Emotion Recognition from EEG Signals Using Principal Component Analysis and Random Forest Classifier

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ABSTRACT

Emotion recognition using EEG signals is a critical task with wide-ranging applications in mental health monitoring, disorders of consciousness, and neurofeedback systems. However, EEG signals are inherently noisy and high-dimensional, posing persistent challenges to accurate emotion classification. Most existing approaches rely on limited preprocessing or employ Principal Component Analysis (PCA) solely for dimensionality reduction, often overlooking the residual artifacts that degrade classifier performance. This study introduces a novel PCA-RF framework that repurposes PCA for dual objectives: targeted noise suppression and feature dimensionality reduction. Uniquely, PCA is applied after frequency-specific filtering to more effectively eliminate residual ocular and cardiac artifacts, thus improving the quality of EEG feature representations. These compact and denoised features are then processed by a Random Forest (RF) classifier, which robustly captures the nonlinear dynamics of the EEG data. Evaluated on the DEAP dataset, the proposed PCA-RF approach achieved state-of-the-art performance, with 96.57% accuracy for arousal and 96.03% for valence classification. The key contribution of this work lies in its strategic integration of PCA for both artifact suppression and feature optimization, setting it apart from conventional pipelines and delivering a reliable and accurate solution for EEG-based emotion recognition.

Keywords-EEG; emotion classification; PCA; RF; noise removal; dimensionality reduction; feature extraction; DEAP dataset

I. INTRODUCTION

Disorders of Consciousness (DoC) encompass a range of conditions characterized by severely impaired awareness of self and environment, usually resulting from traumatic brain injuries or severe neurological disorders [1]. These include the vegetative state, the minimally conscious state, and the coma, where patients show varying degrees of consciousness and wakefulness. Accurate detection and classification of these states are critical for diagnosis, treatment planning, and rehabilitation. In this context, Electroencephalography (EEG) has emerged as a reliable and non-invasive tool to monitor brain activity and assess consciousness levels [2]. EEG-based analysis allows real-time tracking of neural dynamics, providing insight into cognitive states through the assessment of electrical signals. During the past decade, significant attention has been devoted to integrating Artificial Intelligence (AI) methods, including Machine Learning (ML) [3] and Deep Learning (DL) [4], with EEG to improve interpretation and classification. Specifically, EEG-based Brain-Computer Interface (BCI) frameworks have been developed to recognize emotions, as they are intricately connected to brain activity and cognitive function. These AI-driven methods typically involve signal preprocessing, feature extraction, and classification of emotional or consciousness states. However, the success of such systems largely depends on the quality of the EEG signals used.

Despite significant progress in the application of AI to EEG-based emotion and consciousness classification, a critical limitation in current research is inadequate preprocessing of EEG signals. Many studies apply minimal filtering or rely on basic artifact rejection methods, leaving EEG data vulnerable to contamination by muscle activity, eye movements, and environmental noise. This compromised signal quality often propagates through subsequent stages of feature extraction and classification, reducing model performance and reliability. A review of recent works reveals that while advanced neural architectures such as Bidirectional Long Short-Term Memory (Bi-LSTM) networks [4], Recurrent Deep Neural Networks [4], Support Vector Machines [5], Self-Constructing Graph Neural Networks (SCGNN) [6], Transformer-based models [7], and Fractal-Spiked Neural Networks (FSNNs) [8] demonstrate promising classification accuracy, they frequently operate on suboptimally preprocessed data. For instance, in [5], SVM was applied but lacked robust noise removal, while the studies in [7, 9] focused on classification and data augmentation without applying comprehensive artifact elimination. Although [10] introduced low-pass filtering to constrain frequency bands, such linear methods do not adequately address the complex, non-stationary, and multivariate artifacts common in EEG recordings.

This analysis exposes a significant methodological gap, i.e., the lack of an integrated preprocessing strategy that effectively cleans EEG signals and reduces dimensionality before classification. Most existing pipelines emphasize model sophistication over data quality, leading to performance bottlenecks. To address this, this study proposes a preprocessing-centric framework that strategically combines Principal Component Analysis (PCA) for both artifact removal and dimensionality reduction, followed by a Random Forest (RF) classifier for robust emotion recognition. This work selected RF because of its robustness to overfitting, ability to handle high-dimensional data, and minimal sensitivity to hyperparameter tuning, making it well-suited for noisy and artifact-prone EEG data compared with other existing ML models. This approach not only enhances the fidelity of the signal, but also provides a computationally efficient alternative to DL models, making it particularly suitable for clinical and research settings where data quality and interpretability are paramount. This research work was designed with the following objectives:

- Introduce a novel EEG preprocessing framework that efficiently removes artifacts and noise.
- Implement PCA for noise and dimensionality reduction, ensuring only the most informative features are retained.
- Utilize RF as the classifier for effective feature extraction and emotion classification.
- Demonstrate how improved preprocessing directly contributes to enhanced model performance, particularly in EEG-based emotion recognition tasks.

II. METHODOLOGY

This section presents the PCA-RF approach for EEG-based emotion classification, discussing the dataset used, preprocessing techniques for artifact removal, PCA for noise removal and dimensionality reduction, and the RF classifier for emotion classification leveraging extracted EEG features. The proposed PCA-RF approach aims to enhance classification accuracy by addressing preprocessing limitations in existing methods.

A. Architecture

Figure 1 shows the PCA-RF architecture for EEG-based emotion classification. The first step involved collecting EEG data (DEAP dataset), where the dataset had recordings of EEG signals. Raw EEG signals contain unwanted artifacts caused by different types of activity. These artifacts were removed by filtering specific frequency bands associated with these disturbances. PCA was applied to remove residual noise introduced during artifact removal, ensuring clean EEG signals for feature extraction. PCA was also used for dimensionality reduction. The clean preprocessed EEG data were then used as input for RF, which extracted features and classified emotions into valence and arousal. The proposed PCA-RF framework ensures effective artifact removal, feature extraction, and classification, leading to improved accuracy in EEG-based emotion recognition.

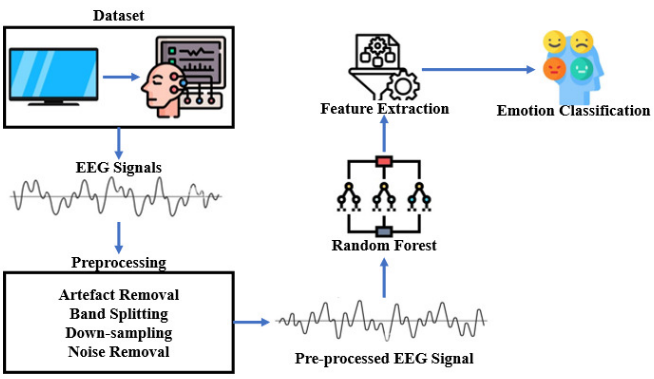

Fig. 1. PCA-RF architecture.

B. Dataset

This study used the DEAP dataset [11], which consists of EEG signal recordings of 32 subjects while watching 40 one-minute videos. The dataset files were originally in BioSemi .bdf format. During the collection of EEG signals, each subject rated each video based on dominance, valence, arousal, and other emotional factors. To capture their physiological responses, an electrode cap was used to record EEG signals from 40 electrodes placed in different regions, including frontal, frontopolar, temporal, central, parietal, occipital, and auricular areas. A total of 32 EEG-related signals were captured. In addition, eight other physiological signals were collected, including Galvanic Skin Response (GSR), Zygomaticus-Major-Electromyography (EMG), horizontal and vertical electrooculography (EOG), Trapezius EMG, temperature, plethysmograph, and respiration belt. These recordings provided a comprehensive dataset for analyzing emotional responses based on EEG physiological signals.

C. EEG Channels

The EEG channels used in the dataset were based on the 10-20 and 10-10 international EEG system [11]. Each electrode was strategically placed on specific regions of the scalp to measure the electrical activity of various brain sections and capture emotion efficiently. The frontal and frontopolar regions include Fp1 and Fp2, which are associated with decision-making and executive functions, while AF3 and AF4 are linked to attention and cognitive processes. The F3 and F4 electrodes correspond to the left and right frontal areas, which play a role in problem-solving, movement and emotion regulation, whereas F7 and F8 are involved in social and emotional processing. Fz, located in the midline frontal region, is crucial for executive control and attention. The fronto-central region consists of FC5 and FC6, which are responsible for motor control and movement preparation, while FC1 and FC2 contribute to motor and cognitive functions. The central region includes C3 and C4, which are located in the primary motor cortex and are essential for voluntary movement, along with Cz, positioned at the central midline, playing a key role in motor and somatosensory processing. The temporal region consists of T7 and T8, which are associated with auditory processing and memory. In the centro-parietal region, CP5 and CP6 contribute to sensory processing, while CP1 and CP2 are involved in sensorimotor functions. The parietal region includes P3 and P4, which play a role in spatial processing and sensory integration, and P7 and P8 are linked to visual attention and perception. Pz, located in the midline parietal region, is associated with consciousness and perception. The parieto-occipital region consists of PO3 and PO4, which are involved in visual processing. Finally, the occipital region, which is responsible for vision, includes O1 and O2, located in the left and right occipital areas, as well as Oz, which processes visual stimuli in the midline occipital region. These electrodes captured brain activity from different functional areas, making them essential for research in emotion analysis, cognitive studies, and neurological investigations. These signals are particularly crucial for identifying emotional responses based on EEG patterns.

D. Preprocessing

As the dataset consisted of 40 channels, only the relevant 32 EEG channels were retained, while the additional 8 physiological channels were removed, as presented in [12]. The main objective of the preprocessing stage was to eliminate artifacts and noise, thereby enhancing the quality of EEG signals across all channels. Since EEG signals often contain artifacts, their removal is essential. The primary sources of artifacts in EEG signals include muscle activity (large artifacts), eye movements, and cardiac artifacts [13]. Following an approach similar to [14], this study employed a specific frequency filtering technique to remove artifacts. Large artifacts, primarily caused by muscle activity, were removed by filtering channels within the 20-300 Hz range [15]. Eye movement artifacts were removed by filtering signals within the 3-15 Hz range [16], while cardiac artifacts were addressed by filtering signals within the 0.3-6 Hz range [17]. To further reduce the size of the EEG signals per channel, the sampling frequency was downsampled from 512 to 128 Hz. For channel frequency evaluation, EEG Power Spectral Density (PSD) was utilized, where each EEG signal was divided into specific frequency bands. Initially, a band-pass filter (0.4-45 Hz) was applied to isolate relevant frequencies. Subsequently, the Fast Fourier Transform (FFT) method was used to decompose EEG signals into five frequency bands, namely Gamma (30-45 Hz), Beta (12-30 Hz), Alpha (8-12 Hz), Theta (4-8 Hz), and Delta (0.4-4 Hz). After artifact removal and signal cleaning, residual noise might still be present, particularly due to eye movement (3-15 Hz) and cardiac (0.3-6 Hz) artifact removal. To address this, PCA was applied for noise removal and dimensionality reduction. As PCA can reduce dimensionality, significant noisy components were removed, resulting in a significantly cleaner EEG signal. The number of PCA components was fixed at 100 based on empirical evaluation, balancing noise reduction and information retention. This choice preserved over 95% of the variance in the data, leading to optimal classification accuracy without overfitting.

In PCA, the data from each frequency band is represented as a data matrix A, consisting of EEG signals across different frequency bands a_1, a_2, a_3,... a_n. The goal of PCA is to remove noise and reduce the matrix size A to B, such that $0 \leq B \leq n$. To achieve this, the PCA covariance matrix was computed, establishing relationships between frequency bands and their corresponding eigenvectors. This allowed PCA to identify directions with the highest variance, aiding in both noise and dimensionality reduction. The covariance matrix was evaluated as follows:

$$Cov(A) = \frac{1}{n} AA^T \quad (1)$$

where A^T represents the matrix after mean subtraction from each feature observation. Using $Cov(A)$, the eigenvectors and eigenvalues of the EEG signal were obtained as:

$$Cov(A) = \Lambda L \quad (2)$$

where Λ represents the eigenvalues of $Cov(A)$, defined as $\Lambda = \text{diag}[\lambda_1, \lambda_2, \dots \lambda_n]$, and L represents the eigenvectors derived from $Cov(A)$. For noise removal, eigenvectors corresponding to features with the highest eigenvalues were selected. Additionally, for dimensionality reduction, the eigenvalues Λ (arranged in descending order as $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n \geq 0$) were used to determine the optimal number of k eigenvectors. Using the selected eigenvectors, a noise-free and dimensionally reduced eigenmatrix B was constructed, ensuring a cleaner EEG signal for further analysis.

E. Feature Extraction and Classification

Using [18], this work presents an RF approach to extract features and classify the emotions. Consider the preprocessed EEG signal represented by the matrix B, which contains noise-free and dimensionally reduced EEG signals obtained through PCA. The goal of RF is to extract features and classify emotions into valence and arousal levels. Let $B \in \mathbb{R}^{m \times n}$ be the input EEG feature matrix, where m represents the number of EEG trials (samples) and n represents the number of extracted features from EEG signals (after PCA). Each row B_i ($i = 1,2, ..., m$) corresponds to an EEG trial with its respective feature set as:

$$B_i = [b_{i1}, b_{i2}, \ldots, b_{ij}] \quad (3)$$

where b_{ij} represents the EEG feature for the i^{th} trial and j^{th} feature. The target labels for classification are defined as Y_v and Y_a, denoting Valence and Arousal. The final target output is:

$$Y = \{Y_v, Y_a\} \quad (4)$$

where $Y \in \{0,1\}^{m \times 2}$ represents the class labels for each trial i in terms of valence and arousal. The RF approach consists of T Decision Trees (DTs), where each tree t is trained on a bootstrapped subset of the dataset. For each DT t, a random subset of features $B_t \subset B$ is defined, along with a splitting function at each node using Gini impurity. Each DT $h_t(B)$ predicts a class label $\hat{Y}_t$. The final predicted label $\hat{Y}$ is obtained through majority voting among all trees using:

$$\hat{Y} = mode\{h_1(B), h_2(B), \ldots, h_T(B)\} \quad (5)$$

where $\hat{Y} \in \{0,1\}^{m \times 2}$ represents the predicted class labels for valence and arousal. Each tree recursively splits nodes using Gini impurity:

$$Gini(D) = 1 - \sum_{c=1}^{c} p_c^2 \quad (6)$$

where p_c is the probability of class c in dataset D. Each tree $h_t(B)$ independently classifies the trial B_i, and the final classification is determined using majority voting:

$$\hat{Y}_i = \arg\max_c \sum_{t=1}^{T} 1(h_t(B_i) = c) \quad (7)$$

where $c \in \{0,1\}$ (low or high emotional states) and 1 is the indicator function. The final classification output is attained as:

$$\hat{Y} = [\hat{Y}_v, \hat{Y}_a] \quad (8)$$

where each row $\hat{Y}_i$ represents the predicted emotional state (low/high) for Valence and Arousal. This RF model efficiently classifies emotions based on EEG features while ensuring robustness.

The novelty of the PCA-RF combination lies in its strategic integration to enhance EEG-based emotion recognition. Unlike traditional methods that use PCA only for dimensionality reduction, this approach applies PCA for both noise removal and dimensionality reduction. Following band-specific artifact filtering, PCA eliminates residual noise, especially from eye and cardiac activity, ensuring cleaner signals for classification. This dual-purpose PCA enhances signal-to-noise ratio, allowing the RF classifier to operate on informative, noise-free data. The ensemble learning nature of RF effectively manages the high-dimensional and nonlinear structure of EEG signals. When combined, PCA and RF form a robust framework that improves the accuracy and generalizability of emotion classification compared to existing methods. PCA parameters were selected based on eigenvalue ranking to retain components with the highest variance, preserving meaningful features while eliminating noise. PCA was applied to frequency-band-decomposed EEG data using a covariance matrix to identify key dimensions that contribute to emotional variance. RF parameters were chosen for robustness: a high number of DTs prevents overfitting, feature subsampling encouraged diversity, and Gini impurity ensured efficient binary classification. Bootstrap training further strengthened the generalization of the model. In addition, the RF classifier is lightweight and faster compared to other existing DL approaches. In general, PCA enhanced signal quality and RF ensured robust classification, making this combination well-suited for complex, noisy EEG datasets.

III. RESULTS AND DISCUSSION

This section discusses the results achieved by the PCA-RF approach, focusing on the performance of the system and the improvements obtained through noise removal and dimensionality reduction. The PCA-RF approach was implemented in a Python environment, set up using the Anaconda distribution. The system utilized for the experiments was equipped with an Intel Core i7 processor and 16 GB of RAM, providing sufficient computational power to handle the data processing and ML tasks efficiently. The key objective was to assess the impact of PCA in removing noise from EEG signals and reducing their dimensionality, which ultimately improves the performance of the RF classifier.

To evaluate the efficacy of the PCA method, specific EEG channels were selected for analysis, with the results for noise removal and dimensionality reduction visualized in Figures 2 and 3. These figures illustrate the results for the Delta frequency band of channel T7 (Figure 2) and the Delta frequency band of channel Oz (Figure 3). In Figure 2, the PCA approach applied to the T7 Delta channel demonstrates a significant noise reduction in the cleaned signal. Similarly, Figure 3 presents the Oz Delta channel, where PCA successfully isolates the relevant signal components while filtering out unwanted noise. The resulting signal is much cleaner and more focused on the underlying neural activity, thus offering a better basis for further analysis. This reduction allows the RF classifier to work more effectively by processing a smaller set of features, leading to faster computation and improved classification accuracy.

The findings in Figures 2 and 3 clearly show that the PCA approach was successful in both noise removal and dimensionality reduction across different EEG channels and frequency bands. By removing noise from the EEG signals and reducing their dimensionality, the PCA method improved the quality of the features extracted by the RF classifier, directly contributing to a better classification performance, as presented in Figure 4.

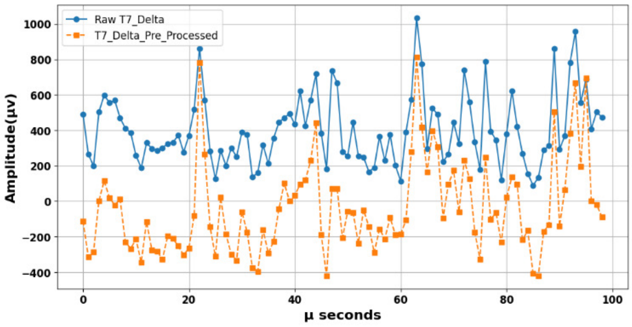

Fig. 2. T7 Delta frequency band preprocessed sample.

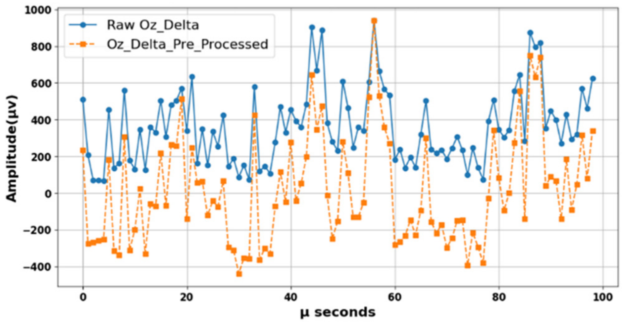

Fig. 3. Oz Delta frequency band preprocessed sample.

To ensure robustness, this work employed five-fold cross-validation, where the dataset was split into five subsets with iterative training and testing. This approach helped minimize overfitting and provided a reliable estimate of model performance across different data segments. The results achieved by the proposed PCA-RF approach after a five-fold cross-validation were compared with those of other state-of-the-art models in the field of EEG-based emotion classification, as presented in Figure 4. The MutaPT model [7] achieved 62.7% accuracy for both Arousal and Valence emotion classifications. While this is a decent performance, it reflects the challenges of accurately classifying emotions from EEG signals, particularly when dealing with noisy data and without effective preprocessing steps for noise removal. The FSNN model [8] demonstrated slightly better performance with 69.61% accuracy for Arousal and 69.84% for Valence. This model introduced a more advanced neural network structure, but still faced limitations in noise handling and dimensionality reduction, which could have contributed to its performance degradation. The GA+GNN approach [9] achieved 66.4% accuracy for Arousal and 64.84% for Valence. This model incorporated a GAN for data augmentation and a GNN for classification, but again, its performance is slightly lower compared to FSNN, likely due to the lack of an advanced preprocessing technique to effectively clean EEG signals before classification. The CNN+LSTM model [10] achieved remarkable results with 90.04% accuracy for Arousal and 89.97% for Valence. This model benefited from the combined strengths of CNN for spatial feature extraction and LSTM for temporal feature learning, but it is likely that it still struggled with residual noise.

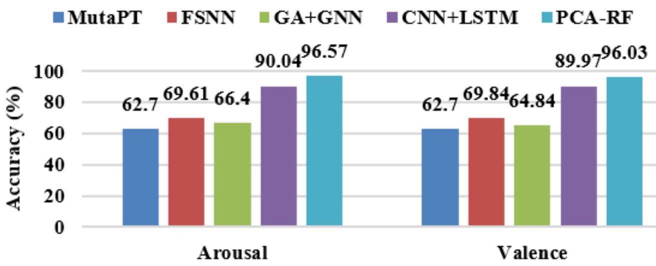

Fig. 4. Accuracy comparison of different approaches for Arousal and Valence.

The proposed PCA-RF model achieved significantly higher accuracy, with 96.57% for arousal and 96.03% for valence, standing out due to its systematic preprocessing method that effectively mitigates noise and reduces dimensionality, thus leading to cleaner EEG signals. The proposed PCA-RF approach not only outperforms other models but also highlights the importance of effective preprocessing techniques, such as PCA, in enhancing the performance of emotion classification systems. The higher accuracy achieved in both Arousal and Valence categories emphasizes the potential of this approach to provide more accurate and robust emotion recognition from EEG signals, especially compared to models that may have been limited by insufficient noise removal or dimensionality reduction strategies.

IV. CONCLUSION

This study presented a novel approach to EEG-based emotion classification using a combination of PCA and RF, called PCA-RF. Emotion recognition from EEG signals is a challenging task due to the presence of noise and artifacts, which can degrade classification performance. Existing methods have explored different techniques, but many still struggle with effective noise removal and dimensionality reduction, impacting their overall accuracy. The problem addressed in this work is the inability of conventional methods to handle noise and extract the most relevant features for emotion classification in a robust way. Existing approaches have made significant improvements in emotion recognition, but they still face limitations in accurately classifying emotions due to their handling of noisy data and dimensionality issues. The proposed PCA-RF approach sought to overcome these limitations by applying PCA to reduce dimensionality and eliminate noise, followed by RF for emotion classification. The method incorporates advanced preprocessing techniques, making it more efficient in dealing with noise and improving feature extraction for classification. The results achieved by PCA-RF were better compared to existing approaches, achieving 96.57% accuracy for Arousal and 96.03% for Valence, highlighting the effectiveness of the PCA-RF framework in emotion classification. Its ability to handle noise and reduce dimensionality ensures accurate and reliable classification, making it a promising tool for future emotion analysis applications. As future work, the proposed method can be extended to extract more features for detecting the consciousness level of DoC patients.

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