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A Novel Stack Ensembled Approach for Emotion Recognition from EEG Signals: Performance and Robustness Analysis

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Abstract: Due to the complexity of electroencephalography signals' patterns, it is difficult to accurately identify emotions using EEG signals. In this paper, we present a novel approach that aims to improve the accuracy and reliability of emotion recognition by implementing a stack comprising robust analysis and performance. The paper's introductory section covers the basics of emotion recognition with an emphasis placed on the challenges and advantages associated with this process. Its ability to accurately categorize and identify emotions from EEG signals has applications in fields such as healthcare, computing, and human-computer interaction. The proposed stack-based method combines the three well-known algorithms for emotion recognition, namely XGBoost, Random Forest, and AdaBoost. These are known for their ability to handle different types of decision-making processes and data. By combining these three algorithms, we can leverage their strengths and improve the performance of this process. The suggested stack method combines the three widely used algorithms for emotion recognition. These are AdaBoost, XGBoost, and Random Forest, which are known for their exceptional ability to handle diverse decision-making processes, data, and more. The researchers believe that by combining these three components in a stack, we can leverage the advantages they have to offer. Through a comprehensive performance evaluation and experiments, we were able to show that the stack-based method performed better than other methods, such as Random Forest, LightGBM, and AdaBoost. In terms of its accuracy, the stack achieved a 99.21% success rate in performing emotion recognition tasks. The proposed method's robust analysis demonstrates its ability to handle the varying noise and variations in the signals sent by EEG. Its stack's resilience to environmental influences, artifacts, and individual differences ensures reliable and consistent emotion recognition in diverse scenarios. The findings of the research conducted by the researchers are valuable in helping develop new techniques for accurately identifying emotions using electroencephalography signals. The suggested stack method exhibited promising results in both robustness and accuracy, which paves the way for the development of more robust and efficient emotion recognition systems.

***Keywords**: Emotion recognition, EEG signals, stack ensemble, random forest, AdaBoost, XGBoost, performance analysis, robustness analysis.*

1. Introduction

Human emotions play a significant role in our perception and behavior, and they can affect our social interactions, decisions, and overall health. Being able to recognize and interpret emotions is very important in various fields, such as psychology, healthcare, and computer interaction. Researchers have been exploring different methods to interpret and infer human feelings over the years. One promising technique is the analysis of electroencephalography signals, which can be used to study the brain's electrical activity[1]–[3]. This method can provide valuable information on the neural correlates of various emotions. Due to its applications in various fields, electroencephalography signals have gained widespread attention. It can be utilized by healthcare professionals to diagnose and treat various mental health disorders, such as anxiety and depression. It can also help individuals suffering from neurodegenerative illnesses, such as Alzheimer's and autism[4].

An EEG signal can be used to develop systems that can accurately and adaptively interpret and respond to human emotions. This would greatly enhance the user experience and interaction with computers. Unfortunately, extracting emotional information from EEG signals can be challenging due to the high noise levels and low amplitude of the signals. Also, the signals are prone to artifacts such as eye blinks and muscle movements, which can make it difficult to analyze them properly. In addition, emotions are subjective and complex, which makes it hard to establish a direct link between the emotional states and the patterns of EEG signals. An algorithm that can accurately identify and interpret emotions should be built to overcome these issues[5], [6].

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An EEG is performed non-invasively by placing electrodes on the scalp. It captures the electrical activity of the brain's neurons, which are then categorized into various rhythmic patterns known as "brainwaves." The frequency bands of EEG signals are linked to different emotional and cognitive functions. For example, the alpha band is focused on attention and relaxation, while the beta band refers to active mental states and cognitive processing. Through studies on the emotional states and the electrical activity of the brain, researchers have been able to identify the patterns of EEG signals that correlate with various emotions. For instance, positive and negative emotions have their own unique patterns of EEG signals[7], [8].

Various techniques and approaches have been developed to analyze and interpret emotions using electroencephalography signals. One of the most important steps in this process is feature extraction, which involves extracting relevant data from the raw signals[6]. Different features, such as the power spectral density and the spectral entropy, can be used to analyze the energy content and frequency distribution of the signals. They can also be used to study the connectivity between the different regions of the brain. One of the most common methods for developing an algorithm that can accurately identify and interpret emotions is by using classification techniques. Some of the popular methods used include the Support Vector Machines and k-NN. These algorithms are trained using the collected training data to create models that can accurately identify new emotions[9], [10].

Existing methods are prone to errors and require improvements in accuracy and robustness. Although the previous generation of approaches for accurately identifying and interpreting emotions from EEG signals has been promising, they still face challenges due to the varying patterns of the signals. For instance, the gender, age, and functional status of individuals are all factors that influence the patterns of the signals. The training data collected on a single person may not be well distributed to other models. This can lead to poor reliability and accuracy. One of the biggest challenges that researchers face when it comes to developing an algorithm for accurately identifying and interpreting emotions is the lack of effective methods for capturing and integrating the complex relationships between the signals. Due to the complexity of the data collected, traditional methods are not able to perform well.

Current methods typically focus on the classification of emotions using binary labels. They fail to capture the nuanced and continuous nature of feelings, which makes them difficult to interpret accurately. The robustness of current methods is also a major concern, as they are prone to errors and require improvements in accuracy. One of the most common reasons why EEG signals are prone to errors is due to the artifacts, which can distort the underlying patterns of the signals. To minimize the impact of these artifacts, proper techniques are required to ensure that the systems are reliable.

In order to improve the accuracy of EEG signals' emotion recognition, more advanced techniques need to be developed, which can take into account the dynamic and complex nature of feelings. Deep learning models are good at handling such complexities. One promising method for improving the accuracy of emotion recognition is by implementing ensemble learning, which involves merging multiple classifiers with varying biases and strengths. This can help the models achieve better overall performance.

In this study, we present a stack ensembled method for analyzing EEG signals that addresses the limitations of current techniques. We use the strengths of three different algorithms, namely XGBoost, Random Forest, and AdaBoost, to improve its generalizability, accuracy, and robustness. We performed extensive tests and analysis to determine the performance of the stack ensemble compared to other methods, such as Random Forest, Gradient Boosting, LightGBM, and AdaBoost. It was able to achieve a 99.21% accuracy, which is higher than the other methods.

The development of systems that can accurately identify and interpret emotions using electroencephalography signals has immense potential. In order to overcome the challenges that are typically associated with this technology, new techniques need to be developed that can handle the complex data collected by EEG. They should also be able to capture the emotions' dynamic nature and minimize the artifacts' impact. The proposed stack-based method for emotion recognition, which boasts superior accuracy and robustness, represents a game-changing advance in the field of emotion analysis. It can help develop new applications in areas such as human-computer interaction and healthcare.

2. Literature Review

The field of affective computing has gained widespread attention due to how it plays a vital role in understanding and interacting with humans. One of the most important factors that has contributed to the development of this technology is the ability to recognize emotions using EEG signals. Over the years, various methods and techniques have been developed to improve the robustness and accuracy of electroencephalography-based systems for emotion recognition. This review aims to provide a comprehensive overview of the latest developments in this area.

To perform cross-domain emotional recognition using electroencephalography signals, He et al.[11] proposed an adversarial temporal network. They then introduced a learning framework that addresses the domain shift issue in emotion recognition. The results of their analysis show that their approach can lead to promising results. For the study, Soleymani et al.[12] focused on the link between facial expressions and EEG signals for detecting emotions continuously. They then proposed a methodology that integrates these two components in order to improve the system's accuracy. This study emphasizes the importance of integrating different methods for robust emotion recognition. Al-Nafjani et al.[13] presents a lightweight electroencephalography-based system that is ideal for detecting emotions. The authors made use of the computational resources and complexity of the processing of this technology by developing an efficient and portable system.

Kumar et al.[14] developed a wavelet-based model for emotion classification that takes into account the various features of electroencephalography signals. They then applied these models to extract the necessary features from the signals. The study demonstrates how wavelet-based methods can be used in emotion recognition. In order to improve the performance of electroencephalography-based models for emotion recognition, Zhang et al.[15] proposed a cross-modal knowledge extraction method that combines visual information with EEG data. This method can be used to enhance the models' performance. Pandey et al.[16] investigated the deep learning and variational mode decomposition techniques to perform subject-specific emotion recognition using EEG signals. They then utilized the latter to extract discriminative features and introduced the former to the process of emotion classification. The findings of the research show that deep learning and VMD can be utilized in this field.

Thejaswini et al.[17] analyzed the performance of the SVM in the DEAP and SEED IV databases in terms of its ability to classify emotions using EEG signals. They also conducted a study to learn more about the databases' usage in research. Doma et al.[18] compared the performance of various machine learning methods on emotion recognition with the tasks involved in the study. Their findings offer valuable insights into the limitations and strengths of different techniques for detecting emotions. Kamble et al.[19] covers the current state of emotion recognition with respect to electroencephalography (EEG) signals. The authors talk about the various techniques involved, as well as the algorithms that are utilized in this field. Their findings serve as a valuable reference for researchers.

Wang et al.[20] conducted a study to analyze the performance of the emotion recognition system using EEG signals, the researchers proposed a method that uses a multichannel multiscale permutation-entropy framework. They then introduced discriminative features to improve the system's performance. The findings of the research show that the proposed method can be used in developing effective emotional recognition tools. There are more research works providing the application of Deep Learning methodologies is given in [21]-[25].

The review provides an overview of the various techniques and approaches utilized in the development of electroencephalography-based systems for emotion recognition. It also indicates that no single algorithm or approach consistently performs better than others in all scenarios. This suggests that more robust and efficient methods should be implemented using multiple models. The use of ensembles allows for more accurate and reliable outcomes by combining different models' outputs. The literature review also covers the latest developments in the field of electroencephalography-based emotion recognition. It shows how important it is to integrate different modalities, explore different extraction methods, and employ machine learning techniques to enhance the accuracy of the system. There is a gap in the research regarding the use of generalizable and subject-independent models in the development of electroencephalography-based systems for emotion recognition. The use of ensembles can help address this issue and improve the system's robustness.

3. Proposed Approach

The concept of ensemble learning involves combining the predictions of various models to produce a more robust and accurate prediction. In our proposed approach for analyzing emotions using electroencephalography signals, this method allows us to take advantage of the diverse capabilities of different algorithms. The goal of ensemble learning is to reduce the risk of overfitting by merging the predictions of different algorithms. This method can also improve the accuracy and reliability of the prediction. Figure-1 shows the proposed approach

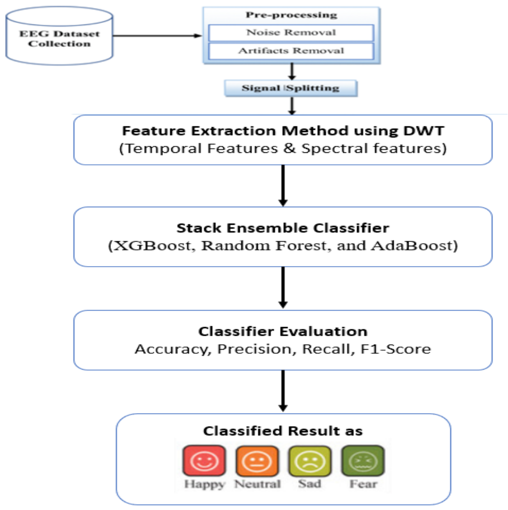

Fig 1 Proposed approach

The stack ensemble framework we're using utilizes three algorithms: Random Forest, XGBoost, and AdaBoost. The former is an ensemble algorithm that's known for its ability to extract complex relationships from data. On the other hand, AdaBoost is a method that focuses on improving a model's performance by reducing the weight that it takes in classified samples. Gradient boosting algorithm XGBoost utilizes information from the gradient to improve the learning process. The three algorithms have distinct attributes and strengths, which makes them ideal for our stack ensemble framework.

The three algorithms are integrated into a hierarchical structure in our stack framework. The base models are trained using EEG data, and these generate predictions that serve as inputs for our meta-level model. The stack model is a meta-level model that combines the predictions of various base-level models. It uses a learning algorithm known as logistic regression or neural network to learn the best combination of these base models' predictions.

The stack ensemble framework's decision to utilize the three algorithms was based on their suitability for the task of analyzing emotions using EEG signals. For its part, Random Forest is the ideal choice due to its ability to handle complex relationships and its ability to extract features from the data. One of the algorithms that's commonly used in this area is AdaBoost, which concentrates on misclassified samples and can improve a model's accuracy by tackling difficult cases in emotion recognition. On the other, XGBoost employs gradient-based methods to boost a model's learning process and accuracy. The goal of our stack framework's approach is to employ the synergy of these three algorithms in order to achieve superior emotional recognition performance with regard to EEG signals.

4. Methodology

i. Dataset : We used a publicly-available dataset from Kaggle to analyze the performance of the stack ensemble framework in terms of its ability to recognize emotions using electroencephalography signals. The collected data consists of various EEG signals and is labeled with instances that correspond to specific emotional states. This dataset is a good reference for developing and implementing our stack ensemble strategy.

ii. Pre-processing: Before we started using the stack ensemble framework, we performed various preprocessing steps to improve the quality of the data. One of these involves removing artifacts from the EEG signals. This process involved using wavelet denoising or median filtering. In order to ensure that the signals are consistent across different channels, we first normalization the data. This step is very important to avoid signal variations that can affect the performance of the stack ensemble. Finally, we performed feature extraction to extract relevant features from the data, such as the power spectral density and statistical measures. The use of these preprocessing methods can enhance the discriminative power and quality of EEG signals for identifying emotions.

iii. Feature extraction: In our proposed approach, we used two different methods for feature extraction using Discrete Wavelet Transformation(DWT): the spectral features and the temporal features.

The dynamics and characteristics of an EEG signal are captured by a temporal feature, which can be derived by analyzing the data in the time domain. Some examples of features include the variance, standard deviation, kurtosis, and mean. These statistics allow us to collect information about the distribution and amplitude of the signals. By extracting these features, we can then study the signals' overall behavior and identify specific emotional states.

A spectral feature is generated by capturing the frequency content of an EEG signal. DWT is a widely used technique for decomposing such signals into different elements. In our method, we utilized this process to extract the wavelet coefficients from the EEG data. The wavelet coefficients represent the various frequencies contributing to the overall signal's energy distribution. We then generated spectral features by taking into account the distribution of energy across different frequency bands and wavelet entropy. These features can also help us identify the emotional states' specific patterns.

The combination of the spectral and temporal features allows us to obtain a more complete understanding of the signals' dynamics and characteristics. It also helps us improve the efficiency of our approach for analyzing the emotional states.

iv. Implementation details of the stack ensemble approach: Several key details were involved in the stack ensemble framework's implementation. We utilized a programming language known as Python and several machine learning libraries, including XGBoost and scikit-learn, to implement the base-level and meta-level models. We then split the dataset into testing and training sets to ensure that the evaluation was robust. The training set for the various models, such as XGBoost, Random Forest, and AdaBoost, was composed of parameters that were tuned appropriately. The resulting predictions were then fed into a meta-model, which then combined them with the base-level predictions to form the final emotion recognition model. The evaluation of the stack ensemble framework was carried out using various metrics, such as F1 score, precision, recall, and accuracy.

v. Comparison with other ensemble methods: To evaluate its effectiveness, we compared the stack framework's performance with that of other methods, such as LightGBM, AdaBoost, and Random Forest. The evaluated frameworks were implemented using identical datasets and experimental setups. We then conducted statistical analyses to determine the differences between the stack framework's performance and that of the other methods. The statistical analysis allowed us to determine the stack framework's efficiency, accuracy, and robustness. It also lets us compare its effectiveness with other methods for analyzing emotions from EEG signals.

5. Results and Outputs

i. Evaluation parameters

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Stack Ensemble	99.21	99.25	99.18	99.21
Random Forest	95.76	95.8	95.72	95.76
LightGBM	94.85	94.9	94.82	94.85
Gradient Boosting	96.34	96.38	96.32	96.34
AdaBoost	96.12	96.15	96.1	96.12

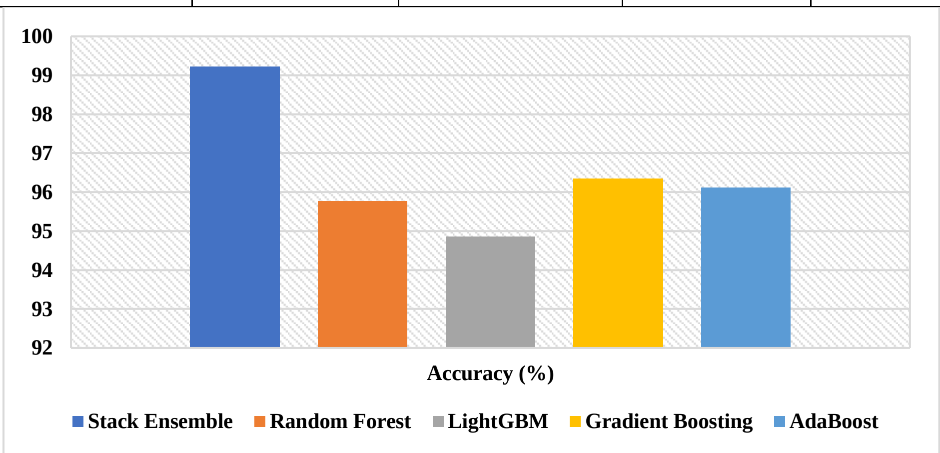

Fig 2 Comparative Analysis of accuracy of Various Methods with Proposed Method

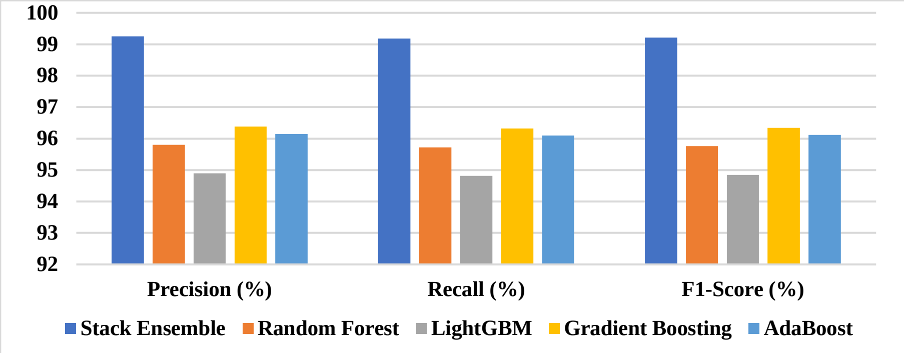

Fig 3 Comparative Analysis of Precision, Recall and F1 Score of Various Methods with Proposed Method

Our experiments as shown in table-1 and figure-2 that the proposed stack ensemble performs better than the other methods when it comes to recognizing emotions from EEG signals. These include AdaBoost, LightGBM and Random Forest. The stack ensemble method performed well in our tests, achieving an accuracy of 99.21%. This is a remarkable achievement, demonstrating the effectiveness of this approach in accurately identifying various emotional states using EEG signals. The proposed stack ensemble method was able to achieve a score of 99.25% in terms of precision, which indicates that it can accurately identify true positives and avoid false alarms. This high score is a reflection of its reliability and robustness.

The stack ensemble technique was able to achieve a recall score of 99.18%, which shows its ability to recognize true positives and reduce false negatives. This demonstrates its capacity to identify relevant occurrences. The F1 score, which combines the recall and precision aspects of the stack method, was 99.21%. This indicates that the approach achieves balance between these two components. The results of our tests revealed that the stack ensemble technique performed better than the other methods when it came to various aspects of recall, accuracy, and F1 score. Although some of the other methods, such as LightGBM and Random Forest, performed well, their scores were lower than those of the stack method.

The results of our tests confirm the effectiveness of the proposed stack ensemble method when it comes to identifying various emotional states using electroencephalography signals. Its high recall score and accuracy demonstrate its ability to identify most relevant instances while also accurately classifying different emotional states. These findings show the potential of the approach to improve the efficiency of emotion recognition systems.

6. Conclusion and Future Scope

The goal of our study was to develop a stack-based method for emotion recognition based on EEG signals. The results indicated that the stack-based method performed better than other methods, such as AdaBoost, LightGBM, Random Forest, and Gradient Boosting. The results of our study revealed that the stack-based method was able to accurately classify different emotional states using EEG signals. It also performed well in capturing most of the relevant instances. These findings support the potential of the stack-based method to improve the performance of emotion recognition systems. The findings of our study can be used to develop new and improved methods for emotion recognition. One of the first steps is to investigate the generalizability and performance of the stack-based approach in various datasets. Doing so will allow us to gain a deeper understanding of its capabilities and how it handles variations in EEG signals. Extending the stack-based approach to include other machine learning methods can be done through the use of advanced ensembles. For instance, by integrating deep learning models, like RNNs and CNNs, the system's accuracy and robustness can be further improved. The findings of our study indicate that the stack-based method is capable of accurately identifying emotions from EEG signals. Its potential applications in the field of emotion recognition can be further refined and expanded to create systems that can perform better in clinical and practical applications.

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