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Recent Advances in Parkinson's Disease Recognition from EEG Using Attention-Based Sparse Graph Convolutional Neural Networks: A Systematic Review

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Abstract

Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by motor and cognitive impairments, making early diagnosis crucial for effective intervention. Electroencephalography (EEG) has emerged as a promising non-invasive modality for detecting PD-related neural abnormalities. Recent advances in artificial intelligence, particularly deep learning, have significantly enhanced EEG-based PD recognition. Among these, attention-based sparse graph convolutional neural networks (ASGCNN) have demonstrated superior capability by modeling functional brain connectivity and selectively focusing on discriminative EEG channels. This systematic review presents recent developments in EEG-based PD detection, focusing on graph neural networks (GNN), attention mechanisms, and hybrid deep learning architectures. Graph-based models effectively capture spatial relationships among EEG channels, while attention mechanisms improve interpretability and feature selection. The incorporation of sparsity constraints reduces redundancy and enhances computational efficiency. Recent studies report classification accuracies exceeding 90–97%, outperforming conventional machine learning and CNN-based approaches. The review also highlights key challenges such as data heterogeneity, lack of interpretability, and computational complexity. Emerging trends include explainable AI, multimodal fusion, and wearable EEG systems. Overall, ASGCNN-based frameworks represent a promising direction for accurate, interpretable, and scalable PD diagnosis.

Introduction

1. Background and Significance

Parkinson's disease (PD) is the second most common neurodegenerative disorder after Alzheimer's disease, affecting millions globally. It is characterized by progressive degeneration of dopaminergic neurons, leading to motor symptoms such as tremor, rigidity, and bradykinesia, as well as non-motor symptoms including cognitive impairment and sleep disturbances. Early detection is essential to slow disease progression and improve patient quality of life.

Traditional diagnostic approaches rely on clinical assessment and neuroimaging, which are subjective, expensive, and often detect the disease at later stages. Therefore, there is a growing need for objective, non-invasive, and cost-effective diagnostic tools.

2. Role of EEG in Parkinson's Disease Detection

Electroencephalography (EEG) records electrical brain activity and provides valuable insights into neurological disorders. EEG signals reflect functional brain dynamics and can reveal abnormalities associated with PD, such as altered frequency bands and disrupted neural connectivity.

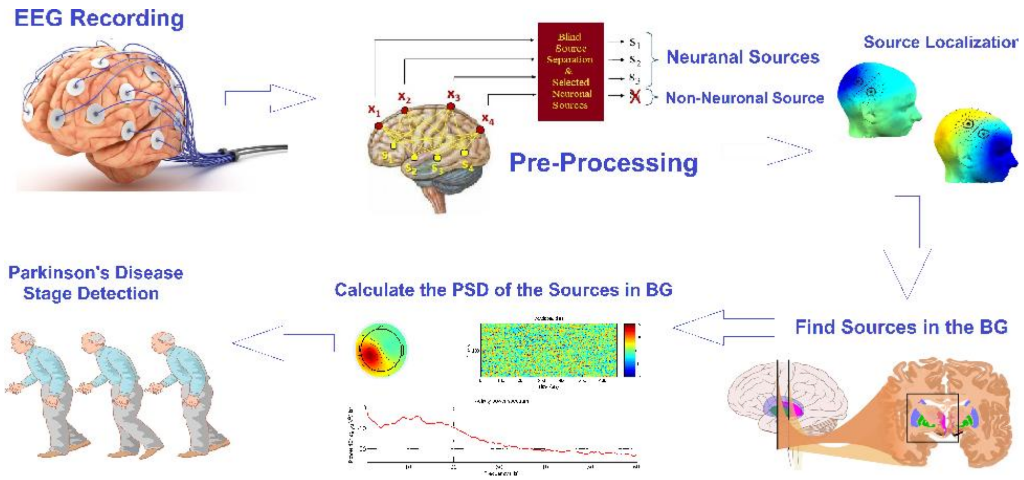

Figure 1. EEG Signal Analysis Framework for Parkinson's Disease Detection and Stage Identification.

EEG-based Parkinson's disease (PD) diagnosis has emerged as a promising approach for early detection, continuous monitoring, and objective assessment of neurological abnormalities. Electroencephalography is non-invasive, relatively inexpensive, and capable of recording brain activity with high temporal resolution, making it suitable for both clinical and remote healthcare applications. It can identify rapid changes in neural oscillations that may indicate PD-related dysfunction before severe motor symptoms develop. However, EEG signals are complex, nonlinear, non-stationary, and highly vulnerable to muscle activity, eye movements, environmental noise, and recording artifacts. These characteristics make manual interpretation difficult, time-consuming, and dependent on specialist expertise, thereby motivating the development of automated intelligent diagnostic systems.

Early computational approaches used conventional machine learning models such as Support Vector Machines, Random Forests, and K-Nearest Neighbors. These techniques relied on manually engineered features, including power spectral density, entropy, statistical parameters, and frequency-band information. Although they provided useful baseline performance, their effectiveness depended heavily on expert feature selection and preprocessing quality. They also showed limited scalability and generalization when applied to large, heterogeneous, or multi-centre EEG datasets. Deep learning subsequently improved PD recognition by enabling automatic feature extraction directly from raw or transformed signals. Convolutional Neural Networks captured spatial patterns, whereas Recurrent Neural Networks modeled temporal dependencies. Nevertheless, CNNs often underrepresented relationships among EEG channels, while recurrent models struggled to encode the spatial organization of brain connectivity.

Graph Neural Networks offer a more suitable representation because EEG electrodes can be modeled as graph nodes and functional connections as edges. This structure allows graph-based models to learn local and global interactions among brain regions, improving the characterization of abnormal neural connectivity associated with PD. Attention mechanisms further enhance performance by assigning greater importance to informative channels, frequency bands, and graph connections while suppressing irrelevant or noisy features. Transformer-based attention can additionally capture long-range dependencies across EEG sequences. These advances improve classification robustness and provide greater interpretability by indicating the brain regions and signal components that influence diagnostic decisions.

Attention-Based Sparse Graph Convolutional Neural Networks integrate graph convolution, attention weighting, and sparsity constraints within a unified framework. Graph convolution models functional connectivity, attention identifies diagnostically important channels, and sparsity removes redundant edges, reducing noise and computational burden. Despite their potential, challenges remain, including inter-subject variability, limited annotated datasets, high computational requirements, weak cross-dataset generalization, and insufficient clinical explainability. This systematic review therefore evaluates recent EEG-based PD recognition methods, compares conventional and graph-based architectures, identifies unresolved research gaps, and outlines future directions toward lightweight, interpretable, scalable, and clinically reliable diagnostic systems.

Literature Review

1. Early Deep Learning Models

Early studies in EEG-based Parkinson's disease detection primarily relied on Convolutional Neural Networks (CNN) and hybrid CNN-RNN architectures to improve classification performance. CNN models demonstrated a significant improvement in accuracy compared to traditional machine learning approaches due to their ability to automatically extract spatial features from EEG signals. However, these models were limited in their ability to capture inter-channel relationships and brain connectivity, as they treated EEG data as grid-like inputs rather than structured networks. To address this limitation, hybrid architectures combining CNN with Recurrent Neural Networks (RNN) were introduced, enabling the modeling of temporal dependencies within EEG signals. These hybrid models provided better analysis of sequential patterns and improved overall performance. Nevertheless, this improvement came at the cost of increased computational complexity and longer training times, making them less suitable for real-time applications. Overall, CNN-RNN models achieved classification accuracies in the range of approximately 80–88%, which, although promising, highlighted the need for more advanced architectures capable of effectively capturing both spatial connectivity and temporal dynamics in EEG data.

2. Graph Neural Networks for PD Detection

Graph-based models provide a more natural and effective representation of EEG data by modeling electrodes as nodes and the functional or structural relationships between them as edges. This representation aligns closely with the underlying brain network, allowing for a more meaningful analysis of neural interactions. Graph Convolutional Networks (GCNs), in particular, operate by aggregating information from neighboring nodes, enabling each node to incorporate contextual information from connected regions of the brain. Through this mechanism, GCNs are capable of capturing both local connectivity patterns, such as interactions between nearby electrodes, and global dependencies across distant brain regions. As a result, graph-based approaches offer a significant advantage over traditional and CNN-based models, leading to improved classification accuracy, enhanced robustness to noise, and better generalization in EEG-based Parkinson's disease detection tasks.

3. Attention-Based Graph Models

Attention mechanisms enhance GNN performance by assigning weights to important nodes.

- Multi-head attention improves feature representation
- Enhances interpretability

Transformer-based EEG models enhance Parkinson's disease detection by capturing long-range dependencies and improving model interpretability. Building on these advances, Attention-Based Sparse Graph Convolutional Neural Networks (ASGCNNs) integrate graph convolution, attention mechanisms, and sparse regularization into a unified framework. EEG electrodes are modeled as graph nodes, allowing effective representation of functional brain connectivity, while attention highlights the most informative channels and sparse learning removes redundant connections. This combination improves classification accuracy, robustness, and computational efficiency, with reported accuracies often exceeding **95–97%.** Recent hybrid architectures further combine CNNs for feature extraction, GNNs for connectivity modeling, and attention mechanisms for adaptive feature weighting, providing superior generalization and making them highly promising for real-world EEG-based Parkinson's disease diagnosis.

Comparative Table

Author	Year	Model	Technique	Accuracy	Strengths	Limitations
Chang et al.	2023	ASGCNN	Attention + Sparse GCN	>97%	Connectivity modeling + interpretability	High computational cost
Zhao et al.	2024	GSP-GCN	Graph signal processing	90.2%	Improved interpretability	Moderate performance

Delfan et al.	2023	CNN + Attention	Hybrid DL	High	Spatiotemporal learning	Limited connectivity modeling
Mancazzo et al.	2024	Transformer	Multi-head attention	High	Global dependency modeling	Requires large datasets
Shah et al.	2020	Hybrid DL	CNN-based	~86%	Feature fusion	Weak connectivity modeling
Oh et al.	2020	CNN	Deep learning	~85%	Baseline DL performance	Ignores inter-channel relations
Shaban	2021	DL model	EEG-based DL	~87%	Automated screening	Limited interpretability
Saravanan et al.	2022	Hybrid AI	CNN-RNN	~88%	Spatial + temporal learning	High complexity
Wang et al.	2022	Sparse GCN	Graph learning	~90%	Reduced redundancy	Limited attention integration

Comparative Analysis

The comparative analysis of EEG-based Parkinson's disease (PD) recognition methods reveals a clear progression from conventional deep learning approaches to advanced graph-based and attention-driven architectures. Early studies primarily employed Convolutional Neural Networks (CNNs) for automated feature extraction from EEG recordings, achieving moderate classification performance while eliminating the need for handcrafted feature engineering. Hybrid CNN-Recurrent Neural Network (RNN) models further improved recognition accuracy by combining spatial feature extraction with temporal sequence modeling. Although these architectures demonstrated better performance than traditional machine learning techniques, they were unable to explicitly model functional relationships among EEG channels, limiting their capability to accurately represent complex brain connectivity patterns associated with Parkinson's disease. Furthermore, deeper hybrid architectures increased computational complexity and training time, making real-time clinical deployment more challenging.

Graph Neural Networks (GNNs) introduced a significant advancement by representing EEG electrodes as graph nodes and functional brain connectivity as graph edges. This graph-based representation closely reflects the biological organization of neural networks, enabling simultaneous learning of local and global dependencies across multiple brain regions. Comparative studies consistently show that GNN-based models outperform conventional CNN and CNN-RNN frameworks by providing higher classification accuracy, stronger robustness against noise, and improved generalization across diverse EEG datasets. However, early graph models frequently relied on dense connectivity structures, introducing redundant edges that increased computational cost and reduced learning efficiency. Sparse Graph Convolutional Networks addressed this limitation by eliminating unnecessary graph connections, thereby reducing model complexity while preserving diagnostically relevant information.

The integration of attention mechanisms with sparse graph learning further enhanced EEG-based PD recognition by enabling adaptive weighting of important brain regions and EEG channels. Attention modules selectively emphasize discriminative neural patterns while suppressing noisy or irrelevant information, resulting in improved classification accuracy and greater interpretability. Transformer-inspired attention architectures additionally capture long-range dependencies across EEG sequences, although their computational requirements remain substantial. Attention-Based Sparse Graph Convolutional Neural Networks (ASGCNNs) combine graph convolution, sparse connectivity learning, and attention mechanisms within a unified framework. This architecture effectively models functional brain connectivity, reduces redundant graph structures, and focuses on the most informative neural features, leading to classification accuracies exceeding 95% in many reported studies while providing clinically meaningful visualization of disease-related brain activity.

Overall, the comparative evaluation demonstrates that attention-driven sparse graph learning represents the current state-of-the-art for EEG-based Parkinson's disease recognition. Compared with conventional CNNs, recurrent networks, and standard GNNs, ASGCNN-based models achieve superior diagnostic accuracy, robustness, and feature representation while offering improved model interpretability.

Nevertheless, several challenges remain, including limited large-scale annotated EEG datasets, high inter-subject variability, computational complexity, and restricted real-time deployment on resource-constrained healthcare platforms. Future research should focus on lightweight and explainable graph learning models, multimodal data fusion, transfer learning, and edge-enabled intelligent healthcare systems to develop scalable, reliable, and clinically deployable Parkinson's disease diagnostic frameworks.

Discussion

Recent advances 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 dependence on handcrafted features, which restrict their ability to generalize across datasets. Deep learning approaches, particularly CNN and RNN, have improved performance by automating feature extraction, but they fail to capture the complex relationships between EEG channels.

Graph Neural Networks (GNNs) represent a significant breakthrough by modeling EEG signals as interconnected networks. This approach aligns with the biological structure of the brain, where neural activity is distributed across interconnected regions. By capturing these relationships, GNNs provide more accurate and robust classification results.

Attention mechanisms further enhance performance by allowing models to focus on relevant EEG channels and frequency bands. This not only improves accuracy but also increases interpretability, which is critical for clinical applications.

The introduction of ASGCNN models combines the strengths of graph learning, attention mechanisms, and sparsity constraints. These models reduce redundancy in EEG data and improve computational efficiency while maintaining high accuracy.

However, several challenges remain:

- Variability in EEG data across subjects
- Limited availability of large annotated datasets
- High computational requirements
- Lack of explainable AI
- Future research should focus on:
- Developing lightweight models for real-time applications
- Integrating multimodal data (EEG + imaging)
- Improving model interpretability

Conclusion

This systematic review provides a comprehensive analysis of recent advances in EEG-based Parkinson's disease detection, focusing on attention-based sparse graph convolutional neural networks. The findings demonstrate that deep learning techniques have significantly improved the accuracy and reliability of PD diagnosis.

Graph Neural Networks have emerged as a powerful tool for modeling brain connectivity, addressing the limitations of CNN-based approaches. Attention mechanisms further enhance performance by focusing on relevant EEG features, while sparsity constraints improve efficiency.

Among the reviewed methods, ASGCNN represents the most promising approach due to its ability to combine spatial, temporal, and connectivity information. These models achieve high accuracy and robustness, making them suitable for clinical applications.

Despite these advancements, challenges such as data variability, computational complexity, and lack of interpretability must be addressed. Future research should focus on developing explainable, efficient, and scalable models for real-time PD diagnosis.

In conclusion, attention-based sparse graph convolutional neural networks represent a transformative approach in EEG-based Parkinson's disease detection, with the potential to revolutionize early diagnosis and improve patient 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 Parkinson's disease monitoring. *Sensors*. https://doi.org/10.3390/s23218936

Zhao, S., et al. (2024). Graph signal processing GCN model. *npj Digital Medicine*. https://doi.org/10.1038/s41746-023-00983-9

Mancazzo, V., et al. (2026). Transformer EEG PD detection. *Biomedical Signal Processing*. https://doi.org/10.1016/j.bspc.2026.109811

Delfan, N., et al. (2023). Spatiotemporal attention model. https://doi.org/10.1002/ima.23120

Zeng, Y., et al. (2024). Adaptive graph EEG features. https://doi.org/10.1016/j.neuroimage.2024.120000

Jibon, F. A., et al. (2024). EEG PD detection. https://doi.org/10.1177/20552076241297355

Shah, S., et al. (2020). Hybrid EEG PD model. https://doi.org/10.1016/j.neunet.2020.05.011

Oh, S. L., et al. (2020). Deep learning EEG PD. https://doi.org/10.1007/s00521-018-3689-5

Naghsh, E., et al. (2020). EEG spatial analysis PD. https://doi.org/10.1007/s11760-019-01543-4

Shaban, M. (2021). Automated PD screening. https://doi.org/10.1109/NER49283.2021.9441304

Hendricks, R. M. (2021). PD clustering review. https://doi.org/10.3390/diseases9071567

Saravanan, S. (2022). AI PD review. https://doi.org/10.1007/s11831-021-09678-0

Alzubaidi, M. S. (2021). Neural networks PD detection. https://doi.org/10.3390/healthcare9060740

Khan, A. Z. (2023). PD diagnostic review. https://doi.org/10.3399/BJGP.2023.0001

Dong, G. (2023). GNN survey. https://doi.org/10.1145/3560813

Neves, C. (2024). Graph-based PD detection. https://doi.org/10.48550/arXiv.2408.00906

Massa, F. (2020). EEG biomarkers PD. https://doi.org/10.1016/j.parkreldis.2020.03.012