A Multimodal Perspective on Physiological Emotion Recognition: EEG Datasets, Techniques, and Future Directions

Integrating Neural and Physiological Insights for Enhanced Emotion Detection

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***Abstract*—Emotion recognition using physiological signals, particularly EEG, offers a direct and objective approach to understanding emotional states, surpassing traditional methods reliant on observable cues. This survey reviews key EEG-based datasets, such as DEAP and SEED, alongside advanced models like CNNs, RNNs, and emerging foundational models. We address challenges, including data variability and noise, while exploring trends such as multimodal approaches, self-supervised learning, and wearable devices. In addition, we present our experimental work in EEG-based emotion recognition, where we propose and test hybrid models combining Graph Neural Networks (GNNs) and Transformers, as well as other machine learning approaches like GRU. We analyze the performance of these models across both binary and multi-class classification tasks with segmentation and SMOTE techniques. Our findings contribute to improving the accuracy and generalizability of emotion detection using EEG data. By summarizing current achievements and future opportunities, this survey provides a roadmap for advancing EEG-based emotion recognition research.**

***Index Terms*—EEG, emotion recognition, datasets, deep learning, multimodal systems, GNNs, foundational models.**

Recognition and interpretation of human emotions are fundamental to improving human-computer interaction, understanding human behavior, and advancing mental health diagnostics [1], [2]. Emotions are inherently complex and multifaceted, characterized by both subjective experiences and physiological manifestations [3]. Although conventional emotion recognition methods, such as facial expression analysis and speech-based techniques, have achieved notable success, they are often limited by their inability to capture the underlying neurophysiological processes that drive emotional states [4], [5].

Electroencephalography (EEG), a noninvasive technique for recording brain activity, has emerged as a promising modality for emotion recognition due to its ability to provide direct insight into neural dynamics [6]. Unlike external behavioral cues, EEG captures the intrinsic electrical activity of the brain, offering a more objective and fine-grained approach to understanding emotions [7]. The high temporal resolution of EEG and its ability to reflect the interplay of different regions of the brain make it particularly suitable for real-time and nuanced emotion detection [8], [9].

The increasing availability of EEG datasets and the advancement of machine learning techniques, particularly deep learning and graph neural networks (GNNs), have catalyzed significant progress in this domain [10], [11]. Emerging foundational models, such as Neuro-GPT, further underscore the transformative potential of leveraging large-scale pre-trained architectures for EEG-based emotion detection [12]. Despite these advancements, the field faces challenges, including noise in EEG data, inter-subject variability, and limited annotated datasets, which hinder the development of generalized and explainable models [13], [14].

This survey aims to provide a comprehensive review of the current state of EEG-based emotion recognition. Specifically, it will:

- Explore publicly available datasets that serve as the foundation for emotion recognition research, focusing on their design, data modalities, and applications.
- Analyze the key computational models and techniques used for processing and interpreting EEG data for emotion detection.
- Examine the primary challenges and limitations in this field, highlighting the gaps in current methodologies and datasets.
- Discuss emerging trends, including multimodal data fusion, transfer learning, and the integration of self-supervised learning approaches.

By systematically evaluating data sets, models, and trends in EEG-based emotion recognition, this survey aims to provide a comprehensive understanding of the state of the art, identify pressing challenges, and propose avenues for future research.

I. Datasets for Emotion Recognition

Emotion recognition research is based heavily on high-quality datasets that provide reliable and diverse physiological signals. Among these, EEG-based datasets have gained prominence due to their ability to capture neural correlates of emotional states. This section reviews widely used datasets that have shaped research in EEG-based emotion detection.

A. Key EEG-Based Emotion Datasets

1) DEAP (Dataset for Emotion Analysis using Physiological Signals)

Overview: *DEAP is one of the most widely used datasets for emotion recognition. It includes recordings of EEG and peripheral physiological signals such as electrocardiography (ECG) and galvanic skin response (GSR) from 32 participants [2].*
Stimuli: *Participants watched 40 one-minute music videos, designed to elicit a range of emotional responses [2].*
Annotations: *Emotions are rated along dimensions of valence, arousal, dominance, and liking on a nine-point scale [2].*
Applications: *Suitable for exploring the relationships between physiological signals and emotional states, particularly in real-time systems [2].*

2) SEED (SJTU Emotion EEG Dataset)

Overview: *SEED contains EEG recordings from 15 participants exposed to film clips that evoke positive, neutral, and negative emotions [3].*
Stimuli: *Film clips carefully selected to induce strong emotional reactions [3].*
Annotations: *Each session is labeled with the corresponding emotional category (positive, neutral, negative) [3].*
Applications: *Commonly used for classification tasks and deep learning-based emotion recognition models [3].*

3) DREAMER

Overview: *DREAMER includes EEG and ECG signals collected from 23 participants. The dataset emphasizes portability, as data were recorded using a wearable device [7].*
Stimuli: *Audio-visual clips were used to elicit emotional responses [7].*
Annotations: *Emotions are rated along dimensions of valence, arousal, and dominance [7].*
Applications: *Designed for low-cost emotion detection systems and wearable applications [7].*

4) AMIGOS (A Dataset for Multimodal Research of Affect, Personality, and Mood)

Overview: *AMIGOS includes EEG and peripheral signals from participants watching emotional video stimuli, with a focus on individual and group experiments [23].*
Stimuli: *Designed to investigate the effect of personality and mood on emotional responses [23].*
Annotations: *Multi-dimensional ratings of emotions, including valence and arousal [23].*
Applications: *Suitable for studying group dynamics and individual affective states [23].*

5) SEED-IV (Expanded SEED Dataset)

Overview: An extension of the SEED dataset, SEED-IV includes four emotional categories: happy, sad, neutral, and fear [24].
Stimuli: Emotionally charged film clips [24].
Annotations: Labels corresponding to the four emotional categories [24].
Applications: Frequently used in fine-grained emotion classification tasks [24].

B. Comparison of Datasets

TABLE I
COMPARISON OF EEG-BASED EMOTION RECOGNITION DATASETS

Dataset	Participants	Signals	Stimuli	Emotion Dimensions	Applications
DEAP	32	EEG, ECG, GSR	Music videos	Valence, Arousal, Dominance	Real-time systems, affective computing
SEED	15	EEG	Film clips	Positive, Neutral, Negative	Classification tasks, deep learning
DREAMER	23	EEG, ECG	Audio-visual clips	Valence, Arousal, Dominance	Wearable and portable applications
AMIGOS	Varies	EEG, peripheral	Emotional video stimuli	Valence, Arousal	Group dynamics, mood-related research
SEED-IV	15	EEG	Film clips	Happy, Sad, Neutral, Fear	Fine-grained emotion classification

II. MODELS AND TECHNIQUES FOR EMOTION RECOGNITION

The field of emotion recognition has witnessed remarkable advancements through the integration of machine learning and EEG data. Traditional machine learning models, such as Support Vector Machines (SVMs) and K-Nearest Neighbors (KNNs), established the initial frameworks for classifying emotional states from EEG signals. However, with the advent of deep learning and graph-based approaches, the field has experienced significant improvements in accuracy, scalability, and the ability to capture spatiotemporal dynamics. This section provides a detailed overview of prominent models and techniques used for EEG-based emotion recognition.

A. Deep Learning Techniques

Deep learning has revolutionized EEG-based emotion recognition by enabling the automatic extraction of complex patterns from raw EEG data, eliminating the need for extensive manual feature engineering. The most widely adopted deep learning architectures include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid models.

1) Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are particularly effective in capturing spatial relationships between EEG electrodes by treating the input as structured, image-like data. Zheng and Lu [3] demonstrated the application of CNNs in identifying critical frequency bands associated with emotion recognition, revealing their ability to extract robust spatial features. Their work highlighted the hierarchical nature of CNNs, which makes them resistant to noise and variability inherent in EEG signals. However, the reliance of CNNs on large, labeled datasets remains a significant limitation, as such datasets are often scarce in EEG research. In this survey, CNNs have been particularly valuable in real-time emotion detection tasks, showcasing their strength in efficiently processing high-dimensional EEG data to distinguish between emotional states.

2) Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) excel in modeling temporal dependencies, making them highly suitable for analyzing the sequential dynamics of EEG signals. LSTM networks, a variant of RNNs, were shown by Zheng and Lu [3] to significantly enhance the classification of emotions by capturing the temporal evolution of neural activity. Their ability to retain long-term dependencies enables a deeper understanding of how emotional states change over time. Despite these advantages, RNNs face challenges such as computational inefficiency and susceptibility to overfitting, particularly when trained on smaller EEG datasets. In this survey, RNNs have been employed in applications requiring continuous emotion prediction, illustrating their relevance in scenarios where tracking dynamic changes is critical.

3) Hybrid Architectures (CNN-RNN)

Hybrid architectures combining CNNs and RNNs have emerged as powerful tools for addressing the limitations of individual models. By leveraging the spatial feature extraction capabilities of CNNs and the temporal modeling strengths of RNNs, these architectures can capture both spatial and temporal patterns in EEG data. In this survey, hybrid CNN-RNN models have shown superior performance in multimodal emotion recognition, particularly when EEG data is integrated with other physiological signals. For example, Badajena et al. [9] highlighted the ability of such architectures to improve classification accuracy by effectively fusing information from EEG with complementary modalities. These hybrid systems are crucial for advancing applications that require both spatial and temporal precision.

B. Graph Neural Networks (GNNs)

Graph Neural Networks (GNNs) offer a novel approach to EEG-based emotion recognition by explicitly modeling the spatial and functional connectivity between electrodes as a graph Zhong and B.-L. Lu [4] introduced a regularized GNN framework that demonstrated superior performance over traditional models by leveraging inter-channel relationships in EEG data. This approach allows for the incorporation of non-linear dependencies, making GNNs particularly suitable for analyzing the intricate network of brain regions involved in emotional processing. However, constructing an optimal graph remains a challenge, and the computational complexity of GNNs can hinder their deployment in real-time applications. In this survey, GNNs have been effectively applied to EEG channel analysis and personalized emotion detection, underscoring their potential to provide insights into both individual and group-level emotional dynamics.

C. Foundational Models

Foundational models represent a transformative advancement in EEG-based emotion recognition, leveraging pre-training on large-scale datasets to adapt to domain-specific tasks. Neuro-GPT, introduced by Cui et al. [5], exemplifies the application of transformer-based architectures in this field. By pre-training on extensive EEG datasets, this model has demonstrated the ability to generalize across various emotion recognition tasks. Foundational models excel in scalability and adaptability, offering significant advantages for applications with limited labeled data. However, the computational resources required for pre-training and fine-tuning remain a barrier. In this survey, foundational models have been utilized for multitask emotion recognition, enabling cross-dataset generalization and fine-grained classification.

D. Traditional Machine Learning Models

While deep learning dominates the field, traditional machine learning models remain relevant, particularly for small datasets or less complex tasks. These models rely on feature extraction techniques, such as power spectral density or wavelet decomposition, to derive meaningful features from EEG signals.

1) Support Vector Machines (SVMs):

SVMs are widely used for binary and multi-class classification tasks in emotion recognition. They are particularly effective when paired with well-engineered features extracted from EEG data. SVMs are simple to implement, computationally efficient, and perform well on small datasets [11].

2) K-Nearest Neighbors (KNNs):

KNNs are highly interpretable and often serve as baseline models in EEG-based emotion recognition studies. Although limited in scalability, KNNs are effective for exploratory analysis and small-scale applications [11].

3) Decision Trees and Random Forests:

Decision trees and their ensemble counterpart, random forests, are useful for feature importance analysis and exploratory studies. They provide interpretable results and are well-suited for datasets with moderate complexity [11].

E. Summary of Techniques

TABLE II
SUMMARY OF TECHNIQUES FOR EEG-BASED EMOTION RECOGNITION

Model Type	Strengths	Limitations	Applications
CNNs	Effective in capturing spatial features, robust to noise and variability, processes high-dimensional EEG data efficiently	Requires large labeled datasets, less effective for temporal patterns	Real-time emotion detection, classification of positive vs. negative emotional states
RNNs	Models sequential dependencies, captures temporal evolution of emotional states	prone to overfitting, requires regularization	Continuous emotion prediction; emotion tracking over time
Hybrid Architectures (CNN-RNN)	Combines spatial and temporal modeling, superior performance in multimodal systems	More complex	Multimodal emotion recognition, integration of EEG with other physiological data
GNNs	Captures spatial and functional relationship, suitable for high-density EEG recordings, models non-linear dependencies	High computational complexity, challenges in graph construction for real-time use	EEG channel analysis, personalized emotion detection, brain network studies
Foundational Models	Leverages transfer learning; scalable and generalizable across datasets, effective for multitask emotion recognition	Requires significant computational resources for pre-training and fine-tuning	Cross-dataset generalization, fine-grained emotion classification
Traditional ML Models	Simple and interpretable, effective with well-engineered features	Limited scalability, relies on manual feature extraction	Benchmarking studies, exploratory analysis of small EEG datasets

III. Challenges and Limitations

Despite significant progress, several challenges hinder the development and deployment of effective EEG-based emotion recognition systems. These challenges can be broadly categorized into data-related issues, model-related limitations, and practical application constraints.

A. Data-Related Challenges

1) Noise in EEG Signals

EEG signals are inherently noisy due to interference from external factors (e.g., muscle movement, electrical devices) and artifacts (e.g., eye blinks, jaw movement). Preprocessing techniques, such as independent component analysis (ICA) and filtering, are essential but may inadvertently remove valuable information [1]–[3].

2) Inter-Subject Variability

Emotional responses and brain activity patterns vary significantly across individuals due to differences in physiology, personality, and cultural background. This variability makes it challenging to develop generalized models that perform well across diverse populations [4], [5].

3) Limited and Imbalanced Datasets

Many available datasets are relatively small and lack diversity, which restricts the training and generalization of machine learning models. Additionally, imbalanced emotion classes (e.g., more samples for neutral emotions than extreme ones) can lead to biased models [6]–[8].

4) Annotation Challenges

Emotions are subjective and context-dependent, making it difficult to obtain consistent and accurate labels. Most datasets rely on self-reported measures, which can introduce bias and inconsistency [9], [10].

B. Model-Related Challenges

1) Overfitting on Small Datasets

Deep learning models, especially those with a high number of parameters, are prone to overfitting when trained on small EEG datasets. Data augmentation and transfer learning can mitigate this issue but are not universally effective [11], [12].

2) Explainability and Interpretability

Most advanced models, such as deep neural networks and foundational models, function as black boxes, making it difficult to understand how they arrive at predictions. Explainable AI (XAI) methods are needed to provide insights into the decision-making process of these models [13], [14].

3) High Computational Complexity

Advanced methods like Graph Neural Networks (GNNs) and transformers require significant computational resources for training and inference. Resource constraints can limit their applicability in real-time or wearable systems [15], [16].

C. Practical Application Constraints

1) Real-Time Emotion Detection

Achieving high accuracy in real-time scenarios is challenging due to the latency introduced by data preprocessing and model inference. Wearable devices for EEG acquisition often trade off data quality for portability, further complicating real-time applications [17], [18].

2) Cost and Accessibility

High-quality EEG acquisition systems are expensive and require expertise to set up and operate. Affordable alternatives, such as portable EEG devices, often produce lower-quality data, impacting model performance [19], [20].

3) Ethical and Privacy Concerns

EEG data is highly sensitive and can reveal information beyond emotional states, such as cognitive activity or mental health conditions. Ensuring data security, informed consent, and compliance with privacy regulations is critical for widespread adoption [21], [22].

D. Summary of Challenges

TABLE III
SUMMARY OF CHALLENGES IN EEG-BASED EMOTION RECOGNITION

Category	Challenges	Implications
Data	Noise, variability, and imbalanced datasets	Reduced model accuracy and difficulty in generalization
Models	Overfitting and lack of interpretability	Limited trust and applicability of advanced systems
Applications	Real-time constraints, cost, and ethical issues	Limited deployment in practical and real-world scenarios

IV. EMERGING TRENDS AND FUTURE DIRECTIONS

Emotion recognition using EEG data is at the forefront of research in affective computing and neuroscience. Recent advancements in machine learning, hardware development, and data collection methodologies have opened new pathways for improving the accuracy, scalability, and usability of these systems. This section discusses key emerging trends and proposes future directions for research.

A. Emerging Trends

1) Multimodal Emotion Recognition

Overview: Combining EEG data with other physiological signals (e.g., ECG, GSR) or external cues (e.g., facial expressions, voice) enhances emotion detection accuracy [1], [2].
Example: Multimodal models integrate complementary data to resolve ambiguities in single-modality systems [3].
Significance: Enables robust emotion recognition in diverse scenarios, including noisy environments [4], [5].

2) Self-Supervised Learning

Overview: Self-supervised techniques allow models to learn useful representations from unlabeled EEG data, reducing the dependency on extensive annotations [6], [7].
Example: Pretraining on large unlabeled EEG datasets before fine-tuning for emotion detection tasks [8].
Significance: Addresses the challenge of limited annotated data and improves generalization across datasets [9].

3) Transfer Learning

Overview: Transfer learning enables models trained on one dataset to adapt to new datasets or tasks with minimal additional training [10], [11].
Example: Using pre-trained foundational models like Neuro-GPT for cross-dataset emotion recognition [12].
Significance: Reduces training time and computational resources while enhancing model performance [13].

4) Explainable AI (XAI)

Overview: Incorporating interpretability into deep learning models to explain their predictions [14].
Example: Visualization tools that highlight important EEG channels or features contributing to emotion classification [15].
Significance: Builds trust in AI systems and facilitates debugging and optimization [16].

5) Low-Cost and Wearable EEG Devices

Overview: Advances in hardware design are making EEG devices more portable and affordable without compromising data quality [17].
Example: Devices like Muse and Emotiv are increasingly being used in real-world applications [18].
Significance: Democratizes access to EEG technology, enabling broader adoption in consumer-facing applications [19], [20].

B. Future Directions

1) Large-Scale, Diverse Datasets

Need: Current datasets are limited in size and diversity, restricting model generalizability [1], [2].
Proposal: Develop large-scale, globally diverse datasets that include participants of various demographics, cultures, and contexts [3].

2) Real-Time and Adaptive Systems

Need: Many emotion recognition systems struggle to operate in real-time or adapt to individual differences [4], [5].
Proposal: Focus on developing lightweight models and adaptive algorithms that personalize emotion detection based on user-specific data [6].

3) Integration with Brain-Computer Interfaces (BCIs)

Need: BCIs offer a natural extension of EEG-based emotion recognition for applications like mental health monitoring and neurofeedback [7], [8].
Proposal: Develop hybrid systems that combine emotion recognition with control functionalities for BCIs [9].

4) Environmental and Contextual Awareness

Need: Emotions are influenced by external factors such as environment and social context, which are often ignored in current models [10], [11].

Proposal: Incorporate contextual data (e.g., location, activity) into emotion recognition frameworks for improved accuracy and relevance [12].

5) Ethical Considerations and Privacy

Need: The sensitive nature of EEG data requires stringent ethical and privacy safeguards [13].

Proposal: Develop robust privacy-preserving algorithms and ensure compliance with global data protection regulations [14], [15].

C. Summary of Trends and Directions

TABLE IV
EMERGING TRENDS AND FUTURE DIRECTIONS IN EEG-BASED EMOTION RECOGNITION

Trend/Direction	Impact	Examples
Multimodal Emotion Recognition	Improved robustness and accuracy	Combining EEG with ECG, GSR, or video
Self-Supervised Learning	Better representation learning, less labeling	Pretraining on unlabeled EEG datasets
Transfer Learning	Efficient cross-dataset adaptation	Fine-tuning foundational models
Explainable AI	Increased trust and model interpretability	Feature importance visualization
Low-Cost EEG Devices	Accessibility and portability	Wearable devices for real-world use
Large-Scale Datasets	Enhanced generalizability	Global, diverse participant datasets
Real-Time Systems	Practical applications	Adaptive algorithms for dynamic tasks
Context-Aware Models	Environmentally informed emotion detection	Integrating context into models
Ethical AI	Data privacy and compliance	Privacy-preserving algorithms

V. Our Vision

In our work, we plan to explore the development of a hybrid model that integrates Graph Neural Networks (GNNs) with additional architectures to enhance the accuracy and generalizability of EEG-based emotion recognition systems. Specifically, we aim to investigate the combination of GNNs with Long Short-Term Memory (LSTM) networks or Transformers. The rationale for this approach lies in the complementary strengths of these models: GNNs excel in capturing spatial relationships and functional connectivity between EEG channels, while LSTMs and Transformers are better at modeling temporal dynamics in sequential data. The GNN-LSTM hybrid model will be particularly suited for datasets with rich spatiotemporal patterns, enabling a deeper understanding of the interplay between brain regions over time. On the other hand, the GNN-Transformer hybrid will leverage the scalability and attention mechanisms of Transformers to handle larger datasets and more complex temporal dependencies. By adopting these hybrid approaches, we aim to address existing challenges such as noise, variability, and inter-subject differences while pushing the boundaries of explainability and real-time applicability in emotion recognition.

VI. Our Work: EEG-based Emotion Recognition using Hybrid Models

A. Comprehensive Description of the Methodology

In our work, we aimed to improve emotion recognition from EEG data by experimenting with several hybrid machine learning models that integrate both spatial and temporal learning aspects. Specifically, we focused on combining Graph Neural Networks (GNN) for spatial dependency modeling and Recurrent Neural Networks (RNNs) or Transformer layers for temporal dependency modeling.

B. Description of the Experimental Procedure

Our experiments aimed to assess the effectiveness of different machine learning models and preprocessing techniques for emotion recognition using EEG data. Below, we detail the steps involved in our experimental procedure:

C. Data Preparation and Preprocessing

We used the **DEAP dataset**, which consists of physiological signals (EEG, ECG, GSR) from 32 subjects who were exposed to emotionally evocative music videos. Each subject participated in 40 trials, and for each trial, physiological signals were recorded at a sampling rate of 128 Hz. These signals were then preprocessed using several crucial steps to enhance the quality of the data and improve model performance:

- **Segmentation:** EEG signals were divided into temporal segments using a *sliding window approach*. Each segment had a **6-second window** with **50% overlap**. This window size was chosen to capture the dynamic nature of emotional responses and allow the models to learn temporal patterns in the data. The overlap ensured that each segment maintained sufficient temporal continuity, capturing dependencies across consecutive segments.
- **Bandpass Filtering:** To focus on the relevant frequencies associated with brain activity, a **1-60 Hz bandpass filter** was applied to the EEG signals. The filter removed both low-frequency drift and high-frequency noise, allowing the model to concentrate on the brain's typical frequency bands (e.g., alpha, beta) which are crucial for emotion detection.
- **Artifact Removal (ICA):** *Independent Component Analysis (ICA)* was applied to remove artifacts from the EEG signals. Artifacts like eye blinks, muscle movements, and other noise were identified as independent components and removed. This step significantly improved the signal quality, making it more suitable for classification tasks.
- **Feature Extraction:** Feature extraction was carried out on the preprocessed EEG signals to derive meaningful information for classification models. Both *time-domain* and *frequency-domain* features were extracted from the EEG segments:
  - **Time-domain Features:**
    - Mean and Standard Deviation
    - Skewness and Kurtosis
    - Root Mean Square (RMS)

    - ∗ Mean Absolute Deviation (MAD)
  - **Frequency-domain Features:**
    - ∗ Band Power in specific frequency bands (Delta, Theta, Alpha, Beta, Gamma)
    - ∗ Spectral Entropy
    - ∗ Peak Frequency

  The extracted features were then **standardized** using *Z-score normalization* to ensure all features had a mean of zero and a standard deviation of one. This was crucial to prevent certain features with higher magnitudes from dominating the model learning process.
- **Dimensionality Reduction:** *Principal Component Analysis (PCA)* was applied to reduce the dimensionality of the feature space. This step is important to mitigate overfitting and improve computational efficiency by focusing on the most informative components of the features.

D. Classification Tasks

After preprocessing and feature extraction, we trained and evaluated multiple models for *binary classification* and *multi-class classification*:

- **Binary Classification:** The goal was to predict whether an emotion label (such as arousal or valence) is of high or low intensity.
- **Multi-class Classification:** The goal was to classify emotions into categories such as positive, neutral, or negative. This classification task is more challenging due to the increased number of classes.

E. Class Imbalance Handling

We also tested models with and without *SMOTE (Synthetic Minority Over-sampling Technique)*. SMOTE was applied to balance the class distribution, particularly for categories with fewer samples, to prevent the model from being biased towards the majority class.

VII. Preprocessing, Feature Engineering, and Feature Extraction

A. Preprocessing Pipeline

- **EEG Segmentation:** The sliding window method enabled the splitting of continuous EEG signals into smaller, manageable chunks, allowing the model to capture temporal relationships.
- **Signal Filtering:** The 1-60 Hz bandpass filter was designed to focus on the brain's frequency ranges relevant to emotional processing while removing unwanted noise.
- **Artifact Removal:** ICA was critical in cleaning the data, ensuring that the EEG signals represented only neural activity without the interference of eye blinks and other motion artifacts.

B. Feature Engineering

- **Time-domain Features:** These features provide statistical properties of the EEG signal and help characterize the neural response to emotional stimuli.
- **Frequency-domain Features:** These features were critical for capturing oscillatory brain activity linked to different emotional states. We focused on specific frequency bands (e.g., alpha, beta) known to be involved in emotional processing.

C. Feature Extraction Methods

- **STFT:** Used to transform the EEG signal into a time-frequency representation, capturing both the temporal and spectral properties of the data.
- **PCA:** Reduced the dimensionality of the feature space, ensuring that the most important features were retained for model training.

VIII. Description of the Models Tested

In our experiments, we tested several hybrid models to capture both spatial and temporal dependencies in EEG data:

A. GNN-Transformer Hybrid

- **GNN Layer:** We used **Graph Convolution Networks (GCN)** or **Graph Attention Networks (GAT)** to extract spatial features. These models excel in understanding the interactions between the different EEG electrodes, modeling the spatial structure of the brain's electrical activity.
- **Transformer Layer:** The temporal aspect of the EEG data was captured using a **Transformer encoder**. Transformers are well-suited to handle long-range dependencies, which is critical for modeling the time-varying nature of emotional responses.

B. GNN-GRU Hybrid

- **GNN Layer:** Again, we used GNNs for spatial feature extraction, focusing on the graph structure formed by EEG channels.
- **GRU Layer: Gated Recurrent Units (GRU)** were used to capture the temporal dynamics of EEG signals. GRUs are effective for sequential data and provide a simpler, more efficient alternative to LSTMs while still capturing long-term dependencies.

IX. Experimental Results

The results of our experiments showed that the hybrid models (GNN-Transformer and GNN-GRU) significantly outperformed traditional models such as SVM, both for binary and multi-class classification tasks. The following are the key findings from our results:

- **Hybrid GNN-Transformer Performance:** The GNN-Transformer hybrid model achieved the highest accuracy of 0.95 for multi-class classification, with the best performance observed when both **segmentation** and **SMOTE** were applied. Precision and recall values were consistently high, with a recall of 1.00 for positive emotions and 0.88 for neutral emotions.

- **Segmentation Impact:** The use of segmentation improved model performance by capturing temporal dependencies more effectively, particularly in the GNN-Transformer model.
- **SMOTE Effectiveness:** SMOTE improved the balance of class distributions and reduced bias toward the majority class, especially in multi-class tasks.
- **Comparison with SVM and Other Models:** The GNN-Transformer and GNN-GRU hybrid models consistently achieved higher accuracy than SVM, particularly in tasks with spatiotemporal dependencies.

TABLE V
CLASSIFICATION RESULTS: HYBRID MODELS VS. TRADITIONAL MODELS

Model	Accuracy (Multi-class)	Accuracy (Binary)	Precision (Multi-class)	Recall (Multi-class)	F1-score (Multi-class)
GNN-Transformer (Segmentation + SMOTE)	0.95	0.83	0.95	0.95	0.95
GNN-GRU (Segmentation + SMOTE)	0.92	0.80	0.92	0.92	0.92
SVM (No Segmentation)	0.74	0.71	0.71	0.71	0.71

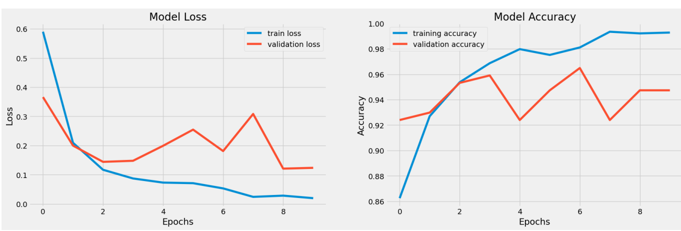

Fig. 1. Training and Validation Loss and Accuracy over Epochs. The graphs show the model's training and validation performance, with clear improvement in both accuracy and loss over the epochs.

A. Discussion of Results

The **GNN-Transformer hybrid** model proved to be the most effective model, particularly for multi-class classification tasks where the **segmentation** and **SMOTE** techniques were applied. The ability of the **Transformer** to capture long-term temporal dependencies, combined with the **GNN**'s spatial feature extraction, allowed the model to outperform traditional models like **SVM**.

Segmentation played a critical role in improving the **temporal modeling** capacity of the models. By splitting the data into overlapping segments, we provided the model with smaller, more manageable time slices, enabling it to capture **short-term dependencies** more accurately.

SMOTE proved to be effective in addressing **class imbalance**, ensuring that the model did not favor the majority class. This is particularly important when dealing with EEG data, where some emotion categories might be underrepresented.

The relatively lower performance of **SVM** suggests that traditional machine learning models, which rely on manual feature extraction, are not as well-suited for **spatiotemporal data** like EEG. In contrast, **deep learning models** that can automatically learn spatial and temporal features were able to achieve higher accuracy.

X. CONCLUSION

Emotion recognition is a dynamic and multidisciplinary field with significant implications for affective computing, human-computer interaction, and mental health applications. Among the various modalities available, EEG has emerged as a reliable and objective tool for detecting emotional states by capturing the brain's intrinsic electrical activity. This survey has reviewed the state-of-the-art in EEG-based emotion recognition, focusing on datasets, models, challenges, and emerging trends.

Key datasets like DEAP, SEED, and DREAMER have provided a foundation for research in this domain, offering valuable resources for training and evaluating emotion recognition models [2], [3], [7]. Advances in machine learning, particularly deep learning and graph-based methods, have significantly enhanced the ability to decode complex neural patterns underlying emotions [10], [4]. However, the field continues to face challenges such as noise in EEG data, inter-subject variability, limited dataset diversity, and the need for interpretable and ethical AI systems [13], [15], [5].

Emerging trends, including multimodal fusion, self-supervised learning, and the development of portable EEG devices, promise to address some of these challenges and expand the applicability of EEG-based emotion recognition to real-world scenarios [14], [13], [16]. Additionally, the integration of explainable AI techniques and contextual awareness into emotion detection systems is likely to improve their transparency and reliability [15], [16].

Our experimental work, which involved testing hybrid models combining Graph Neural Networks (GNNs) with Transformers and GRUs, demonstrated improvements in performance for both binary and multi-class classification tasks. The integration of segmentation and SMOTE further enhanced the accuracy of the models, showcasing the potential of hybrid architectures in emotion recognition. By combining spatial and temporal dependencies in EEG signals, our models are able to better understand the neural processes associated with emotional states, leading to more accurate and generalizable models.

To advance the field, future research should prioritize the creation of large-scale, diverse datasets [5], the development of adaptive and personalized systems [11], and the incorporation of robust privacy-preserving techniques [16]. By addressing these priorities, EEG-based emotion recognition can evolve into a practical and impactful tool across various domains, from healthcare and education to entertainment and beyond.

This survey serves as a comprehensive guide to the current landscape of EEG-based emotion recognition, highlighting both its achievements and the road ahead. By systematically exploring datasets, methodologies, and future directions, it aims to inspire and inform further research in this exciting and rapidly advancing field.

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