



EEG SIGNAL FOR EMOTION CLASSIFICATION USING MACHINE LEARNING

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Abstract:

This project is to develop an automated system designed to detect and categorize stress levels based on brainwave patterns observed through electroencephalogram (EEG) recordings. EEG is a non-invasive technique that captures electrical activity in the brain, providing valuable insights into neural dynamics that reflect emotional and cognitive states, including stress. Stress, a significant factor impacting health, productivity, and overall well-being, induces a complex physiological response characterized by alterations in brainwave activity. Research has shown that elevated stress levels are often associated with an increase in beta wave activity and a decrease in alpha wave activity, indicating a state of

heightened alertness, cognitive arousal, and sometimes anxiety. By implementing advanced signal processing techniques, such as wavelet transforms and feature extraction, the system will pre-process EEG data to isolate relevant brainwave characteristics linked to stress responses. The development of a data-driven, scalable solution for stress monitoring reflects the growing need for innovations that support mental health, and this system stands to make a meaningful contribution in both research and real-world application.

[1] INTRODUCTION

Emotions play an important role, and recognizing emotions is key for natural interactions. As machines become more integrated into our lives, building systems that can accurately recognize emotions is vital for advanced human-machine interaction. Emotion recognition methods fall into three main categories: facial and speech analysis, which are non-intrusive but may be less accurate in varied settings; physiological signals like heart rate and skin conductance, which provide detailed insights but can be influenced by factors other than emotion; and brain signals, particularly EEG, which offer deep insights into emotional states.

Electroencephalography is a non-invasive method that uses electrodes placed on the scalp to record the electrical activity of the brain. The intricate interaction of brain oscillations that take place during different mental and emotional states is reflected in the signals recorded by EEG. Both good and negative emotions have quantifiable effects on brain activity. EEG is a tool that helps to recognize emotions based on different emotions (such as happy, sadness, anger, fear, horror, etc.) are linked to different patterns of brain activation.

1.1. General Introduction

Different frequency bands associated with distinct cognitive states and mental activities can be seen in the electrical activity of the brain is measured by electroencephalography. Among these frequency ranges are:

Delta (1-4 Hz): sleep state.

Theta (4-8 Hz): relaxed state.

Alpha (8-13 Hz): alert and relaxed states.

Beta (13-30 Hz): active thinking.

Gamma (30-100 Hz): Associated with higher cognitive processes like attention and thinking.

These brain oscillations are modified when people are exposed to various emotions, the resulting EEG signal will show significant changes in the energy distribution of frequency bands.

1.2. Problem Statement

The ability to accurately recognize when an individual is experiencing stress is crucial for providing timely support and interventions. However, current emotion recognition systems frequently struggle with reliability and consistency, as many methods that analyse facial expressions or vocal cues can be influenced by cultural differences and situational factors, leading to inaccurate assessments. Existing approaches that utilize physiological signals or brain activity can be complex and require specialized equipment, making them less practical for everyday use in the workplace. This limits their effectiveness in high-stress situations where identifying stress levels promptly is essential for maintaining a healthy work environment.

This project aims to develop a straightforward emotion recognition system focused specifically on identifying stress in individuals. By leveraging a combination of audio, visual, and physiological signals, this system seeks to enhance accuracy and reliability, enabling better support for employees experiencing stress and fostering a more positive workplace atmosphere.

2. EXISTING METHODOLOGY

The existing system for EEG signal for emotion classification in our base paper focuses on using advanced deep learning

techniques to achieve emotion classification. Deep learning techniques are used individually to attain the best results. The EEG signals are pre-processed using PCA(Principal Component Analysis) and the features are extracted from pre-processed dataset using EMD(Empirical Mode Decomposition). The classification is done by RNN(Recurrent Neural Network) architecture, specifically LSTM(Long Short-Term Memory).

2.1. DISADVANTAGE

Need for Advanced Machine Learning Techniques: The paper emphasizes the need for advanced machine learning techniques, such as convolutional neural networks, to improve emotion recognition accuracy.

Potential for False Positives: The use of particular machine learning algorithms for emotion recognition may lead to false positives, which can be challenging to address. Usage of more algorithms and comparing the results of different algorithms helps to give most accurate result.

3.PROPOSED METHODOLOGY

In this proposed system for automated stress detection, Utilizing EEG recordings from 32 participants, starting with pre-processing to filter noise and segment the data into relevant epochs. Sub band decomposition will be performed using wavelet transform to analyze different frequency bands associated with stress. Features will be extracted from the pre-processed signals, including time-domain, frequency-domain, and wavelet coefficients, followed by dimensionality reduction was performed using PCA. The classification is done using hybrid algorithms and different algorithm metrics are compared to get the maximum accuracy.

3.1. ADVANTAGE

The proposed system aims to give solutions to all the problems in the existing system. In this system, advanced machine learning algorithms are used to improve emotion recognition accuracy. The usage of hybrid algorithm and analysis prevents the false-positive scenarios.

4.METHODS

4.1 PRE-PROCESSING

Principal component analysis is an algorithm used to pre-process. PCA is a potent preprocessing method for EEG signals, particularly in machine learning-based emotion classification tasks. Its main function is dimensionality reduction, which helps to make the data easier to handle while maintaining the key characteristics needed to classify emotions.

4.1.1 Data Standardization

Data standardization is a preprocessing technique used to rescale features so that they have a mean of 0 and a standard deviation of 1. This transformation ensures that each feature contributes equally to the model and prevents features with larger scales from dominating those with smaller scales.

$$\tilde{X}_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j}$$

4.1.2 Select Top Principal Components

Selecting top principal components is the process of choosing the most important directions (principal components) from the results of PCA (Principal Component Analysis) that capture the maximum

variance in the data. These components represent the most meaningful structure in your data while reducing dimensionality and noise.

$$W_k = [v_1, v_2, \dots, v_k]$$

4.1.3 Project Data to Lower Dimension

Projecting data to a lower dimension is the final step in Principal Component Analysis (PCA), where the original high-dimensional data is transformed into a smaller set of new features (principal components). This projection keeps the most important information (variance) while reducing noise and computational cost.

$$Z = \tilde{X}W_k$$

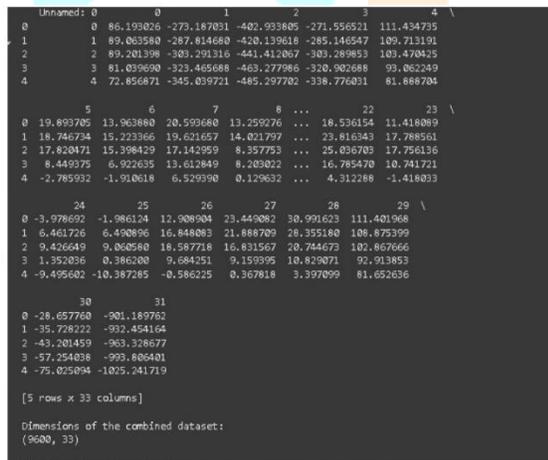


Figure 3.1

The above figure 3.1 shows how the dimensions of the dataset are reduced using PCA. These reduced datasets are further used for feature extraction.

4.2 Feature Extraction

EMD- Empirical Mode Decomposition is a powerful tool for analyzing non-linear and non-stationary time-series data. A signal can be broken down into its inherent modes of oscillation, known as Inherent Mode Functions (IMFs), using a signal processing

technique called Empirical Mode Decomposition (EMD). For non-stationary or non-linear signals, such as electroencephalogram (EEG) signals, EMD is especially well suited. EMD can extract significant features from EEG data that are suggestive of various emotional states when used for emotion categorization. A signal can be broken down into its inherent modes of oscillation, known as Inherent Mode Functions (IMFs), using a signal processing technique called EMD. For non-stationary and non-linear signals, such as electroencephalogram (EEG) signals, EMD is especially well-suited.

4.2.1 Apply EMD to Principal Components EEG Signal Decomposition:

The pre-processed EEG signal can be broken down into a collection of Intrinsic Mode Functions (IMFs) using the EMD technique. The complexity of the EEG data and the decomposition halting conditions determine how many IMFs are needed. How to Interpret IMFs: A distinct frequency band or oscillation component of the signal is represented by each IMF. distinct IMFs may capture distinct characteristics of emotional responses, such as slow (low-frequency) and fast (high-frequency) oscillations, in the context of emotion classification.

$$x(t) = \sum_{i=1}^N \text{IMF}_i(t) + r(t)$$

4.2.2 Feature Extractions from IMFs

Several elements that can be utilized for emotion categorization can be derived from the EEG signal once it has been broken down into IMFs

Features in the time domain

The basic statistical measurements of each IMF—mean, variance, and standard deviation—can shed light on the general behaviour of the signal. The signal's energy is indicated by the Root Mean Square (RMS). Skewness and Kurtosis: Indicate the IMF's peakedness and asymmetry.

Features in the frequency domain

Each IMF's power in the multiple frequency bands (Delta, Theta, Alpha, Beta and Gamma) can be measured with the use of Power Spectral Density (PSD). Band Power: Determine the band power in the following predetermined frequency bands: Alpha: 8~13 Hz, Beta: 13~30 Hz, Gamma: 30~40 Hz, Theta: 4~8 Hz, and Delta: 0.5~4 Hz. Power shifts in these bands are frequently linked to emotional states. Peak Frequency: The frequency within a particular IMF where the most energy is present.

Features that are not linear

Hurst Exponent: A signal's self-similarity or long-term memory that may be connected to the brain's emotional control. The signal's intricacy and irregularity are captured by the fractal dimension. The EEG signal's fractal dimension may alter in response to emotional emotions.

Features based on entropy

Measures of the signal's complexity and unpredictability include sample entropy (SampEn) and approximate entropy (ApEn). The entropy of EEG signals can be affected by emotional states. Another indicator of signal complexity that may be helpful in distinguishing between various emotional states is permutation entropy.

Higher-level data

Bispectrum/Bispectral Analysis: Helpful in identifying non-linear signal interactions that could be indicative of emotional states.

Features of Correlation and Coupling

Measure the relationship between various IMFs or between signals from various EEG channels using cross-correlation and coherence.

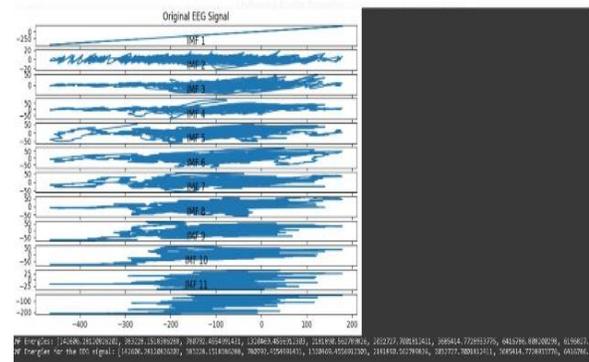


Figure 4.1

The above figure 4.1 shows the IMF's obtained from the principal components using EMD and these IMF's are further used for classification.

4.3 CLASSIFICATION

4.3.1 XGBoost(Extreme Gradient Boosting)

XGBoost (Extreme Gradient Boosting) is a powerful machine learning algorithm used for EEG classification, which involves identifying patterns in brain signals to categorize mental states or neurological conditions. EEG signals are first preprocessed to remove noise and extract meaningful features like band power, power

spectral density (PSD), wavelet coefficients, and statistical measures. These features are used as inputs for the XGBoost model. XGBoost builds an ensemble of decision trees, where each tree improves on the previous one, making it highly accurate and efficient. It can handle nonlinear data, missing values, and is resistant to overfitting due to its regularization techniques. EEG classification using XGBoost is useful in applications like brain-computer interfaces (BCIs), seizure detection, emotion recognition, and mental workload monitoring. The model requires labeled data, representing different mental states or tasks, for supervised learning. After training, the model can classify new EEG data with high precision. Its speed and scalability make it suitable for real-time and large-scale EEG analysis. Overall, this algorithm provides a robust solution for interpreting complex brain signals.

$$\mathcal{L}(\phi) = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t)}) + \sum_{k=1}^t \Omega(f_k)$$

4.3.2. CNN(Convolutional Neural Network)

Convolutional Neural Networks (CNNs) are widely used for EEG classification tasks, such as distinguishing between stress and non-stress states, due to their ability to automatically extract complex spatial and temporal patterns from multichannel EEG signals. In EEG-based stress classification, CNNs are typically applied to either raw EEG time series data or transformed inputs like time-frequency representations (e.g., spectrograms or wavelet images). The CNN architecture often includes multiple layers of 1D or 2D convolution operations, which detect local patterns across time or space, followed by pooling layers that reduce dimensionality and enhance feature

invariance. These convolutional layers are usually followed by fully connected layers that interpret the learned features and make the final classification. EEG data often undergo preprocessing steps like filtering, artifact removal, normalization, and segmentation before being fed into the CNN. CNNs can learn subtle differences in brainwave activity, such as variations in alpha or beta power, that correlate with stress responses. By leveraging CNNs, researchers can bypass the need for manual feature extraction, enabling end-to-end learning from raw or minimally processed EEG data. This makes CNNs a powerful and efficient approach for real-time, automated stress detection systems.

4.3.3 LSTM (Long Short-Term Memory)

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) particularly well-suited for processing sequential data, making them highly effective for EEG classification tasks, such as stress vs. non-stress detection. EEG signals are inherently temporal and non-stationary, meaning patterns evolve over time. LSTMs are capable of capturing these temporal dependencies by maintaining memory over long sequences, which is critical when analyzing the dynamic changes in brainwave activity. Unlike standard RNNs, LSTMs overcome the vanishing gradient problem through specialized gating mechanisms: the input gate, forget gate, and output gate. These gates regulate the flow of information, allowing the network to retain relevant features over time while discarding irrelevant ones

$$y_{\text{pred}} = \sigma(W_{\text{out}}h_T + b_{\text{out}})$$

4.3.4 CNN-LSTM

A CNN-LSTM hybrid model combines the strengths of Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs), creating a powerful architecture capable of learning both spatial and temporal patterns from EEG signals. This hybrid model is particularly useful when dealing with time-series data like EEG, where the spatial information (e.g., from different channels or frequency features) and the temporal relationships (e.g., time-dependent patterns) both play a crucial role in classification tasks.

5.RESULTS

Model Evaluation Metrics

Model	Accuracy	Precision	Recall	F1 Score
XGBoost	0.48	0.47	0.48	0.47
CNN	0.49	0.49	0.56	0.52
LSTM	0.49	0.49	0.89	0.63
CNN-LSTM	0.50	0.50	0.86	0.63

Figure5.1

The above figure 5.1 shows the model performances of three different algorithms and a hybrid algorithm. The accuracies obtained are different for each algorithms. The comparison between different algorithms helps to get an accurate result.

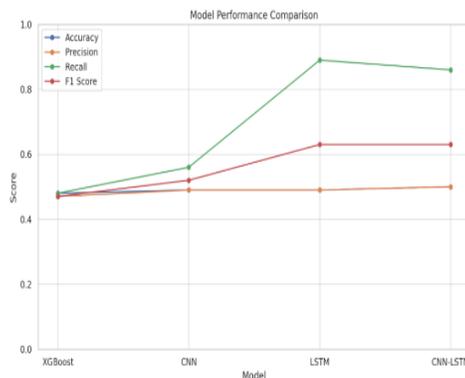


Figure 5.2

The above figure 5.2 shows the performance comparison of all four models across accuracy, precision, recall, and F1 score. Thus the EEG signal for emotion classification using machine learning classify whether a person is stressed or not-stressed using four different algorithms and the result of these four algorithms are compared to produce maximum accurate result.

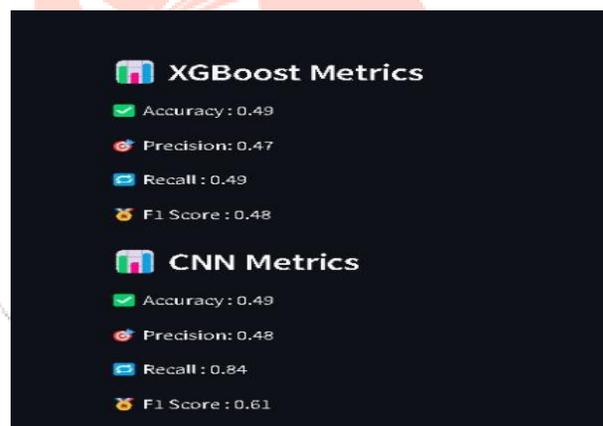


Figure5.3

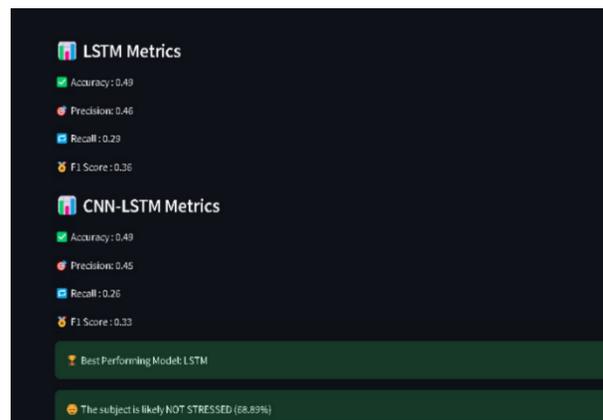


Figure5.4

The above figures 5.3 and 5.4 illustrates that the EEG signal for emotion classification process the EEG data and classify the dataset using different algorithms and give results of different algorithms. It also compare and analyze the results of all the algorithms and produce overall result(Stressed \Not Stressed) and the best performing model. The EEG stress classification results show that all models achieved an accuracy of 0.49. LSTM was chosen as the best model, due to consistent output or configuration settings. The system predicted the subject as likely not stressed with 68.89% confidence

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