A Taxonomy and Comprehensive Survey of Brain Graph based Approaches for Schizophrenia Detection with Graph Neural Networks

Ambili P S[1,2], Neethu P S[3]

[1] Lincoln University College, 47301, Petaling Jaya, Selangor Darul Ehsan, Malaysia; [2] REVA University, Rukmini Knowledge Park, Bangalore, Karnataka, India; [3] Christ University, Bangalore Kengeri Campus, Karnataka, India.

amispillai20@gmail.com

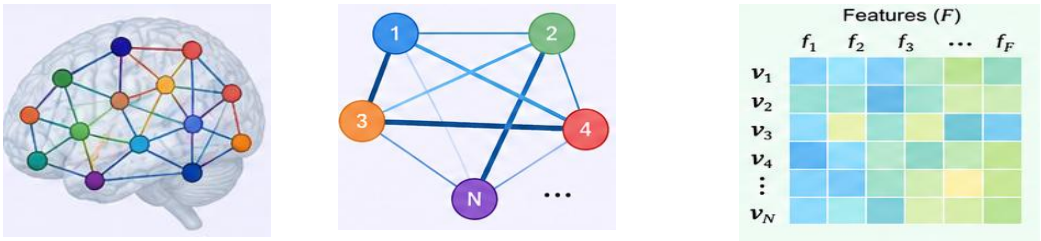
Abstract: Schizophrenia is a long term complex neuropsychiatric condition characterized by abnormal functional interactions between the parts of the brain. Brain can be modelled as a graph structure with brain regions as nodes and functional connections as the edges. Since the abnormalities causing Schizophrenia are not restricted to a single brain region, many latest developments in neuroimaging and graph learning for classification and detection of schizophrenia from brain graph structure connectivity patterns focused on applying Graph Neural Networks (GNNs). This work is a comprehensive review of developments in schizophrenia detection using brain graphs and GNN architectures including GCNs, GATs and hybrid models. The authors have systematically analysed recent studies published between 2019 to 2026, comparing the performance and methodological trends with focus on the data modalities such as structural MRI, functional MRI and resting state functional MRI. The key challenges for accurate prediction of schizophrenia include dataset heterogeneity, domain shift, interpretability limitations and external validation barriers. The analysis reveals that GNN based approaches to intelligent schizophrenia detection using resting state functional connectivity MRI are promising.

Keywords: Schizophrenia; Resting-State fMRI; Graph Neural Networks; Graph Attention Network; Deep Learning.

Introduction

Schizophrenia is a complex psychic disorder that can affect a person's thinking, behaviour, perception, and emotions. It is not exactly same as dissociative identity disorder, but it can affect a person's ability to function as normal in daily life. Most commonly it is seen in people in late adolescence and early adulthood, and symptoms may vary from person to person and may occur in episodes [1,12]. Schizophrenia is caused due to variations in brain development, brain connectivity, and neurotransmitter disfunction, along with other genetic and environmental influences. Functional Magnetic Resonance Imaging (fMRI) and Resting state fMRI (rs-fMRI) has become powerful techniques in the field of neuroimaging. These techniques can effectively be used to analyse spontaneous brain activity via the assessment of functional connectivity between different brain regions [3]. FCNs are functional connectivity networks that have been shown to be useful markers for schizophrenia and other neurological diseases.

Brain can be represented as a graph, $G = (V, E, X)$ where, V= { v_1,v_2,v_3,……, v_N } is the nodes or brain regions; $E \subseteq V \times V$ denote the edges which are set of functional connections**;** X represents the node feature matrix. This is represented diagrammatically in Figure 1.



(a) *(b)* *(c)*

Figure 1. (a) Brain graph (b) Functional connections (c) Node feature matrix

Recently, researchers are shifting their attention to Graph Neural Networks (GNNs) and brain connectivity analysis based on EEG, rs-fMRI, DTI and multimodal neuroimaging data with a view of discovering abnormalities of different brain disorders like schizophrenia, Alzheimer's disease, Parkinson's disease, and autism spectrum disorder. Traditional machine learning techniques struggle to maintain the intricate interconnections between brain regions, while graph-based deep learning models are adept at capturing the intricate structures and connections of the brain. The key contributions of this survey include (i) The importance of fMRI and rs-fMRI to brain graph transformation in schizophrenia analysis (ii) a detailed survey of GNN based schizophrenia detection methods and other network-based architectures such as GCN and GAT.

Literature Review

The accuracy of disease classification, interpretability, and biomarker discovery have been enhanced by several studies that have created advanced frameworks including GCN, GAT, DGCNN, STRGCN, and multimodal GNN architectures. This section presents a systematic review of literature methodologies, advantages and limitations regarding brain connectivity analysis and the detection of schizophrenia using Graph Neural Networks and other graph based deep learning techniques.

Yi Hao Chan et al. [1] presented a systematic review on how Graph Neural Networks (GNNs) can be applied on resting-state fMRI to identify psychiatric disorders, including schizophrenia. The study reviewed GNN architectures, brain-graph construction methods and made use of explainability techniques to identify the key brain regions and connections. The work explored challenges in biomarker reproducibility, interpretability, and generalization across datasets.

R. Gnanajeyaraman and L. Reetha [2] proposed a neurobiological graph learning approach for schizophrenia diagnosis. The study presents verbal auditory hallucinations (VAH) as a key symptom. The integration of neurobiological information and graph based AI techniques to capture relationships among brain regions associated with auditory hallucinations is the highlight in this research.

The study on exhaustive bibliometric analysis to provide an overview of brain network research dynamics was done by Mamat M et al. [3]. The study explored the synergy between graph theory and neuroimaging techniques for understanding complex brain networks, neurological and psychiatric disorders. The survey underscored multimodal neuroimaging, brain connectivity, and network-based analysis as the key emerging directions. A detailed literature review is presented in table 1.

Table 1. Literature study presenting model used, methodology and limitations of each study

Literature	Model	Methodology	Limitations
E. Pitsik, S. Kurkin, A. Hramov, R. Paunova, D. Simeonova, S. Kandilarova and D. Stoyanov (2023) [4]	GCN	Graph representation of brain connectivity, GraphConv layer, ReLU activation, Batch Normalization, Dropout, Adam Optimizer, Functional Connectivity Analysis	Small dataset size, risk of overfitting, limited validation data, single-layer architecture may restrict feature extraction capability
X. Xu, G. Zhu, B. Li, P. Lin, X. Li and Z. Wang (2024) [5]	STRGCN	GCN, Temporal Convolution, Residual Learning, Attention Layer, Wavelet Coherence (WC), EEG Functional Connectivity Analysis, Cross-Channel Feature Learning	Small dataset size, limited generalization on diverse populations, dependency on Wavelet Coherence adjacency matrix.
D. S. Ghosh and S. Ghosh (2025) [6]	DV-GCN	Multiscale GCN, Spectral Graph Convolution, Graph Diffusion, Sparsification, Chebyshev Polynomial Approximation, Explainable AI	Small dataset size, under-review preprint, limited clinical validation, computational complexity due to multiscale processing
Y. Yu, X. Kan, H. Cui and C. Yang et al. (2023) [7]	DABNet	Directed Acyclic Graph (DAG) Learning, GNN, SVAR Model, Effective Brain Connectivity, End-to-End Learning, GCN	High memory usage for large time-lag values, computational complexity for large ROI datasets, performance depends on DAG regularization.
G. Sunil, S. Gowtham et al. (2024) [8]	GNN& ML Techniques	GNN Conventional Machine learning techniques for classification	Lacking precise GNN architecture and explainability method. Generalization across device heterogeneity.
P. Gao, X. Zheng et al. (2024) [9]	GNN	Brain graph representations to learn relationships among brain regions and emotion recognition.	Focusing on emotion classification rather than schizophrenia detection.
Q. Chang et al. (2021) [10]	GNN	Brain network formation from input and applies GNN for classification.	Concern on performance due to class imbalance and limited sample size. Requires validation.
J. Liu, T. Fang and H. Huo (2024) [11]	GNN	node connectivity strength Graph neural message passing techniques.	Not designed for brain imaging. Reliable graph construction is dependent on node strength features.
Kalmady, S.V., Greiner, R., Agrawal, R. et al., (2019) [12]	EMPaSchizan Ensemble algorithm	rs- fMRI is projected to predefined brain parcellation schemes. PCA to reduce dimensionality. Logistic	Generalization performance on different clinical settings remains uncertain. Multiple parcellations

		regression classifier to combine probabilities.	may generate overlapping features. No early prediction
Y. Zhu, H. Cui, L. He, L. Sun and C. Yang (2022) [13]	GNN	Mental illness diagnosis by learning from a shared embedding from structural and functional connectivity graphs.	Multimodal fusion can be affected by missing modalities and inconsistent graph scales. Lacking external validation.
W. Tong et al. (2023) [14]	GNN	The method captures the topological relationships and interactions among brain regions to help the model learn disease related variations in brain connectivity.	Accuracy is dependent on fMRI preprocessing, ROI selection and graph construction, external validation lacking.
Yuhang Liu and Cheng Luo et al., (2026) [15]	MF-HGNN	Models both static functional connectivity and dynamic functional connectivity. In order to capture variations in connectivity patterns, a sliding-window approach.	Not a schizophrenia study. Disorder classification only, not addressing early stage prediction.

Conclusion

The recent advancements in brain graph based approaches for schizophrenia detection using neuroimaging are studied, with particular emphasis on rs-fMRI, functional connectivity, and Graph Neural Networks (GNNs). The techniques including GNN, GCN, GAT, heterogeneous, and biologically informed graph models, are potential contributors for automated schizophrenia identification. Future research should move towards early stage and longitudinal detection reducing the severity and long term impact of the disorder. Integrating explainability can improve model transparency, facilitate ease in clinical interpretability and trustworthiness.

References

[1] Yi Hao Chan, Deepank Girish et al., “Discovering Robust Biomarkers of Psychiatric Disorders from Resting-State Functional MRI Via Graph Neural Networks: A Systematic Review”, NeuroImage, Volume 319, 2025, 121422, https://doi.org/10.1016/j.neuroimage.2025.121422.

[2] R. Gnanajeyaraman and L. Reetha, "Neurobiologically Informed AI for Schizophrenia Diagnosis: A Study on Verbal Auditory Hallucinations Using Graph Learning", ATiGB, Danang, Vietnam, 2025, pp. 688-693, doi: 10.1109/ATiGB66719.2025.11142174.

[3] Mamat M, Wang Z, Jin L, He K, Li L and Chen Y " Beyond Nodes and Edges: A Bibliometric Analysis on Graph Theory and Neuroimaging Modalities", Front. Neurosciences, 18:1373264, 2024, doi: 10.3389/fnins.2024.1373264.

[4] E. Pitsik, S. Kurkin, A. Hramov, R. Paunova, D. Simeonova, S. Kandilarova and D. Stoyanov, “A Graph Convolutional Network for Classification of Resting-State fMRI Data”, International Conference on Informatics, Electronics and Vision (ICIEV), 2023.

[5] X. Xu, G. Zhu, B. Li, P. Lin, X. Li and Z. Wang, “Automated Diagnosis of Schizophrenia Based on Spatial–Temporal Residual Graph Convolutional Network”, BioMedical Engineering OnLine, 2024.

[6] D. S. Ghosh and S. Ghosh, “Decision Voting Based Multiscale Convolutional Learning of Brain Networks with Explainability”, bioRxiv, 2025.

[7] Y. Yu, X. Kan, H. Cui and C. Yang et al., “Deep DAG Learning of Effective Brain Connectivity for fMRI Analysis”, IEEE 20th International Symposium on Biomedical Imaging (ISBI), 2023.

[8] G. Sunil, S. Gowtham et al., “Graph Neural Network and Machine Learning Analysis of Functional Neuroimaging for Understanding Schizophrenia,” BMC Neuroscience, 2024.

[9] P. Gao, X. Zheng et al., “Graph Convolutional Neural Network Based Emotion Recognition with Brain Functional Connectivity Network,” International Journal of Crowd Science, 2024.

[10] Q. Chang, and C. Wang et al., “Classification of First-Episode Schizophrenia, Chronic Schizophrenia and Healthy Control Based on Brain Network of Mismatch Negativity by Graph Neural Network”, IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2021.

[11] J. Liu, T. Fang and H. Huo, “Graph Neural Networks with Node Connectivity Strength for Node Classification,” in 2024 6th International Communication Engineering and Cloud Computing Conference (CECCC), 2024.

[12] Kalmady, S.V., Greiner, R., Agrawal, R. et al., “Towards artificial intelligence in mental health by improving schizophrenia prediction with multiple brain parcellation ensemble-learning”, Schizophrenia, 5, 2 (2019). https://doi.org/10.1038/s41537-018-0070-8.

[13] Y. Zhu, H. Cui, L. He, L. Sun and C. Yang, "Joint Embedding of Structural and Functional Brain Networks with Graph Neural Networks for Mental Illness Diagnosis," EMBC, Glasgow, United Kingdom, 2022, pp. 272-276, doi: 10.1109/EMBC48229.2022.9871118.

[14] W. Tong et al., "fMRI-Based Brain Disease Diagnosis: A Graph Network Approach," in IEEE Transactions on Medical Robotics and Bionics, vol. 5, no. 2, pp. 312-322, May 2023, doi: 10.1109/TMRB.2023.3270481.

[15] Yuhang Liu and Cheng Luo et al., “MF-HGNN: A Multi-View Fusion Heterogeneous Graph Neural Network for Psychiatric Disorder Diagnosis”, Biomedical Signal Processing and Control, Volume 123, 2026, https://doi.org/10.1016/j.bspc.2026.11062.