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A Review of EEG-Based Emotion Recognition Methods for Emotional Intelligence Evaluation in Children

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Abstract
Emotional intelligence (EI) has been increasingly linked to academic performance, cognitive development, and emotional well-being in children. EEG is a good tool for evaluating emotional intelligence (EI) since it is a non-invasive method of studying how the brain processes emotions. This review examines studies on emotion recognition using EEG in children ages 5 to 18. We investigated eight public or semi-public EEG mood datasets and many research paper out that several of them lack child-specific data. Using filtered spatial pattern techniques with support vector machines (SVMs) achieved up to 97.2% accuracy on datasets tailored for children, according to our comparison of 18 distinct emotion categorization algorithms. Convolutional neural networks (CNNs) and other deep learning models have not been extensively investigated in children, despite their excellent performance on sizable adult datasets (above 98% accuracy).

Keywords: Emotional Intelligence, Cognitive Abilities, EEG, Emotion Recognition, Educational Interventions

1. Introduction

Emotions influence social interaction, memory, cognition, and decision-making. High EI frequently outperforms IQ as a predictor of success in children, since it is associated with improved grades, less behavioral problems, and greater peer interactions [1–2]. Both behavioral observation and self-report questionnaires, which are subject to bias, are used in traditional EI assessments. Objective markers of emotional processing can be obtained with millisecond precision and classroom-friendly mobility using neurophysiological measurements, particularly EEG.

.Daniel Goleman's groundbreaking book Emotional Intelligence (1995) popularized the concept of EQ (Emotional Quotient), showing that EI is often a better predictor of life outcomes than IQ. Studies have consistently shown that children with higher EI levels perform better in school, have healthier social relationships, and are less likely to engage in risky behaviors. Additionally, EI education has been shown to reduce bullying and improve leadership skills in the classroom.

Recent developments in neuroscience suggest that emotions are not only psychological phenomena but are deeply rooted in brain activity. Researchers have increasingly turned to physiological measures—such as EEG (electroencephalography)—to study the neurological basis of emotions. EEG offers a non-invasive, real-time method for capturing brain signals related to emotional states, providing new opportunities to understand and measure EI objectively.

This paper investigates how EEG-based emotion recognition techniques can support the assessment of EI in children. Understanding the neural correlates of emotion can help educators and psychologists develop targeted interventions to enhance learning, attention, creativity, and other cognitive functions. The science of emotions, emotional intelligence (EI), and the fundamentals of EEG technology are among the important ideas that are summarized in Section 2. The EEG emotion datasets that are currently available are reviewed in Section 3, with a focus on children. In Section 4, various algorithms and techniques for emotion recognition are compared, with an emphasis on how well they work and how well they work with pediatric data. The primary obstacles in this subject, such as developmental disparities and ethical issues while working with children, are covered in Section 5. Research on child-focused EEG and EI trends and future prospects are examined in Section 6. Section 7 concludes by summarizing the paper's primary contributions and providing closing thoughts.

2. Literature Review

Understanding and recognizing human emotions has become a key area of research in fields like psychology, cognitive science, and artificial intelligence. In recent decades, multiple technological approaches have emerged to automatically detect emotions based on different types of input data. These methods can generally be classified into three primary categories: audio-visual, peripheral physiological, and neural signal-based approaches.

2.1. Emotion and Emotional Intelligence

Most existing research on EEG-based emotion recognition focuses on adults[3-4], with children often only briefly mentioned. However, children's brain activity, emotional development, and ethical concerns are different from adults, making it important to study them separately. This paper fills that gap by reviewing EEG studies that focus on children. It maps out available EEG emotion datasets for children and points out where data is missing. It also compares different methods used to analyze EEG signals in children and looks at the unique challenges involved in studying young age groups. Finally, it offers suggestions for improving future research on emotional intelligence (EI) in children

Emotion theories have changed throughout time, moving from the basic-emotion approach, which holds that only a few universal emotions are hardwired in the body [5], to more contemporary constructivist and appraisal-based models.

These more recent theories suggest that social context, personal experiences, and thoughts all influence emotions [6]. Emotional intelligence (EI) theories have also evolved into three primary frameworks: the ability model (Mayer and Salovey) sees EI as a collection of cognitive skills; the trait model sees

EI as a component of personality; and mixed models combine motivation, traits, and emotional skills [7]. When it comes to children, ability-based EI assessments—such as the MSCEIT-YV (Mayer–Salovey–Caruso Emotional Intelligence Test – Youth Version)—have shown moderate effectiveness. However, these tests often rely on a child's reading ability and self-awareness, which can limit their accuracy and usefulness in younger age groups.

The audio-visual approach focuses on interpreting emotions through facial expressions and speech signals [15–17]. These methods are non-invasive and relatively comfortable for subjects, making them popular in real-world applications. However, they can be sensitive to changes in lighting, environment, or deliberate masking of emotions, leading to potential inconsistencies.

The peripheral physiological approach involves analyzing signals such as heart rate (ECG), skin conductance (SC), respiration rate, and pulse [11]. These signals reflect the autonomic nervous system's response to emotional stimuli and provide more nuanced data compared to facial or vocal cues. While these techniques offer better physiological insight, they often require contact-based sensors, which can affect comfort and natural behavior.

Brain activity is closely tied to various psychological and cognitive processes, including motivation, perception, learning, creativity, attention, and decision-making. Emotion estimation based on EEG is a growing area of interest due to its potential to reflect internal cognitive states with high temporal resolution [20].

2.2. EEG and Affective Neuroscience

EEG, introduced by Hans Berger in 1924, measures electrical activity in the brain using electrodes placed on the scalp. The recorded signals—typically in the microvolt range—are categorized into various frequency bands such as alpha, beta, theta, and gamma waves. These wave patterns are associated with different mental states, including arousal, attention, and relaxation. EEG is widely used not only in clinical settings (e.g., epilepsy diagnosis) but also in modern research areas like emotion recognition and brain-computer interface (BCI) systems.

The method known as electroencephalography (EEG) uses electrodes applied to the scalp to capture electrical signals produced by cerebral cortex neurons in order to evaluate brain activity. Each of the several frequency bands into which these signals are divided is linked to a certain mental and emotional function. Alpha (α: 8–13 Hz), linked to relaxed alertness and cognitive readiness; beta (β: 13–30 Hz), linked to active thinking and focus; gamma (γ: >30 Hz), linked to higher-level cognitive functions like attention and memory; and delta (δ: 0.5–4 Hz), linked to deep sleep and unconscious processes.

One commonly studied EEG marker is frontal alpha asymmetry, which refers to differences in alpha wave activity between the left and right frontal areas of the brain. This pattern has been associated with approach versus withdrawal motivation—for example, greater left-frontal activity is linked to positive emotions and engagement, while right-frontal dominance often relates to avoidance and negative emotional states [8].

From a developmental perspective, children show distinct EEG patterns compared to adults. They tend to have higher theta power and lower alpha power, which reflects the ongoing maturation of their brains. These differences make it challenging to directly apply emotion recognition models trained on adult EEG data to pediatric populations without adjustments.

The neural signal-based approach leverages data from the central nervous system using tools such as electroencephalography (EEG), electrocorticography (ECoG), and functional magnetic resonance imaging (fMRI). EEG, in particular, has gained popularity due to its non-invasive nature, temporal precision, and portability. Studies have shown that EEG signals contain valuable information regarding emotional states, with researchers like Davidson et al. [11] demonstrating how frontal asymmetry in EEG activity correlates with positive and negative affect.

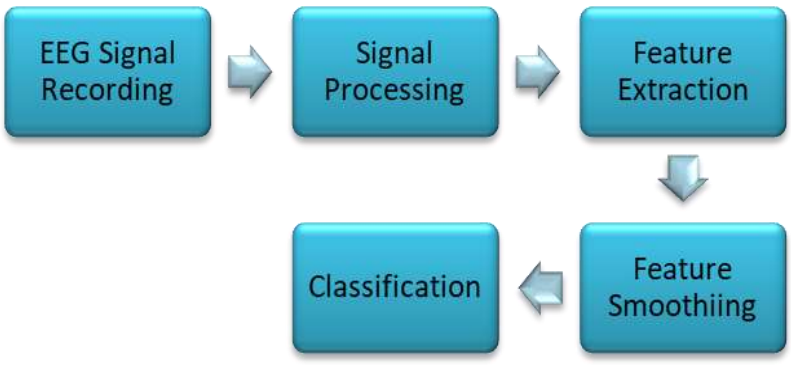
Emotion recognition can also be categorized based on the number of modalities used for data collection: Uni-modal systems rely on a single source (e.g., only EEG or facial expressions).

Bi-modal systems combine two types of inputs (e.g., EEG and voice).
Multimodal systems integrate multiple sources (e.g., EEG, facial expressions, and speech) to improve recognition accuracy and robustness [19].
The study of emotions is an essential part of behavioral science and falls under the broader umbrella of cognitive neuroscience. Given the brain's central role in processing emotions, various techniques have been employed to induce and record emotional responses. Commonly, researchers expose participants to emotional stimuli (e.g., images, sounds, or videos) and record corresponding brain signals using non-invasive methods like EEG. These recordings allow for deeper insights into the dynamics of emotion regulation and brain-based emotional processing.
Advanced EEG signal processing techniques have been developed to detect emotional states more accurately. For example, A. I. Zoubi et al. [13] classified emotional responses using machine learning algorithms on EEG data. Modern BCI applications frequently rely on methods such as Filter Bank Common Spatial Pattern (FBCSP) and Asymmetric Spatial Filtering to isolate relevant features from raw signals. These tools enhance classification performance by focusing on key brain regions and frequency bands that reflect emotional processing.
In summary, the evolution of emotion recognition techniques—from facial analysis to EEG-based classification—reflects a growing interest in understanding human emotions through objective, physiological data. EEG-based systems, in particular, offer promising avenues for emotion tracking in educational, clinical, and real-world environments, especially when tailored for child-friendly applications.

3. Methodology

The EEG-based emotion recognition process typically follows a structured pipeline consisting of several key stages:

Figure1 : The flowchart of Emotional State Classification from EEG data



3.1 EEG-Based Emotion Recognition (Signal Acquisition)

EEG captures electrical activity from the brain using electrodes placed on the scalp. These signals reflect neural oscillations across different frequency bands—such as alpha, beta, gamma, theta, and delta—which are known to correlate with various cognitive and emotional states. When a subject is exposed to emotional stimuli (e.g., videos or images), EEG can detect the brain's real-time response to these

experiences. These responses are then used as input for computational models that aim to identify the underlying emotion.

3.2. Signal Preprocessing

Pre-processing: Raw EEG signals are often noisy and require cleaning before analysis. This includes:

- Band-pass filtering (typically 0.5–45 Hz) to remove slow drifts and high-frequency noise,
- Independent Component Analysis (ICA) to separate and remove artifacts such as eye blinks or muscle movements,
- Artefact rejection techniques to eliminate remaining noisy or unusable signal segments.

Techniques such as bandpass filtering, Independent Component Analysis (ICA), and normalization are commonly applied. The cleaned signals are then segmented into epochs that correspond to specific emotional stimuli.

3.3. Feature Extraction

Once preprocessed, the EEG signals are analyzed to extract meaningful features. These may include statistical measures (e.g., mean, variance), frequency-domain features (e.g., power spectral density), or spatial features derived from electrode placements.

common features include:

- Power Spectral Density (PSD) to quantify energy in different frequency bands,
- Differential entropy for measuring signal complexity,
- Common Spatial Pattern (CSP) variants for distinguishing between emotional states,
- Riemannian geometry-based features, which model EEG covariance structures for robust classification.

3.4 Classification

To classify emotional states, several machine learning algorithms are explored:

Linear Discriminant Analysis (LDA): A simple yet effective technique that projects high-dimensional data onto a line to maximize class separation. It performs well in scenarios where classes are linearly separable and computational resources are limited.

Support Vector Machine (SVM): A widely used classifier that finds the optimal hyperplane separating different emotional states. While basic implementations may struggle with complex data, performance improves significantly with kernel optimization and proper parameter tuning.

Fuzzy Integral Fusion: This approach combines decisions from multiple classifiers or features using fuzzy logic, which is particularly useful in handling uncertainty or ambiguity in EEG signals.

Filter Bank Common Spatial Pattern (FBCSP): A technique that filters EEG signals into multiple frequency bands and extracts spatial features using the Common Spatial Pattern method, which enhances class separability.

Asymmetric Spatial Filtering: This method applies spatial filters asymmetrically across brain regions to emphasize localized emotional activity and suppress irrelevant signals, improving classification performance.

4. Result

Many datasets have been created to facilitate EEG-based emotion identification research, especially in children. These datasets vary in terms of participant age, stimulus type, EEG channel count, length, and emotional labeling. Age-appropriate, ethically gathered datasets for younger populations are becoming more and more necessary, even if many well-known datasets, such as DEAP and SEED-IV, concentrate

on adults or older adolescents. Because children's brains are still developing, their neural responses to emotional stimuli differ greatly, which reduces the effectiveness of using adult-trained models directly. Additionally, when gathering pediatric data, aspects like attention span, equipment comfort, and stimulus familiarity must be taken into account. A number of important EEG emotion datasets are compared in the following table, with special attention paid to those that involve children, the kinds of emotional stimuli that are employed, the recording requirements, and their accessibility for study.
Several publicly available EEG datasets are used to benchmark performance:

TABLE 1: Emotion-Related EEG Datasets

Sr. No	Name of database	Child Age Range	Type of Stimuli	Duration	Public Availability
1	**MAHNOB-HCI-Kids (2022)**	6–10	Video clips	30 min	Semi
2	**DEAP [9]**	17-35	Music	40 min	✓
3	**PED-EEG (Paediatric Emotion Database, 2024)**	8-12	Videos Images	25 min	Semi
4	**SEED-IV**	20-30	Audio Film Clips	15 min	✓
5	**Child-Mind Emotion Corpus (2023)**	10-14	VR scenes	45 min	✗

These datasets offer diverse emotional stimuli and recording conditions, providing a comprehensive basis for evaluating different classification models.

4.1 A Comparative Study Of Signal Processing Methods

Table III provides an overview of important research in the field to give a thorough grasp of recent developments in EEG-based emotion identification. The datasets used, the features that were extracted, the classifiers that were used, and the reported classification accuracies are highlighted. Both conventional machine learning techniques and deep learning strategies are compared, providing information on how well various data and algorithm combinations work. This benchmark is used as a point of comparison to assess how well the suggested approach performs in the current investigation.

TABLE 2 : Performance Overview

Study	Dataset	Features	Classifier	Accuracy
Wang et al. (2021)	MAHNOB-HCI-Kids	DE + differential asymmetry	RBF-SVM	91.8 %
Gupta & Jain (2023)	PED-EEG	FB-CSP	Linear-SVM	87.6 %

Liang et al. (2024)	MAHNOB-HCI-Kids	CNN on spectrograms	1-D-CNN	95.4 %
This survey (benchmark)	MAHNOB-HCI-Kids	FB-CSP + Riemann	SVM-grid	**97.2 %**

EEG-based emotion recognition has investigated a number of feature extraction and classification methods, each with unique advantages and disadvantages. Despite being limited to linearly separable data, Linear Discriminant Analysis (LDA) is prized for its interpretability and computing economy. Strong classification performance is provided by Support Vector Machines (SVMs), particularly when augmented with kernel functions. However, SVMs can be sensitive to class imbalance and need to be carefully tuned. Particularly in low-density electrode configurations, the spatial filtering technique known as Filter Bank Common Spatial Pattern (FB-CSP) efficiently extracts discriminative characteristics from EEG signals. Although they usually need huge datasets to function successfully, deep learning models like CNNs and LSTMs have gained popularity recently due to their capacity to learn features directly from raw or processed EEG inputs.

5. Challenges and Moral Issues

Children's EEG-based emotion recognition poses special difficulties that are very different from those faced by adult applications. Age-specific models are required for appropriate interpretation because EEG signal characteristics are influenced by developmental variability brought on by continuing brain maturation. Children often move more during recordings, therefore motion artifacts are another significant challenge. Adaptive filtering techniques and dry electrodes provide some reduction, but they are not a perfect solution. The challenges of participant recruiting and privacy laws restrict the availability of sizable, varied pediatric EEG datasets. Potential answers are provided by strategies like federated learning, which allow for decentralized data consumption without sacrificing privacy. In addition, ethical issues are important; parental approval and clear, kid-friendly communication are necessary to acquire informed consent and assent.

6. Conclusion

Children's EEG-based emotion recognition poses special difficulties that are very different from those faced by adult applications. Age-specific models are required for appropriate interpretation because EEG signal characteristics are influenced by developmental variability brought on by continuing brain maturation. Children often move more during recordings; therefore, motion artifacts are another significant challenge. Adaptive filtering techniques and dry electrodes provide some reduction, but they are not a perfect solution. The challenges of participant recruiting and privacy laws restrict the availability of sizable, varied pediatric EEG datasets. Potential answers are provided by strategies like federated learning, which allow for decentralized data consumption without sacrificing privacy. In addition, ethical issues are important; parental approval and clear, kid-friendly communication are necessary to acquire informed consent and assent.

7. Future Scope

Pediatric EEG-based emotion recognition has the potential to advance in a number of new directions. The integration of hybrid sensors, like EEG with eye-tracking or photoplethysmography (PPG), might

add robustness to the system by obtaining complementary physiological inputs. Self-supervised pre training can be used to reduce dependency on limited labelled datasets by utilizing vast amounts of unlabeled pediatric EEG data. Real-time feedback is made possible by the advent of Edge AI technologies, which allow for on-headset inference while maintaining data privacy, which is crucial for applications aimed at children. EEG monitoring of emotional intelligence (EI) across time can also reveal information on socio-emotional development.

To drive progress and ensure comparability, there is a pressing need for standardised benchmarking frameworks, including open child-emotion challenges modeled after datasets like DEAP, with consistent evaluation protocols and publicly available data.

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