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A STUDY ON GRAPH AND HYPERGRAPH NEURAL NETWORK MODELS FOR EEG-BASED DEPRESSION DETECTION

Sudipta Priyadarshinee[1] and Madhumita Panda[2*]
[1]School of Computer Science, G.M. University, Sambalpur, Odisha, India
E-mail:sudiptapatel88@gmail.com
[*2]School of Computer Science, G.M. University, Sambalpur, Odisha, India
E-mail: mpanda.gmu@gmail.com

ABSTRACT
Electroencephalography (EEG) provides a promising non-invasive modality for depression diagnosis by capturing brain activity patterns. However, conventional machine learning and deep learning techniques struggle to model the complex spatio-temporal and higher-order inter-channel relationships present in EEG signals. This review explores recent advancements in graph and hypergraph neural network architectures—particularly Graph Convolutional Networks (GCNs), Hypergraph Convolutional Networks (HGCNs), and spatio-temporal fusion methods—for EEG-based depression detection. The study systematically analyzes existing approaches and identifies key research limitations, including oversimplified graph construction, inadequate integration of spatial-temporal features, poor generalizability due to inter-subject variability, and redundancy in feature representation. Emphasis is placed on the need for unified, adaptive models that can effectively capture individual-specific brain dynamics and higher-order channel interactions. This work provides a critical synthesis of the current landscape and outlines future directions for developing robust and interpretable EEG-based diagnostic tools for mental health assessment.

Keywords: *EEG-based Depression Detection, Graph Neural Networks, Hypergraph Convolution, Spatio-Temporal Modeling, Mental Health Diagnostics.*

1. INTRODUCTION
Depression is a multifaceted and widespread mental health disorder characterized by persistent feelings of sadness, loss of interest, and impaired emotional, cognitive, and behavioral functioning. It affects millions globally and is recognized as a leading cause of disability by the World Health Organization (WHO). Beyond its psychological symptoms, depression is often accompanied by neurobiological alterations, including disrupted brain connectivity and imbalanced neurotransmitter activity. The complexity and heterogeneity of depressive symptoms make early detection and accurate diagnosis particularly challenging [1-2].

Traditional diagnostic methods primarily rely on subjective tools such as clinical interviews, behavioral observations, and self-report questionnaires like the Beck Depression Inventory (BDI). While these tools are widely used, they are susceptible to biases, underreporting, and misinterpretation, often leading to delayed diagnosis or inappropriate treatment plans.In this context, Electroencephalography (EEG) has emerged as a promising neuroimaging modality for the objective assessment of depression. EEG records electrical activity generated by neuronal firing across different regions of the cerebral cortex, offering a non-invasive, cost-effective, and temporally precise window into brain function. Unlike other imaging techniques such as fMRI or PET, EEG provides real-time insights into the dynamic interplay of neural networks.Importantly, research has shown that individuals with Major Depressive Disorder (MDD) often exhibit abnormal EEG patterns, such as altered alpha asymmetry, decreased coherence, and disrupted functional connectivity [3-4]. These electrophysiological markers highlight the potential of EEG as a biomarker for detecting depressive states.Recent advances in artificial intelligence—particularly in machine learning and deep learning—have revolutionized the analysis of EEG signals. However, conventional models frequently overlook the topological structure and temporal evolution inherent in EEG data. This has led to growing interest in graph-based approaches, which model EEG channels as nodes and their interdependencies as edges, allowing for a more nuanced understanding of brain network dynamics in depression [5].

This review paper aims to examine recent developments in EEG-based depression detection, focusing on spatio-temporal and graph-based deep learning methods. We analyze the methodologies, highlight current challenges, and identify research gaps to guide future work in building more robust and interpretable models for mental health diagnostics.

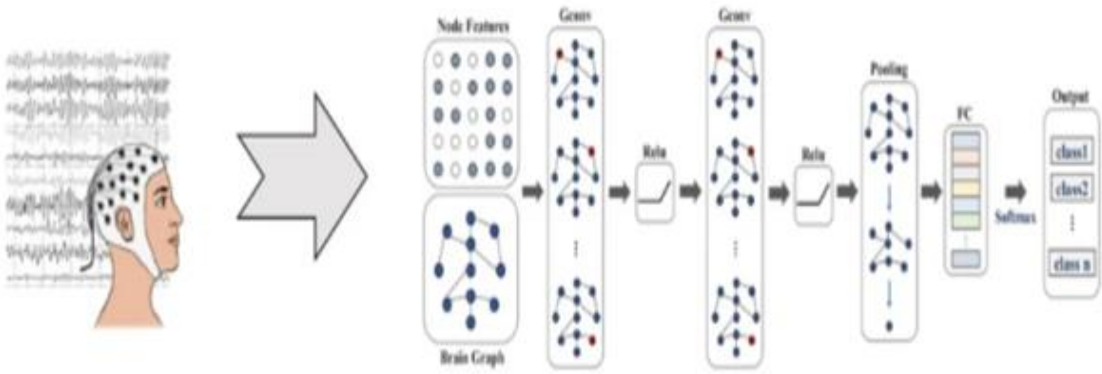

Fig.1 Graph convolution network-based EEG signal analysis

2. RELATED WORK

In recent years, the application of deep learning to analyse EEG-based brain activity has shown significant potential in the automated detection of depression. The literature on EEG-based depression detection broadly falls into two categories: conventional machine learning (ML) approaches and deep learning (DL)-based methods.

Machine Learning (ML)-Based Approaches: Traditional ML techniques typically rely on handcrafted features extracted from EEG signals. These features include statistical characteristics, power spectral densities, alpha asymmetry, signal entropy, and brain laterality. In many studies, channel-wise EEG data are processed using techniques like spectrum analysis, functional connectivity measures, and network-based features to train classifiers such as Support Vector Machines (SVM), k-Nearest Neighbour (KNN), and Random Forests. While effective to an extent, these methods often fail to generalize due to variability in EEG signals and limited ability to model spatial or temporal dynamics.

Deep Learning (DL)-Based Approaches: To overcome the limitations of manual feature extraction, DL models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and their hybrids (e.g., CNN-LSTM, Deep Hybrid Neural Networks) have been widely adopted. CNNs are primarily employed to learn spatial features from EEG signal maps, treating them as 2D inputs, whereas LSTMs and GRUs (Gated Recurrent Units) model temporal dependencies in the sequential EEG data. For example, studies such as [5], [6], and [7] use CNNs to extract frequency-based features like Theta, Alpha, and Beta waves, followed by LSTM or GRU networks for temporal classification. While these architectures improve upon traditional ML methods, they often treat spatial and temporal features in isolation, missing out on the rich inter-channel interactions within EEG signals.

Graph-Based Deep Learning Models: More recently, researchers have explored the graph-based nature of EEG data, treating EEG channels as nodes and defining edges based on functional or spatial relationships. Graph Convolutional Networks (GCNs) and their variants have been used to capture this topological structure. In [8], differential entropy features were used to generate adjacency matrices using Pearson correlation. Other works, such as [9] and [10], employ attention mechanisms or phase-locking values to construct graphs, but these often rely on predefined, static connectivity patterns that fail to reflect the dynamic nature of brain activity.

Some models like [11] use Euclidean distance between electrodes to define channel relationships, which simplifies the spatial structure but disregards the strength or context of functional interactions. In [12], self-attention mechanisms were introduced to rank channels by importance, but they lacked the ability to capture hierarchical or inter-layer dependencies. These approaches, though innovative, often struggle to model the temporal evolution of brain networks or adapt to individual variability among subjects.

Spatio-Temporal Fusion Limitations: Despite advancements, a persistent challenge in EEG-based depression detection is the integration of spatial and temporal information. Most studies extract spatial features using CNNs and process temporal dependencies separately using RNNs or GRUs, as seen in works like [13]. However, these methods fall short in modelling how inter-channel relationships evolve over time. The majority of models process EEG data as independent frames or sequences, which does not fully leverage the spatio-temporal richness inherent in brain signals.

Graph Spatio-Temporal Models and Limitations: To better capture brain connectivity, spatio-temporal graph-based models have emerged. These represent EEG signals as dynamic graphs where nodes (channels) evolve over time, and edges (connectivity) reflect changing relationships. Yet, many of these models rely on static, pre-computed adjacency matrices and do not adapt to the unique patterns of each individual. Moreover, they often represent only pairwise interactions and fail to model higher-order connections that may be critical in identifying depressive symptoms.

Models such as GCNs [11-13], Self-Attention GNNs [13], and pooling-based networks have made strides in learning local-global representations. However, these approaches still lack the ability to model subject-specific variations and higher-order channel interactions simultaneously. This underlines the need for unified frameworks that can integrate channel-level spatial relations with subject-level temporal dynamics.

To better illustrate the evolution of techniques used in EEG-based depression detection, Table 1 provides a concise comparison of traditional Machine Learning (ML), Deep Learning (DL), Graph Convolutional Networks (GCNs), and Hypergraph Convolutional Networks (HGCNs). The comparison highlights their methodological foundations, core strengths, and critical limitations.

Table 1. Comparative Summary of Key EEG-Based Depression Detection Methods

Method	Approach	Strengths	Limitations
Machine Learning (ML)	Handcrafted features (e.g., entropy, PSD, alpha asymmetry); classifiers like SVM, KNN, RF	Simple, interpretable, requires small datasets	Limited spatial-temporal modeling, low generalizability
Deep Learning (DL)	CNNs for spatial patterns; LSTM/GRU for temporal patterns; hybrids (e.g., CNN-LSTM)	Learns features automatically; better than ML in accuracy	Treats spatial and temporal aspects separately; ignores topological structure
Graph Convolutional Networks (GCNs)	EEG channels as nodes; edges from correlations or distances; static adjacency matrix	Captures topological/channel relationships; local-global modeling	Fixed connectivity; ignores higher-order/channel redundancy
Hypergraph Convolutional Networks (HGCNs)	Uses hyperedges for modeling multi-channel dependencies	Models higher-order relationships; better spatial info	Computationally complex; lacks dynamic adaptation over time

3. RESEARCH GAPS

Despite the notable progress made in EEG-based depression detection, several critical research gaps persist in the current body of work:

1. **Limited Representation of Higher-Order Brain Connectivity:** Most existing models utilize pairwise connections to represent relationships between EEG channels. However, such binary interactions fail to capture the complex and higher-order functional dependencies inherent in brain networks. The brain's connectivity structure is inherently multi-dimensional, requiring models that can go beyond simplistic adjacency matrices to better reflect neural dynamics.

2. **Inadequate Fusion of Spatial and Temporal Dependencies:** While many studies effectively model spatial (e.g., using CNNs or GCNs) and temporal (e.g., using LSTM or GRU) patterns independently, there is a lack of unified frameworks that can simultaneously and effectively fuse both types of information. This leads to sub-optimal modeling of how neural signals evolve over time within and across different brain regions.

3. **Oversimplified Graph Construction Techniques:** A large number of graph-based methods construct adjacency matrices using fixed metrics like Euclidean distance between electrode positions. This approach overlooks the fact that functionally meaningful brain interactions may not always correspond to spatial proximity. Ignoring the strength and context of these inter-channel interactions weakens the discriminative power of such models.

4. **Neglect of Inter-Subject Variability:** Existing models often represent EEG signals using 3D tensors or static structures that fail to consider variations in brain activity across different individuals. As a result, the learned representations may not generalize well across populations, limiting the clinical applicability of these methods.

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5. **Redundancy in Brain Network Modeling:** Many approaches suffer from including redundant channel-channel relationships, especially among spatially adjacent electrodes that capture similar signals. This leads to inflated and noisy feature spaces, making it difficult for models to focus on informative patterns relevant to depression detection. Although attention and pooling mechanisms have been proposed to mitigate this issue, a more effective solution would involve explicit redundancy reduction during graph construction.

4. CONCLUSION

This paper systematically reviews the progression of EEG-based depression detection methods, emphasizing the transition from traditional machine learning to advanced deep learning, and more recently to graph-based and hypergraph neural network models. Among these, Graph Convolutional Networks (GCNs) have proven effective in modeling the topological structure of EEG channels, while Hypergraph Convolutional Networks (HGCNs) further enhance this by capturing higher-order interactions, offering improved representation of brain connectivity patterns. These graph-based methods outperform conventional approaches in capturing spatial-temporal dynamics critical for identifying depressive states. However, challenges such as static graph construction, limited inter-subject generalization, and redundancy in brain network modeling persist.

5. FUTURE WORK

Future research should focus on dynamic graph construction, subject-specific adaptation, and reducing redundancy in EEG channel connectivity. Lightweight models for real-time diagnosis using wearable devices also hold strong potential for practical deployment.

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