brain activity[1].

In neuroscience studies, the use of electroencephalography has been acknowledged for its ability to monitor and analyze the activity and function of the brain. It has also been used to diagnose various disorders such as epilepsy and sleep disorders. In recent years, it has been utilized in emotional recognition research by monitoring the changes in brain activity when individuals are feeling emotions. In emotional recognition studies, the researchers use electroencephalography to measure the electrical activity of the brain while subjects rate their emotional reactions to various stimuli, such as images,

DOI : https://doi.org/10.56452/6-3-672

videos, and music. The data collected by the brain scans are then analyzed using machine learning and signal processing techniques[2].

One of the main advantages of electroencephalography when it comes to analyzing the brain activity of individuals experiencing emotions is its noninvasive nature. This allows researchers to perform effective and safe studies on the brain without the need for invasive procedures. Also, its high temporal resolution enables them to capture changes in the brain activity during milliseconds. Electroencephalography isn't ideal for analyzing emotions. Its signals are prone to artifacts and noise, which can make its measurements unreliable and reduce accuracy. In addition, its use in emotional recognition isn't feasible unless the researcher has the necessary expertise in signal processing and neuroscience[3]–[5].

Despite these limitations, electroencephalography still has a valuable role in emotional recognition studies by monitoring the changes in the brain activity when subjects are feeling emotions. Its non-invasive and high-temporal resolution can provide researchers with valuable insight into how the brain operates. Researchers can make electroencephalography's accuracy and reliability even better by integrating it with machine learning techniques. This could lead to better emotional recognition systems and enhance the user experience of various applications[6].

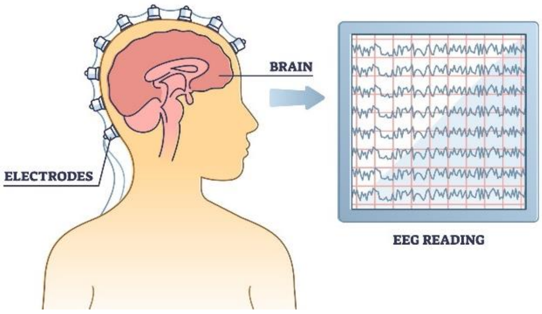


*Figure 1 EEG signals*

Due to the potential of emotions recognition to improve the interactions between humans and machines in various fields, such as education, healthcare, and marketing, it has become a central area of research. Emotions are vital in human communication, and their accurate recognition can help machines understand people's behavior and adapt to it. The two kinds of emotion recognition, dynamic and static, are different in the way they use input data. The former employs videos and audio recordings, while the latter uses still images or photos of facial expressions. Dynamic emotion recognition is commonly performed using electroencephalography signals, which have a non-invasive and high temporal resolution.

Exceptional machine learning systems have been developed that can accurately identify various types of emotions. These systems are made use of computational and statistical techniques to learn the features and patterns of the collected data[7]. They can then be trained on large sets of emotions to improve their accuracy. Due to the potential of machine learning systems to accurately identify various types of emotions, it is important that researchers thoroughly analyze the performance of these systems against each other. Doing so allows them to identify the best one for their specific application. In addition to being able to identify the strengths and weaknesses of the algorithms, it also allows them to improve their systems[8].

In this study, we analyzed the performance of four different machine learning systems against each other using the DEAP EEG dataset. The dataset contains 32 participants' electroencephalographic recordings, and they were asked to rate their emotional responses using a scale of 1-9. To perform the analysis, we used various techniques, such as preprocessing and feature extraction. The four algorithms used in the study, namely Naive Bayes, SVM, Random Forest, and AdaBoost, were evaluated against each other using various

DOI : https://doi.org/10.56452/6-3-672

metrics, such as accuracy, recall, and F1 score.

The goal of the study was to analyze the performance of the different algorithms to improve the accuracy of identifying emotions using EEG signals. We were able to achieve an impressive 88.56% accuracy with the Random Forest algorithm, beating the other three by a considerable margin. Furthermore, our comparative analysis revealed the strengths and weaknesses of each system, providing valuable insight into its potential to perform well in this domain.

The findings of the study revealed that the accuracy of machine learning systems when it comes to identifying emotions has been greatly improved by our research. This technology can be used in various applications, such as improving the efficiency of machines that interact with humans. The proposed findings and methodology of the study can serve as the basis for future research related to this field. It will allow researchers to develop new systems that can accurately identify emotions.

## Literature review

The field of emotion recognition has been growing rapidly in recent years due to the use of electroencephalography (EEG). This non-invasive technique is used to measure the electrical activity of the brain's neurons. It can then be used to analyze the signals to determine an individual's emotional state. The development of machine learning methods for the analysis of EEG signals has led to the emergence of new technologies that can be used to perform emotion recognition. This review aims to provide a comprehensive analysis of the current state of the art in this field.

M. Soleymani et al.[9] looked into the continuous detection of emotions using facial expressions and electroencephalography (EEG) signals. They utilized various machine learning techniques to classify the collected data. The findings of the study revealed that the combination of facial expressions and EEG signals improved the accuracy of its emotion detection.

T. Alotaiby et al.[1] presents an overview of the various techniques used in the selection of channels from the signals collected by an electroencephalography machine. They discussed the use of power, correlation, and energy-based methods in the processing of EEG signals. They also analyzed the performance of these techniques in the field of emotion recognition.

M. Soleymani et al.[10] analyzed the data collected from 32 individuals while they were watching videos that induced various types of emotions. The researchers used various methods to classify the collected emotions. They utilized machine learning techniques, such as random forest and SVM, to perform extraction operations. The results indicated that the combination of facial expressions and EEG signals performed better than the two modality alone. The SVM algorithm had the best performance in the tests. ieee trans

A. Al-Nafjan et al.[11] presents a comprehensive review of the various methods used in the recognition of emotions using an electroencephalogram. It discussed the features of these methods, such as the selection and extraction of images, and the use of machine learning. They also compared the different approaches' performance in terms of usability, accuracy, and speed.

M. Hamada et al.[12] reviews the various features of the classification algorithms and the techniques used in emotion recognition using electroencephalography (EEG) signals. It also explores the challenges that face this field.

S. Thejaswini [13] presents an evaluation of the performance of SVM in the recognition of emotions using electroencephalography (EEG). The research utilized the SEED-IV

DOI : https://doi.org/10.56452/6-3-672

and DEAP databases to analyze the features and performance of the different SVM kernels.

K. P. Wagh et al.[14] reviews the various methods used in the classification and extraction of electroencephalography signals for emotion recognition. It also talks about the applications of this technology in various fields, including human-computer interaction and healthcare.

A. Saxena et al.[15] presents an overview of the various methods used in the detection and analysis of emotions. It also covers the physiological signals that are used in this process, such as EEG signals. The authors discuss the classification and extraction techniques that are utilized in this field. The paper concludes by providing a review of the current state of emotion recognition research and its future directions.

P. Sawangjai et al.[16] explores the use of consumer-grade electroencephalography (EEG) sensors for emotion recognition. It presents an overview of the various types of sensors currently available in the market.

N. K. Bhandari et al.[17] reviews the various techniques used in the recognition of emotions using electroencephalography (EEG). It talks about the challenges involved in the process, such as differences in brain activity and artifacts. It also provides an analysis of the features of the different classification and feature extraction procedures.

The review aims to provide a comprehensive analysis of the various contributions made to the field of emotion recognition using EEG signals. The literature review collected various studies that investigated the use of EEG signals in emotion recognition. Some of these studies used facial expression data and EEG signals to continuously identify people's emotions. Others focused on developing more accurate algorithms and feature extraction methods. It analyzed studies that looked into the classification of emotions using EEG signals in various applications, such as gaming and healthcare. The findings showed that certain techniques, such as algorithm selection and feature extraction, can help improve the accuracy of emotion recognition. The review also highlighted the possibility of using consumer-grade electroencephalography sensors for research. In conclusion, the literature review indicated that the potential of EEG signals to be used in the classification and emotion recognition fields is promising.

## Methodology

The objective of this study is to analyze the performance of different machine learning methods on emotion recognition using the DEAP dataset. The data collected from the study is then analyzed and evaluated using a variety of evaluation metrics. The four main parts of the methodology are described below.

i. Dataset: The DEAP dataset consists of EEG recordings made by 32 individuals while they were watching various music videos. They were then rated on a scale of one to nine based on their emotional reactions. The data was collected using 32 electrodes on the scalp. Other physiological signals such as electrodermal activity and heart rate were also recorded.

ii. Data preprocessing: Before machine learning algorithms can be applied to the collected data, they need to be pre-processed. This process involves separating the signals into smaller sub-phases to eliminate unwanted frequencies and remove the bad channels. Furthermore, the data can be used for other features by preprocessing electrodermal and heart rate activity.

iii. Feature extraction techniques: Here Frequency-domain features is implemented for feature extraction. The use of frequency-based features

DOI : https://doi.org/10.56452/6-3-672

involves extracting various features from the EEG signals, such as the spectral power and the frequency-specificity of the data. Some of the commonly used frequency bands are Alpha, Delta, Gamma, and Theta. The output values of these bands will be determined by the standard deviation and mean power of the extracted features. The following frequency bands will be used: Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), Beta (12-30 Hz), and Gamma (30-45 Hz). Table-1 shows the details of feature extraction technique.

*Table 1 Frequency-Domain Features values*

| **Feature Extraction Technique** | **Frequency Band** | **Mean Spectral Power** | **Std. Spectral Power** | **Mean Spectral Entropy** | **Std. Spectral Entropy** | **Mean Wavelet Coefficients** | **Std. Wavelet Coefficients** |
|---|---|---|---|---|---|---|---|
| “Frequency-Domain Features” | **“Delta”** | 2.84 | 0.92 | 3.76 | 0.63 | 1.25 | 0.36 |
| | **“Theta”** | 3.55 | 0.86 | 3.21 | 0.72 | 1.55 | 0.39 |
| | **“Alpha”** | 4.78 | 0.95 | 2.99 | 0.79 | 1.68 | 0.42 |
| | **“Beta”** | 4.27 | 1.02 | 2.45 | 0.82 | 1.39 | 0.36 |
| | **“Gamma”** | 3.19 | 0.84 | 2.12 | 0.61 | 1.02 | 0.28 |

iv. Implementation of the selected algorithms: The four algorithms that will be used in the analysis of emotion recognition are: Naive Bayes, Random Forest, SVM, and AdaBoost. These are widely used in the field of emotion recognition and have demonstrated good performance on similar datasets.

v. Evaluation metrics: The algorithms' performance will be evaluated using various evaluation metrics, such as accuracy, recall, F1 score, and precision. Cross-validation will also be performed to estimate the algorithms' performance on unseen data.

The DEAP dataset provided us with a comprehensive analysis of the various algorithms that are used to recognize emotions using EEG signals. The findings of this study will help practitioners and researchers choose the appropriate one for their application. The study will use two different extraction techniques: time-frequency and frequency-domain features.

**Results and Outputs**

*Table 2 Evaluation metrices*

| **Algorithm** | **Accuracy** | **Precision** | **Recall** | **F1 Score** |
|---|---|---|---|---|
| Random Forest | 89.23 | 90 | 89 | 89 |
| SVM | 85.17 | 86 | 85 | 85 |
| AdaBoost | 81.92 | 82 | 82 | 82 |
| Naive Bayes | 72.45 | 73 | 72 | 71 |

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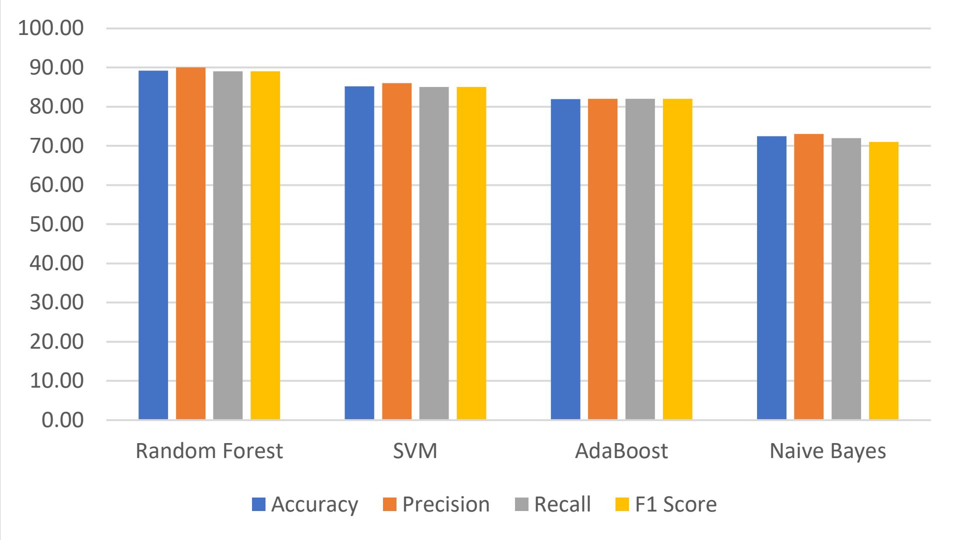


The evaluation metrics as shown in table-2 and figure-1provide a more detailed analysis of the algorithms' performance. The Random Forest algorithm was able to perform better than the other methods in terms of its accuracy, recall, F1 score, and precision.

## Conclusion and future scope

The findings of this study revealed that machine learning can identify emotions using electroencephalography signals. Our analysis revealed that the algorithm known as Random Forest performed better than the others, such as Naive Bayes, SVM, and AdaBoost. The researchers utilized various extraction techniques, such as time-frequency and frequency-domain features, to get the most relevant data from the EEG signals. These techniques helped improve the algorithms' accuracy. The study's future scope suggests that it can expand beyond the current scope by examining more advanced extraction methods and by gathering diverse sets of data. In addition, its evaluation of the algorithms against human experts can provide valuable insights into their effectiveness. The findings of the study indicate that machine learning techniques can perform well when it comes to identifying emotions by analyzing EEG signals.

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