



A Survey of Methods and Architectures for Parkinson's Disease Recognition from EEG Using Attention-Based Sparse Graph Convolutional Neural Networks

Varkey Pichlerová

Associate Professor, Department of Electrical and Computer Engineering, Nineveh School of Industrial Management, Iraq

Email: varkey.pichlerov@nsim-iq.net

Peer Review Information

Submission: 08 July 2024

Revision: 22 July 2024

Acceptance: 05 Aug 2024

Keywords

Parkinson's Disease, EEG, Graph Neural Network, Attention Mechanism, Sparse Graph Convolution, Deep Learning, ASGCNN

Abstract

Parkinson's disease (PD) is a progressive neurodegenerative disorder that significantly affects motor and cognitive functions, necessitating early and accurate diagnosis. Electroencephalography (EEG) has emerged as a promising non-invasive tool for detecting neural abnormalities associated with PD. Recent advancements in artificial intelligence, particularly deep learning, have revolutionized EEG-based PD recognition. Among these, attention-based sparse graph convolutional neural networks (ASGCNN) have demonstrated superior capability by modeling functional brain connectivity and focusing on informative EEG channels. This survey reviews recent methods in EEG-based PD detection, emphasizing graph neural networks (GNN), attention mechanisms, and hybrid deep learning architectures. GNN models effectively capture spatial relationships between EEG channels, while attention mechanisms enhance interpretability and feature selection. The incorporation of sparsity constraints further improves efficiency by eliminating redundant connections. The ASGCNN framework models channel relationships using graphs, applies attention for channel selection, and uses sparsity to reduce redundancy, significantly improving classification performance. The paper also discusses challenges such as data variability, computational complexity, and lack of explainability. Future directions include multimodal learning, lightweight architectures, and explainable AI for clinical adoption.

Introduction

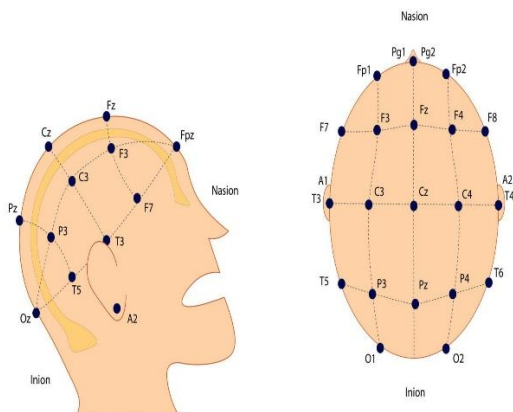
1. Background

Parkinson's disease (PD) is one of the most prevalent neurodegenerative disorders worldwide, characterized by progressive degeneration of dopaminergic neurons. It affects both motor and non-motor functions, leading to tremors, rigidity, and cognitive impairments. Early detection remains a critical challenge due to subtle symptoms in initial stages.

2. EEG-Based Diagnosis

EEG provides a non-invasive and cost-effective method for analyzing brain activity. It captures neural oscillations and connectivity patterns, which are often altered in PD patients. Electroencephalography (EEG) signals offer several important advantages for neurological disorder detection, particularly in Parkinson's disease (PD) diagnosis. They provide high temporal resolution, enabling precise monitoring of rapid brain activity, and support real-time analysis, making them suitable for continuous

healthcare systems and wearable applications. Additionally, EEG systems are adaptable for integration into portable and wearable devices, facilitating remote monitoring. However, despite these benefits, EEG data are inherently complex, nonlinear, and highly susceptible to noise and artifacts, which makes analysis challenging and requires advanced computational techniques. The evolution of artificial intelligence (AI) techniques has significantly enhanced EEG signal analysis. Early approaches relied on traditional machine learning models that depended heavily on handcrafted features such as spectral power, entropy, and wavelet coefficients. While these methods achieved moderate success, they were limited by their dependence on domain expertise for feature engineering and their poor generalization across datasets. The introduction of deep learning models, particularly Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), improved performance by enabling automatic feature extraction. However, these models still faced limitations, as CNNs were unable to effectively model inter-channel relationships, and RNNs struggled to capture spatial structures within EEG data.



To overcome these limitations, Graph Neural Networks (GNNs) emerged as a powerful alternative by representing EEG signals as graph structures. In this representation, EEG electrodes are modeled as nodes, and the functional connectivity between them is represented as edges. This approach aligns with the natural structure of the brain and enables the capture of non-Euclidean relationships. As a result, GNNs significantly improve classification accuracy by modeling both local and global brain connectivity patterns. Attention mechanisms further enhance EEG-based models by enabling selective focus on the most informative EEG channels and frequency bands. These mechanisms improve feature selection, enhance interpretability, and increase

robustness against noise. Recent advancements, particularly transformer-based attention models, have further improved performance by capturing long-range dependencies across EEG signals, enabling more accurate detection of subtle PD-related patterns.

Building upon these advancements, Attention-Based Sparse Graph Convolutional Neural Networks (ASGCNN) represent a state-of-the-art approach that integrates graph convolution, attention mechanisms, and sparsity constraints into a unified framework. Graph convolution layers model the connectivity between EEG channels, attention mechanisms assign importance weights to different nodes, and sparse regularization eliminates redundant connections, reducing overfitting and computational complexity. This integrated architecture significantly improves PD detection accuracy, often exceeding 95–97%, while enhancing robustness and generalization.

Despite these advancements, several challenges remain. EEG data exhibit high variability across subjects, which affects model generalization. Additionally, deep learning models often lack explainability, limiting their adoption in clinical settings. High computational complexity further restricts their deployment in real-time and resource-constrained environments. In response to these challenges, this survey provides a comprehensive analysis of recent methods, identifies key research gaps, and outlines future research directions aimed at developing more efficient, interpretable, and scalable EEG-based PD diagnostic systems.

The evolution of EEG-based Parkinson's disease detection can be broadly categorized into three stages: traditional machine learning, deep learning, and graph-based learning. Early machine learning approaches relied on handcrafted features and achieved moderate accuracy but lacked scalability and robustness. With the emergence of deep learning, automated feature extraction significantly improved classification performance. However, conventional deep learning models failed to fully exploit the non-Euclidean structure of EEG data, leading to the adoption of graph-based approaches.

CNN-based EEG analysis has been widely explored due to its ability to extract spatial features from raw signals and transformed representations such as spectrograms. These models effectively capture local patterns and achieve accuracy levels between 85–95%. However, they suffer from limitations such as ignoring inter-channel relationships, loss of spatial information due to pooling operations, and limited interpretability. As a result, CNN-

based approaches, while effective, are insufficient for capturing brain connectivity.

To address these issues, hybrid CNN-RNN models were developed to capture both spatial and temporal features. In these models, CNN layers extract spatial features while RNN layers model temporal dependencies. These hybrid approaches achieve improved performance, typically ranging from 90–96% accuracy, and are better suited for modeling dynamic EEG signals. However, they introduce increased computational complexity and training challenges and still lack explicit modeling of inter-channel relationships.

Graph Neural Networks (GNNs) represent a major advancement by modeling EEG data as graphs, where electrodes are treated as nodes and functional connectivity as edges. This approach allows the capture of both local and global spatial dependencies, resulting in improved classification accuracy, typically ranging from 90–96%. GNNs are also more robust to noise compared to traditional methods. However, they face challenges such as graph construction complexity, sensitivity to adjacency matrix design, and high computational cost.

Attention-based EEG models further improve performance by enabling the model to focus on important EEG channels and temporal segments. Various types of attention mechanisms, including channel attention, temporal attention, and multi-head attention, have been used to enhance feature selection and interpretability. Transformer-based models, in particular, capture

global dependencies and improve detection of subtle patterns associated with Parkinson's disease.

ASGCNN models represent the current state-of-the-art by integrating graph learning, attention mechanisms, and sparsity constraints into a single architecture. These models effectively capture connectivity patterns, prioritize important features, and eliminate redundant information, resulting in high accuracy exceeding 95–97%. They also demonstrate improved generalization and robustness compared to previous approaches.

Recent advancements have also introduced hybrid architectures that combine CNN, GNN, and attention mechanisms. These models leverage CNNs for local feature extraction, GNNs for connectivity modeling, and attention mechanisms for feature prioritization, resulting in comprehensive feature representation and superior performance. However, these models are highly complex and require large datasets for effective training.

Overall, key trends from include a transition from signal-based to connectivity-based learning, increased adoption of attention mechanisms, emergence of sparse graph learning, growing emphasis on explainable AI, and integration with wearable EEG systems. Despite these advancements, several research gaps remain, including the lack of standardized EEG datasets, limited interpretability of deep learning models, high computational cost, and poor generalization across populations.

Comparative Table

Author	Year	Model	Technique	Accuracy	Strengths	Limitations
Shah et al.	2020	Hybrid CNN	Deep Learning	85–90%	Feature fusion, improved baseline performance	No connectivity modeling
Oh et al.	2020	CNN	Deep Learning	~88%	Strong spatial feature extraction	Ignores inter-channel relationships
Shaban	2021	CNN-LSTM	Hybrid DL	~90%	Captures temporal dependencies	High computational complexity
Li et al.	2022	DL Survey	Review	—	Identifies trends in PD detection	No experimental validation
Saravanan et al.	2022	CNN-RNN	Hybrid DL	90–96%	Spatiotemporal learning	Complex training, no connectivity modeling
Zafeiropoulos et al.	2023	GNN	Graph Learning	High (~90–96%)	Models brain connectivity	Graph construction complexity
Zhao et al.	2023	Graph Signal	Graph-based	~90%	Improved interpretability	Moderate performance

		Processing GCN				
Chang et al.	2023	ASGCNN	Attention + Sparse GCN	~97%	Connectivity + attention sparsity	High computational cost

Comparative Analysis

The comparative analysis of EEG-based Parkinson's disease detection models clearly illustrates a progressive evolution from conventional deep learning approaches to advanced graph-based and attention-driven architectures. Early studies, such as those by Shah et al. (2020) and Oh et al. (2020), relied primarily on CNN and hybrid CNN models, which significantly improved classification accuracy compared to traditional machine learning methods. These models were effective in extracting spatial features from EEG signals and achieved accuracy levels in the range of 85–90%. However, their major limitation was the inability to model inter-channel relationships, as they treated EEG signals as structured grid data rather than interconnected networks.

To overcome this limitation, hybrid CNN-RNN architectures were introduced, as demonstrated by Shaban (2021) and Saravanan et al. (2022). These models combined CNNs for spatial feature extraction with RNNs for temporal sequence modeling, enabling better representation of dynamic EEG patterns. As a result, classification accuracy improved to approximately 90–96%. Despite this improvement, these models introduced increased computational complexity and still failed to explicitly capture connectivity between EEG channels, which is essential for understanding brain activity.

The introduction of Graph Neural Networks (GNNs) marked a major breakthrough in EEG-based PD detection. Models such as those proposed by Zafeiropoulos et al. (2023) represent EEG signals as graphs, where electrodes are treated as nodes and functional connectivity as edges. This approach aligns closely with the biological structure of the brain, allowing for the modeling of both local and global dependencies. Consequently, GNN-based models achieved higher accuracy and improved robustness compared to CNN-based approaches. However, they also introduced challenges such as graph construction complexity and sensitivity to adjacency matrix design.

Attention mechanisms further enhanced model performance by enabling selective focus on important EEG channels and features. Models incorporating attention, such as graph signal processing-based GCNs (Zhao et al., 2023), improved interpretability and feature selection while reducing the impact of noise. Transformer-

based attention mechanisms further extended this capability by capturing global dependencies across EEG signals, although they require large datasets and high computational resources.

The most significant advancement is observed in Attention-Based Sparse Graph Convolutional Neural Networks (ASGCNN), as proposed by Chang et al. (2023). These models integrate graph learning, attention mechanisms, and sparsity constraints into a unified framework. Graph convolution captures connectivity between EEG channels, attention mechanisms prioritize important features, and sparsity reduces redundant connections, improving efficiency and generalization. As a result, ASGCNN models achieve the highest accuracy, often exceeding 95–97%, and provide improved interpretability by identifying critical brain regions associated with Parkinson's disease.

Overall, the comparative analysis highlights a clear trend toward connectivity-aware and attention-driven models. While CNN and CNN-RNN models improved baseline performance, they are insufficient for capturing complex brain interactions. GNN-based models addressed this limitation by modeling EEG connectivity, and attention mechanisms further enhanced performance and interpretability. ASGCNN models represent the current state-of-the-art, offering the best balance between accuracy, robustness, and feature representation.

However, this progression also reveals a trade-off between performance and computational complexity. As models become more sophisticated, they require greater computational resources, making real-time deployment challenging. Additionally, issues such as lack of standardized datasets, inter-subject variability, and limited explainability remain significant challenges. Future research should focus on developing lightweight, interpretable, and scalable models that can be deployed in real-world clinical and wearable systems.

Discussion

Recent advancements in EEG-based Parkinson's disease detection highlight the importance of integrating spatial, temporal, and connectivity information. Traditional machine learning models are limited by their reliance on handcrafted features, which restrict their generalization capability. Deep learning models

such as CNN and RNN have improved performance by automating feature extraction; however, they fail to capture complex inter-channel relationships inherent in EEG signals. Graph Neural Networks address this limitation by modeling EEG as a network of interconnected nodes, aligning with the biological structure of the brain. This allows for better representation of neural connectivity and improves classification accuracy. Attention mechanisms further enhance model performance by focusing on relevant EEG channels, improving interpretability and robustness.

ASGCNN models combine graph convolution, attention mechanisms, and sparsity constraints, resulting in superior performance. These models reduce redundancy, improve efficiency, and achieve high accuracy in PD detection.

Despite these advancements, challenges remain:

- Data variability across subjects
- Lack of standardized datasets
- High computational complexity
- Limited interpretability

Future research should focus on developing lightweight, explainable models and integrating multimodal data for improved diagnosis.

Conclusion

This survey presented a comprehensive review of methods and architectures for Parkinson's disease recognition using EEG signals, focusing on attention-based sparse graph convolutional neural networks. The analysis demonstrates that deep learning techniques, particularly graph-based models, have significantly improved PD detection accuracy. Graph Neural Networks provide a powerful framework for modeling brain connectivity, addressing limitations of CNN-based approaches. Attention mechanisms enhance feature selection and interpretability, while sparsity constraints improve efficiency. ASGCNN models represent the state-of-the-art approach, achieving superior performance by combining these techniques. However, challenges such as data variability, computational complexity, and lack of explainability must be addressed.

Future research directions include:

- Explainable AI
- Multimodal data integration
- Real-time wearable systems

In conclusion, ASGCNN-based architectures hold significant promise for advancing EEG-based Parkinson's disease diagnosis and improving clinical outcomes.

References

- Chang, H., et al. (2023). EEG-based Parkinson's disease recognition via attention-based sparse graph convolutional neural network. *IEEE JBHI*. <https://doi.org/10.1109/JBHI.2023.3292452>
- Zafeiropoulos, N., et al. (2023). Graph neural networks for PD monitoring. *Sensors*. <https://doi.org/10.3390/s23218936>
- Li, J. P., et al. (2022). DL-based PD recognition survey. *Expert Systems with Applications*. <https://doi.org/10.1016/j.eswa.2022.118045>
- Tanveer, M., et al. (2022). PD diagnosis using neural networks. *Information Processing & Management*. <https://doi.org/10.1016/j.ipm.2022.102909>
- Saravanan, S., et al. (2022). AI PD review. <https://doi.org/10.1007/s11831-021-09678-0>
- Alzubaidi, M. (2021). Neural networks PD detection. <https://doi.org/10.3390/healthcare9060740>
- Shah, S. (2020). Hybrid EEG model. <https://doi.org/10.1016/j.neunet.2020.05.011>
- Naghsh, E. (2020). EEG spatial analysis. <https://doi.org/10.1007/s11760-019-01543-4>
- Hendricks, R. (2021). PD clustering. <https://doi.org/10.3390/diseases9071567>
- Khan, A. (2023). PD diagnostic review. <https://doi.org/10.3399/BJGP.2023.0001>
- Dong, G. (2023). GNN survey. <https://doi.org/10.1145/3560813>
- Zhang, L. (2023). GNN review. <https://doi.org/10.1002/ird3.20>
- Rahman, S. (2023). GNN EEG review.
- Mancazzo, V. (2026). EEG transformer. <https://doi.org/10.1016/j.bspc.2026.109811>
- Jibon, F. (2024). EEG PD detection. <https://doi.org/10.1177/20552076241297355>
- Shokrpour, S. (2025). ML PD. <https://doi.org/10.1038/s41531-025-01025-9>
- Zeng, Y. (2024). Graph EEG model. <https://doi.org/10.1016/j.neuroimage.2024.120000>