# Advances in EEG-Based Emotion Recognition: Methods and Challenges

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Abstract: EEG-Based emotion recognition is a key area in affective computing and brain-computer interfaces (BCI), offering real-time insights into human emotional states. Unlike facial expressions or speech, EEG provides direct neural activity data, making it a robust tool for emotion decoding. However, several challenges hinder its effectiveness, including low signal-to-noise ratio (SNR), individual variability, and dataset inconsistencies. These issues affect model generalizability and classification accuracy, limiting real-world applications. This review is about the preprocessed EEG, machine as well as deep models, as well as cross-dataset generalization challenges. Comparative evaluation with traditional models such as SVM as well as the PCA is given with the implementation of the deep models such as the CNNs, LSTMs, as well as the implementation of the Transformer. Cross-subject variance reduction as well as standardization of databases is necessary for the advancement of emotional decoding with the use of the EEG. Future research should be targeted toward light models of AI, as well as the implementation of multiple modes as well as the domain adaptation.

## 1 INTRODUCTION

Human emotion perception as well as interpretation is a significant area in BCI, as well as affective computing. Of the numerous forms of the kinds of body's physiological signals, electroencephalography is a highly promising method toward the recognition of emotions due to the close correspondence with the processes at the level of the neurons. Compared with expressions or voice, electroencephalography measures inherent emotional states with less likelihood of being masked, thus being a credible measure for use in affective computing. EEG signals have the preference due to their high temporal resolution as well as the presence of portable as well as low-cost devices. EEG has been forwarded as a more effective method toward the recognition of emotions compared with other forms of the body's physiological signals due to the close correspondence with the activities at the level of the neurons as well as the resistance toward being masked through voluntary expressions (Rahman et al., 2021). These attributes coupled with the portability of electroencephalography as well as the provision of real-time details have made it a preferable candidate for use in affective computing systems.

Despite its potential, EEG-based emotion recognition faces several challenges. Firstly, the EEG signal is characterized by a low signal-to-noise ratio (SNR), making it susceptible to various artifacts from muscle movements and environmental interference. Improper preprocessing can significantly impact classification accuracy in EEG-based emotion recognition (Liu et al., 2011). Secondly, individual differences remain a significant issue, as emotional responses differ across individuals due to personal experiences, cultural influences, and neurophysiological variations. The need to identify more fundamental and universal emotion patterns has been emphasized, requiring the use of convolutional layers or attention mechanisms, as well as a deeper understanding of human emotions (Abibullaev et al., 2023). Additionally, the limited availability of standardized EEG emotion datasets hinders the development and validation of generalized models. Existing datasets have inconsistencies in stimulus types and labeling methodologies (Wang & Wang, 2021). Finally, existing machine learning and deep learning models struggle with generalization across different datasets, limiting their real-world applicability. Challenges in cross-dataset adaptation and transfer learning in EEG-based emotion recognition have been extensively discussed (Jafari et



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al., 2023).

This review is purposed as a broad overview of the varied signal processing techniques utilized in emotional recognition using EEG, the signals processed in the frequency as well as the time domains. A brief introduction is given to the emotions theories before proceeding. It also compares the performance of machine learning (ML) as well as deep learning (DL) techniques with their limits. Further, the current EEG emotional databases as well as the cross-dataset learning challenges are explored. Finally, the current applications of emotional recognition using EEG in the fields of monitoring of mental health, adaptive learning systems as well as experience-based immersive situations using virtual experience is explored.

# 2 EMOTION THEORIES

Emotion is the essential ingredient of cognition as well as behavior in humans, influencing decision-making, perception, as well as social interaction. Emotion is characterized in the multiple theories of emotion in psychology as well as neuroscience.

One of the more popular models is the Discrete Emotion Model, which acknowledges the presence of the core emotions of happiness, sadness, anger, fear, surprise, and disgust. These have been characterized as being present in all societies and being accompanied by certain facial expressions as well as certain bodily reactions. This model, originally advanced in 1992 by Ekman, is also being explored with regard to cognitive as well as bodily significance (Lench et al., 2011). Nevertheless, despite the categorical framework of this model being quite unique, the model cannot adequately capture the diversity as well as the complexity of emotional experience.

An alternative is the Dimensional Emotion Model, the Valence-Arousal model specifically, originally proposed by Russell in 1980 and later extended (Harmon-Jones et al., 2017). It locates emotions in a dimensional plane: valence, from positive through to negative emotions, and arousal, the intensity of the emotional state. For example, joy is at the point of high valence and high arousal, but sadness is at low valence and low arousal. It is widely applied in the area of EEG-based emotional recognition because it is a flexible as well as scalable method of representing emotional states.

In addition to these models, the Component Process Theory emphasizes that emotions are not discrete categories but rather dynamic processes that are determined by cognitive appraisals, physiological reactions, and situational contexts (Scherer, 2001). This theory is well compatible with EEG-based emotion decoding since EEG records the real-time dynamics of brain activity related to emotional reactions.

In EEG-based emotional recognition, the V-A model is utilized in the tagging of emotional states in multiple databases like SEED, DREAMER, and DEAP, thereby cementing its use in computational models. EEG's ability to capture discrete patterns of the brain for different valences as well as arousal levels makes the method highly suited for the examination of affective states. Understanding these models is required for the creation of EEG-based emotional recognition models because these models control the process of feature extraction, classification method, as well as model evaluation procedures.

# 3 EEG SIGNAL CHARACTERISTICS & PREPROCESSING TECHNIQUES

## 3.1 EEG Signals and Emotional Correlation

Electroencephalography (EEG) is widely utilized for the identification of emotions due to the precision with which the activity of the brain can be measured. Brain oscillations as represented through the signals of EEG correspond with distinct frequency bands, each with specific cognitive as well as emotional processes. Frequency bands also serve as vital signals for the decoding of emotional states (Wang & Wang, 2021).

Delta (0.5–4 Hz) is largely associated with unconsciousness and deep sleep but is also linked with emotional regulation and stress. Similarly, Theta (4–8 Hz) is associated with emotional arousal and processing of the memory, with increased theta activity observed with the processing of emotional stimuli. Alpha (8–13 Hz), on the other hand, is linked with relaxation as well as inhibitory control, with alpha asymmetry in the front highly correlated with the state of emotions. Beta (13–30 Hz) is involved in cognitive processing as well as elevated emotional states with increased activity observed with tasks of emotional intensity. Subsequently, Gamma (>30 Hz) is involved with higher-level cognition, emotional perception, as well as integrative processing. Emotional processing is not uniform in the distribution across the brain but is localized in specific regions. For instance, the prefrontal cortex of the frontal lobe is responsible for the regulation of emotional responses as well as the process of decision-making (Val-Calvo et al., 2020). Meanwhile, the temporal lobe, the amygdala, as well as the hippocampus, is involved with emotional recognition as well as the process of encoding the memory. Subsequently, the parietal lobe processes sensory as well as emotional input, with the process being integral in emotional perception as well as regulation.

## 3.2 Signal Processing Techniques

EEG signals are very prone to noise from different sources such as muscle activity, eye movement, and environmental interference. Preprocessing is necessary to enhance signal quality and increase classification accuracy. Typical preprocessing methods are filtering, artifact removal, and signal transformation.

### 3.2.1 Filtering Techniques

Independent Component Analysis (ICA) separates EEG sources into statistically independent components, thereby aiding in the removal of artifacts (Dadebayev et al., 2022). Similarly, Principal Component Analysis (PCA) reduces dimensionality and retains the most informative EEG components, which is particularly useful for classification tasks (Wang & Wang, 2021). In addition, Wavelet Transform (WT) decomposes EEG signals into different frequency bands, effectively enhancing signal denoising and further improving signal processing (Dadebayev et al., 2022).

### 3.2.2 Time-Domain vs. Frequency-Domain Approaches

Time-domain features, such as entropy, variance, and statistical properties, are commonly used to describe EEG amplitude fluctuations related to emotions (Dadebayev et al., 2022). Furthermore, frequency-domain features, including Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT), decompose EEG signals into different frequency bands, providing deeper insights into affective states (Luo et al., 2020). However, a primary challenge in EEG emotion recognition is inter-subject variability, where differences between individuals lead to inconsistent EEG patterns. Cross-subject adaptation methods, such as domain adaptation and transfer learning, aim to mitigate these inconsistencies (Dadebayev et al., 2022).

### 3.2.3 Experiment: Comparison of EEG Preprocessing Methods

The objective of this study is to evaluate the effectiveness of Bandpass Filtering, Independent Component Analysis (ICA), Principal Component Analysis (PCA), and Wavelet Transform in improving EEG signal quality. To achieve this, the DEAP, SEED, and DREAMER datasets will be utilized. The methodology involves comparing signal-to-noise ratio (SNR) variations before and after preprocessing, using EEG visualization techniques to assess the effects of filtering, and training SVM and CNN classifiers to evaluate emotion classification accuracy. The results will include a comparison of SNR values (numerical data), a table summarizing classification accuracy, and figures illustrating EEG signals before and after preprocessing. The expected conclusion is that ICA will be highly effective for artifact removal, while Wavelet Transform will provide superior denoising capabilities.

Traditional feature extraction methods, such as FFT and PCA, remain widely used. However, deep learning-based methods, particularly CNNs and Transformers, are demonstrating promising results in automatically extracting relevant EEG features for emotion recognition.

# 4 MACHINE LEARNING VS. DEEP LEARNING FOR EEG EMOTION DECODING

## 4.1 Traditional Machine Learning Approaches

Traditional machine learning (ML) approaches have been widely used for the recognition of emotions from EEG since they possess the advantage of being low computational cost as well as being interpretable. Most traditional ML approaches leverage hand-engineered characteristics from the EEG signals such as PSD, Hjorth parameters, as well as other statistical metrics.

Support Vector Machines (SVMs), k-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), and Random Forest (RF) classifiers have been extensively applied in the field of EEG emotion decoding. SVMs have been seen as a strong classifier for the recognition of emotions from EEG, as also other models such as Decision Trees and Random Forests (Dadebayev et al., 2022). Decision-level fusion-based random forest classifiers, when applied, also support the enhancement of the recognition of emotions from EEG under noisy conditions (Wang et al., 2022). However, the greatest limitation of these models is their inability to capture the temporal dependencies in the EEG signals effectively.

Though limited, traditional ML models are still a suitable choice for applications where interpretability is essential. Feature selection is critical to enhance EEG-based emotion classification accuracy, especially to counteract limited feature availability and excessive signal noise (Luo et al., 2020). As EEG datasets increase in complexity and size, however, traditional ML methods are confronted with mounting difficulties in generalization and scalability.

## 4.2 Deep Learning Models

Deep learning (DL) revolutionized the use of EEG-based emotional recognition through the automatic acquisition of hierarchical representations from the EEG signals. Compared with traditional ML models that rely upon hand-coded features, DL models learn the spatial and temporal dependencies from the raw EEG signals.

### 4.2.1 CNN for Spatial Feature Extraction

Convolutional Neural Networks have been extensively utilized in the modeling of EEG signals as patterned spatial data, considering the placements of the electrodes as image-like topographic representations. CNNs have been utilized for the extraction of spatial features with notable accuracy improvements in the classification of emotions compared with the use of traditional ML methods (Jafari et al., 2023). The use of CNNs in the analysis of EEG signals has been widely explored, specifically their processing of the spatial features (Dadebayev et al., 2022).

### 4.2.2 RNN/LSTM for Sequential EEG Modeling

Though CNNs can effectively capture spatial characteristics, RNNs and LSTM networks are more suited for representing temporal dependencies in the case of EEG. LSTM networks have been effectively utilized in the pipelines of EEG emotion recognition, demonstrating their capabilities for representing long-range dependencies in the sequences of EEG as well as improving the accuracy of classification (Hassouneh et al., 2020).

### 4.2.3 Transformer-Based EEG Emotion Decoding

Recent advances in the area of deep learning have seen the use of Transformer-based models applied in the recognition of emotions from EEG. In contrast with RNNs, the use of self-attention mechanisms ensures long-term dependencies without vanishing gradients. Transformer models have been found to have enhanced classification accuracy (Abibullaev et al., 2023). Some of the benefits of self-attention have been found in the analysis of EEG, specifically the capture of long-term dependencies more effectively compared with RNNs and LSTMs (Dadebayev et al., 2022)).

### 4.2.4 Experiment: Traditional vs. Deep Learning Feature Extraction

The objective of this study is to compare the performance of hand-crafted features, such as Power Spectral Density (PSD) and Hjorth parameters, against deep learning-based features derived from models like CNN and Transformer in emotion classification. To achieve this, the DEAP and SEED datasets will be utilized. The traditional approach involves extracting features like PSD and Hjorth parameters, while the deep learning approach focuses on training CNN and LSTM models for automated feature extraction. For classification, both SVM and CNN will be trained and their performance evaluated. The results will include a comparison of classification accuracy between traditional and deep learning methods (presented in a table) and a visualization of CNN-extracted features using t-SNE. The expected conclusion is that CNN-extracted features will outperform hand-crafted features, with Transformers potentially further enhancing classification performance.

### 4.3 Hybrid & Advanced Deep Learning Models

To leverage the strengths of different architectures, hybrid models have been proposed to enhance EEG-based emotion recognition. One such approach involves CNN-LSTM fusion models, which combine the spatial feature extraction capabilities of CNNs with the sequential modeling capabilities of LSTMs. This hybrid architecture has been shown to significantly improve EEG emotion classification accuracy (Wang et al., 2022). Another emerging approach is the use of Spiking Neural Networks (SNNs), which mimic biological neural mechanisms for energy-efficient processing. SNNs have demonstrated superior performance compared to traditional FFT-DWT processing in EEG-based emotion recognition by preserving more neurophysiological information (Luo et al., 2020).

## 5 CHALLENGES AND FUTURE RESEARCH DIRECTIONS

### 5.1 Open Challenges

Despite significant research in the area of EEG-based emotional recognition, there have been numerous essential challenges. A significant problem is the low signal-to-noise ratio of the EEG signals, which makes the extraction of meaningful emotional characteristics problematic. Noise from eye movements, eye blinks, as well as other electronic interferences, also compromise the quality of the signals, with the resultant classification accuracy being low (Zeng et al., 2024).

Another persistent challenge is inter-subject variability, where differences in brain activity across individuals result in inconsistent model performance. Inter-subject variability poses a significant challenge in EEG-based emotion recognition, as individual differences in EEG signals affect model generalizability, making subject-independent models perform worse than subject-dependent models (Dadebayev et al., 2022).

Existing EEG emotional databases, SEED and DEAP, have discrepancies in the method of recording signals, recording conditions, as well as the population under investigation, introducing variance in research results as well as cross-dataset generalization difficulties (Yang et al., 2024). A unified experiment set with standardized protocols is necessary for improved model comparability. Constraints of processing in real-time also hinder the use of emotion decoding models in actual systems. Most of the present recognition models have been created for offline processing due to the computational overhead of feature extraction and classification, which makes their implementation in real-time impossible (Liu et al., 2011).

### 5.2 Promising Future Directions

To address these challenges, several promising research directions have emerged. Hybrid deep learning models, such as CNN-LSTM and Spiking Neural Networks (SNNs), offer potential solutions by combining spatial and temporal feature extraction, improving generalization and efficiency (Luo et al., 2020).

Another promising method is multimodal fusion, wherein the EEG signals can be coupled with other body signals such as the galvanic skin response (GSR) and facial expressions. Research has proved the use of multiple modalities can be more robust with enhanced classification accuracy in the recognition of emotions (Yang et al., 2024).

The development of light AI models for implementation in real-time BCI is also receiving attention. Low power-efficient models are being proposed and being low power-optimized for low power devices, enabling the implementation of real-time EEG emotional recognition in wearable devices. To mitigate dataset bias and improve model generalization, researchers are exploring techniques for better cross-dataset learning. Strategies such as optimizing multimodal datasets and improving emotion classification models contribute to more robust and generalizable approaches in EEG-based emotion recognition (Yang et al., 2024). Future EEG emotion decoding research must focus on mitigating cross-subject variability and dataset biases. Multimodal fusion and domain adaptation hold promise for improving accuracy, while lightweight AI models will be essential for real-time BCI applications.

## 6 CONCLUSION

EEG-based emotion recognition has become an essential part of affective computing and brain-computer interfaces. In the last decade, there has been considerable advancement in feature extraction, machine learning models, and deep learning methods to allow more precise emotion classification from EEG signals.

Traditional machine learning models like SVM and Random Forest have been the basis for classification using EEG but have been limited in their capabilities in extracting intricate temporal patterns, which have given birth to the use of deep models. LSTMs, Transformer models, as well as CNNs, have been found to perform much better in extracting significant features as well as classification accuracy. But these models use large databases as well as require large computational power, which makes them non-practicable in the context of real-time.

Despite advancements, there continue to be significant challenges with the use of EEG-based emotional decoding due to the low signal-to-noise ratio, the large inter-subject variance, as well as the non-availability of a standard EEG dataset. Cross-dataset adaptation techniques, multimodal fusion, as well as the implementation of hybrid deep networks, can be utilized in countering these challenges.

Future research would be directed toward real-time BCI implementation, wherein the light models of AI, being highly efficient, can be utilized with portable and wearable EEG devices. Also, incorporating multimodal paradigms through the combination of EEG with facial expressions, voice, and body signals like GSR can be used to boost the accuracy of recognizing emotions. Domain adaptation and transfer learning will play a crucial role in creating models that generalize well across different EEG datasets and recording conditions.

In summary, though EEG-based emotion recognition is progressing, making it practical to deploy in real-world scenarios is still a persisting challenge. Standardized datasets, refined deep learning models, and real-time inference optimizations are the key to moving the field forward and enabling EEG-based emotion decoding as a practical approach for affective computing and BCI applications.

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