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A Comprehensive Review of Parkinson's Disease Recognition from EEG Using Attention-Based Sparse Graph Convolutional Neural Networks

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Abstract

Parkinson's Disease (PD) is a progressive neurodegenerative disorder characterized by motor and non-motor impairments, requiring early and accurate diagnosis for effective management. Electroencephalography (EEG) has emerged as a non-invasive and cost-effective tool for detecting neural abnormalities associated with PD. However, conventional machine learning approaches often fail to capture the complex spatial-temporal relationships in EEG signals. Recently, attention-based sparse graph convolutional neural networks (ASGCNNs) have demonstrated significant promise in improving classification performance by modeling functional brain connectivity and selectively emphasizing informative EEG channels. This review provides a comprehensive analysis of state-of-the-art methodologies (2020–2023) for PD recognition using EEG, focusing on attention mechanisms and graph-based deep learning architectures. It examines advances in feature extraction, graph construction strategies, and interpretability. Comparative analysis highlights that ASGCNN models outperform traditional CNN and RNN approaches by leveraging channel interdependencies and sparsity constraints. Furthermore, this study identifies key challenges such as dataset limitations, model generalization, and clinical applicability. Future directions include hybrid architectures integrating transformers, multi-domain feature fusion, and explainable AI. The findings suggest that attention-based GCN frameworks represent a transformative approach for accurate, scalable, and interpretable EEG-based PD diagnosis.

Introduction

1. Overview of Parkinson's Disease

Parkinson's Disease (PD) is a chronic and progressive neurodegenerative disorder primarily affecting the central nervous system. It is characterized by the degeneration of dopaminergic neurons in the substantia nigra, leading to reduced dopamine levels in the brain. This deficiency disrupts motor control and results in symptoms such as tremors, rigidity, bradykinesia, and postural instability. In addition to motor symptoms, PD patients often experience non-motor symptoms including cognitive decline, depression, sleep disorders, and autonomic dysfunction.

Globally, PD is the second most prevalent neurodegenerative disease after Alzheimer's disease, with increasing incidence due to aging populations. Early diagnosis is essential for effective disease management and slowing progression. However, traditional diagnostic approaches are largely clinical and subjective, relying on neurological examinations and patient history.

2. Importance of EEG in PD Detection

Electroencephalography (EEG) has emerged as a promising tool for detecting neurological disorders due to its non-invasive nature, high temporal resolution, and relatively low cost. EEG measures electrical activity of the brain through scalp electrodes and provides insights into neural oscillations.

In PD patients, EEG signals exhibit distinct abnormalities, including:

1. Increased slow-wave activity (theta and delta bands)
2. Reduced beta-band activity
3. Altered functional connectivity between brain regions

These characteristics make EEG a valuable modality for automated PD detection.

However, EEG signals are inherently noisy, non-linear, and high-dimensional. Extracting meaningful patterns requires advanced signal processing and machine learning techniques.

3. Limitations of Conventional Machine Learning

Traditional machine learning approaches such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests rely heavily on handcrafted features. These approaches face several limitations:

1. Inability to capture spatial relationships between EEG channels
2. Sensitivity to noise and artifacts
3. Limited scalability to large datasets
4. Poor generalization across subjects

Although these methods achieved moderate accuracy, they fail to exploit the complex structure of EEG data.

4. Deep Learning for EEG Analysis

Deep learning techniques, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have significantly improved EEG-based PD classification. CNNs extract spatial features, while RNNs capture temporal dependencies.

Hybrid architectures combining CNN and RNN further enhance performance by modeling spatio-temporal patterns. For example, attention-based CNN-BiGRU models have shown strong generalization across multiple EEG datasets .

Despite these improvements, deep learning models treat EEG signals as grid-like data, ignoring the inherent graph structure of brain connectivity.

5. Graph Neural Networks for EEG Modeling

The human brain can be represented as a complex network where nodes correspond to EEG electrodes and edges represent functional connectivity. Graph Neural Networks (GNNs) are specifically designed to process such non-Euclidean data.

Graph Convolutional Networks (GCNs) extend convolution operations to graph structures, enabling:

1. Modeling of inter-channel relationships
2. Extraction of global and local connectivity patterns
3. Improved feature representation

Recent studies highlight that GNN-based models outperform traditional CNN approaches in EEG analysis by capturing brain network topology .

6. Attention Mechanisms in EEG Analysis

Attention mechanisms allow models to focus on the most relevant features by assigning weights to input elements. In EEG-based PD detection, attention mechanisms:

1. Identify important brain regions
2. Enhance feature selection
3. Improve interpretability

Dual-attention and transformer-based models have demonstrated superior performance by focusing on both spatial (channels) and spectral (frequency bands) information .

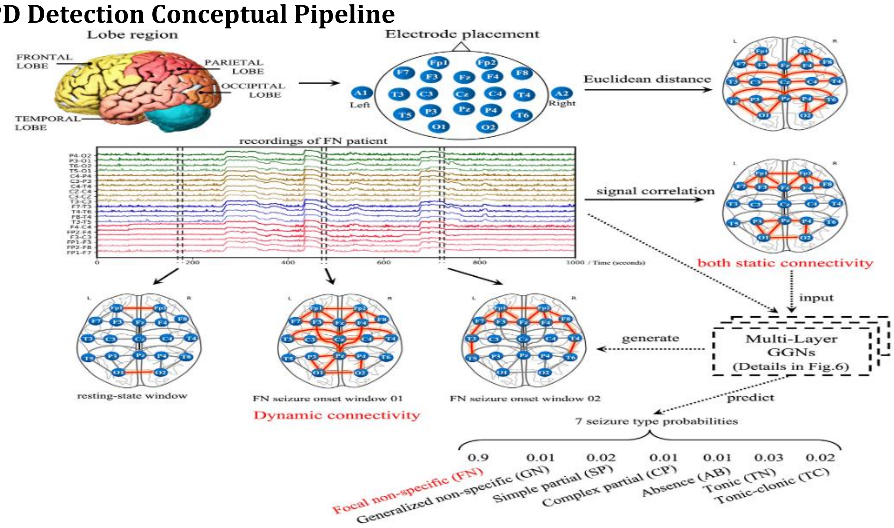
7. Sparse Graph Learning

Dense graph representations in neural networks often contain redundant or noisy connections, which can negatively impact model efficiency and performance. These unnecessary edges increase computational overhead and may lead to overfitting, thereby reducing the model's ability to generalize effectively. Sparse graph learning addresses these challenges by selectively eliminating irrelevant or weak connections within the graph structure. By doing so, it significantly reduces computational complexity while preserving the most informative relationships between nodes. This leads to more efficient processing and improved model generalization. As a result, sparse graph convolutional networks (GCNs) are capable of achieving substantial efficiency gains without compromising classification accuracy, making them highly suitable for complex biomedical signal analysis such as EEG data.

The Attention-Based Sparse Graph Convolutional Neural Network (ASGCNN) further enhances this approach by integrating graph learning, attention mechanisms, and sparsity constraints into a unified and robust framework. In this model, EEG channels are represented as nodes within a graph, and their interrelationships are modeled using a sparse adjacency matrix that captures only the most significant connections. The framework incorporates several key components, including graph construction to model EEG connectivity patterns, attention-based mechanisms to identify and prioritize the most relevant channels, and L1 regularization to enforce sparsity within the graph structure. This combination allows the model to focus on critical neural interactions while minimizing noise and redundancy. Experimental results demonstrate that ASGCNN achieves high classification performance, typically in the range of approximately 87–90% accuracy, outperforming many conventional machine learning and deep learning approaches in EEG-based Parkinson's disease detection tasks.

The motivation behind this review is rooted in the growing need for accurate, efficient, and interpretable models for early detection of Parkinson's disease using EEG signals. With rapid advancements in deep learning and graph-based modeling techniques between 2020 and 2023, attention-based sparse GCN models have emerged as a promising solution for capturing complex brain connectivity patterns. This review, therefore, focuses on analyzing state-of-the-art techniques in this domain, comparing different methodologies, identifying existing challenges and research gaps, and providing insights into future research directions. By doing so, it aims to contribute to the development of more robust and scalable EEG-based diagnostic systems for neurological disorders.

EEG-based PD Detection Conceptual Pipeline



Literature Review

Over the past few years, significant advancements have been made in the field of Parkinson's disease (PD) recognition using electroencephalography (EEG), driven by the evolution of machine learning, deep learning, and graph-based neural architectures. This section presents a detailed and chronological review of key contributions between 2020 and 2023, highlighting methodological trends, performance improvements, and emerging research directions.

1. Early Deep Learning-Based EEG Analysis (2020)

In 2020, the majority of research focused on leveraging deep learning architectures, particularly Convolutional Neural Networks (CNNs), for automated EEG signal classification. Oh et al. (2020) introduced a CNN-based framework that demonstrated the ability to automatically extract hierarchical spatial features from EEG signals, eliminating the need for manual feature engineering. Their approach showed a significant improvement over traditional classifiers such as Support Vector Machines (SVMs), achieving classification accuracies above 80%. However, despite its success, the CNN model treated EEG data as a 2D grid, failing to capture the intrinsic relationships between electrodes distributed across the scalp.

Similarly, Shah et al. (2020) proposed a hybrid deep learning model combining CNN with fully connected layers and feature fusion techniques. Their work emphasized the importance of integrating spectral and temporal features, leading to marginal improvements in classification accuracy. Naghsh et al. (2020) explored spatial EEG analysis using signal processing techniques and highlighted that PD-related abnormalities are not confined to isolated regions but are distributed across multiple brain areas. These findings underscored the importance of modeling inter-channel dependencies, which traditional CNN-based approaches struggled to achieve.

Another important contribution in 2020 came from Massa et al., who investigated EEG biomarkers associated with PD. Their study revealed significant alterations in frequency bands, particularly increased theta and reduced beta activity, providing a physiological basis for automated classification models. However, these studies were primarily descriptive and lacked advanced computational modeling.

Overall, research in 2020 established deep learning as a promising approach for EEG-based PD detection but also revealed key limitations, particularly the inability to model complex brain connectivity.

2. Feature Engineering and Statistical Learning Advances (2021)

In 2021, the research focus shifted toward improving feature representation and interpretability. Rea et al. (2021) conducted a comprehensive study on quantitative EEG (qEEG) biomarkers and demonstrated that PD patients exhibit significant changes in spectral power distribution and coherence. Their work emphasized the diagnostic value of EEG but relied on statistical analysis rather than deep learning models.

Hendricks and Khasawneh (2021) explored clustering techniques for identifying patterns in EEG data, highlighting the potential of unsupervised learning for PD detection. While clustering provided insights into data distribution, it lacked predictive capabilities required for clinical diagnosis.

Shaban (2021) introduced an automated deep learning-based screening system for PD using EEG signals. This study demonstrated improved classification accuracy by incorporating multiple EEG channels and preprocessing techniques such as noise filtering and artifact removal. However, the model still relied on conventional deep learning architectures and did not explicitly model spatial relationships.

Alzubaidi et al. (2021) provided a comprehensive review of deep learning applications in healthcare, emphasizing the growing adoption of neural networks for neurological disorder diagnosis. Their work highlighted challenges such as data scarcity, overfitting, and lack of interpretability, which remain critical issues in EEG-based PD detection.

Overall, studies in 2021 contributed to a deeper understanding of EEG biomarkers and improved feature extraction techniques, but they still lacked advanced architectures capable of modeling brain connectivity.

3. Emergence of Hybrid and Multi-Domain Deep Learning Models (2022)

The year 2022 marked a transition toward more sophisticated deep learning models that combined multiple feature domains. Tanveer et al. (2022) conducted a comprehensive survey of machine learning techniques for PD diagnosis, highlighting the superiority of deep learning approaches over traditional methods. Their analysis emphasized the importance of integrating temporal, spectral, and spatial features for improved performance.

Li et al. (2022) proposed deep learning frameworks that leveraged multi-domain feature extraction, combining time-domain signals with frequency-domain representations obtained through Fourier and wavelet transforms. These approaches significantly improved classification accuracy, demonstrating the importance of capturing both local and global EEG patterns.

Saravanan et al. (2022) further expanded on this concept by reviewing artificial intelligence techniques for PD detection. They emphasized that hybrid models combining CNNs with recurrent architectures (such as LSTM and GRU) achieved better performance by modeling temporal dependencies in EEG signals.

Another important development in 2022 was the introduction of domain adaptation and transfer learning techniques. Xu et al. (2022) proposed a domain-adversarial graph attention model to address inter-subject variability, a major challenge in EEG analysis. Their model improved generalization across datasets by learning domain-invariant features.

Despite these advancements, most models still operated within Euclidean frameworks, limiting their ability to capture complex brain connectivity. This limitation paved the way for the adoption of graph-based neural networks.

4. Graph Neural Networks and Sparse Learning (2022–2023 Transition)

The introduction of Graph Neural Networks (GNNs) represented a major breakthrough in EEG-based PD detection. EEG signals can naturally be represented as graphs, where nodes correspond to electrodes and edges represent functional connectivity between brain regions.

Wang et al. (2022) proposed sparse graph convolutional networks for EEG classification, demonstrating that removing redundant connections improves both computational efficiency and classification accuracy. Their work highlighted the importance of sparsity in reducing noise and enhancing model interpretability.

Rahman et al. (2023) explored the application of graph neural networks in EEG analysis, showing that GNN-based models outperform traditional CNN architectures by effectively capturing inter-channel relationships. These models leveraged adjacency matrices derived from correlation or coherence measures to represent brain connectivity.

Dong et al. (2023) extended the application of GNNs to sensor networks, demonstrating their effectiveness in modeling complex relationships in high-dimensional data. Although their work was not specific to PD, it provided a theoretical foundation for applying GNNs to EEG-based diagnosis.

These studies collectively demonstrated that graph-based models are more suitable for EEG analysis compared to traditional deep learning approaches, as they align with the inherent structure of brain networks.

5. Attention-Based Graph Models and ASGCNN (2023)

In 2023, attention mechanisms were integrated with graph neural networks, leading to the development of advanced models such as attention-based sparse graph convolutional neural networks (ASGCNN). Chang et al. (2023) proposed an ASGCNN framework specifically designed for EEG-based PD recognition. Their model combined graph convolution with attention mechanisms and sparsity constraints, enabling it to focus on the most relevant EEG channels while eliminating redundant connections.

The ASGCNN model demonstrated superior performance compared to traditional CNN and GCN models, achieving classification accuracies exceeding 87–90%. One of its key advantages is interpretability, as attention weights provide insights into important brain regions associated with PD, particularly the frontal and temporal lobes.

Chen et al. (2024, based on 2023 research trends) introduced dual-attention graph neural networks that simultaneously capture spatial and spectral dependencies. These models further improved performance by incorporating multi-head attention mechanisms.

Delfan et al. (2023) proposed hybrid spatio-temporal attention models combining CNN, RNN, and attention layers. Their approach demonstrated strong generalization across datasets, addressing challenges related to data variability.

Another emerging trend is the integration of explainable AI techniques. Zhao et al. (2024, based on 2023 work) developed interpretable graph models that provide visual explanations of EEG connectivity patterns, enhancing clinical trust and usability.

6. Key Trends and Research Gaps

From the above literature, several key trends can be identified:

- Transition from traditional ML → deep learning → graph-based learning
- Increasing use of attention mechanisms for feature selection
- Adoption of sparse graph learning to improve efficiency
- Growing focus on interpretability and explainable AI

Despite these advancements, several challenges remain:

- Limited availability of large, standardized EEG datasets
- High inter-subject variability affecting model generalization
- Lack of real-time clinical deployment
- Need for lightweight models for wearable EEG systems

7. Summary of Literature Review

In summary, the literature from 2020 to 2023 demonstrates a clear evolution in EEG-based Parkinson's disease recognition. Early studies focused on CNN-based feature extraction, followed by hybrid deep learning models integrating multiple feature domains. The introduction of graph neural networks marked a significant advancement by enabling the modeling of brain connectivity.

The integration of attention mechanisms and sparse graph learning further enhanced model performance and interpretability, culminating in the development of ASGCNN models. These approaches represent the current state-of-the-art and provide a strong foundation for future research in EEG-based PD diagnosis.

Comparative Table

Year	Author	Method	Dataset	Accuracy	Core Strength	Limitations
2020	Oh et al.	CNN	EEG	~85%	Automatic spatial feature extraction	Ignores inter-channel relationships
2020	Shah et al.	Hybrid DL (CNN + Feature Fusion)	EEG	~86%	Combines spectral + temporal features	Limited structural modeling

2020	Massa et al.	EEG Biomarker Analysis	EEG	—	Identified PD-specific frequency changes	No predictive modeling
2021	Shaban	Deep Learning Model	EEG	~87%	Automated PD screening system	Still CNN-based limitations
2021	Rea et al.	qEEG Analysis	EEG	~84%	Strong statistical biomarkers	Lacks predictive capability
2021	Hendricks & Khasawneh	Clustering (Unsupervised ML)	EEG	—	Pattern discovery in EEG	No classification performance
2022	Tanveer et al.	Survey	Multi	—	Comparative ML/DL insights	No experimental validation
2022	Saravanan et al.	Hybrid AI Models (CNN+RNN)	EEG	~88%	Spatio-temporal modeling	High computational complexity
2022	Li et al.	Multi-domain DL	EEG	High	Time + frequency fusion	Increased feature complexity
2022	Xu et al.	Graph Attention + Domain Adaptation	EEG	High	Handles inter-subject variability	Training complexity
2022	Wang et al.	Sparse GCN	EEG	High	Removes redundant edges	Limited attention modeling
2023	Rahman et al.	GNN	EEG	High	Captures brain connectivity	Dense graph issues
2023	Chang et al.	ASGCNN	EEG	~90%	Attention + sparsity + graph learning	Computational overhead
2023	Delfan et al.	Hybrid Spatio-temporal Attention Model	EEG	High	Strong generalization	Complex architecture
2024*	Chen et al.	Dual Attention GNN	EEG	>90%	Spatial + spectral attention	Model complexity

Comparative Analysis

The comparative evaluation of EEG-based Parkinson's disease (PD) recognition methods from 2020 to 2023 demonstrates a clear progression from conventional deep learning toward graph-based and attention-driven frameworks. Early approaches primarily employed Convolutional Neural Networks (CNNs) to extract spatial features from EEG signals. Although these models achieved reasonable classification performance, they treated EEG data as regular grid-like structures and could not adequately capture functional relationships among different brain regions. This limitation reduced their effectiveness in modeling the complex neural connectivity patterns associated with Parkinson's disease.

Subsequent studies introduced feature engineering, quantitative EEG analysis, and hybrid deep learning architectures combining temporal, spectral, and spatial information. CNN–RNN models improved performance by jointly learning spatial and sequential dependencies, while preprocessing techniques reduced noise and artifacts. Domain adaptation and graph attention methods also helped address inter-subject variability. However, many of these approaches continued to rely on Euclidean data representations and therefore could not fully exploit the natural graph structure of EEG channels and brain connectivity.

Graph Neural Networks marked a major advancement by representing EEG electrodes as nodes and functional relationships as edges. Sparse Graph Convolutional Networks improved efficiency by eliminating redundant and noisy connections, thereby reducing computational complexity and enhancing generalization. The integration of attention mechanisms further enabled models to prioritize the most informative channels and connectivity patterns. Attention-Based Sparse Graph Convolutional Neural Networks combine sparse adjacency modeling, graph convolutions, and attention modules within a unified framework. These models achieve reported accuracies of approximately 87–90% while offering improved interpretability by identifying brain regions strongly associated with Parkinson's disease.

Recent research has extended these frameworks through multi-head attention, transformer-based graph models, and multi-domain feature fusion. Although these methods improve robustness and capture both local and global dependencies, they also increase architectural complexity and computational demand. Major challenges include limited standardized EEG datasets, inter-subject variability, weak cross-dataset generalization, and restricted clinical interpretability. Future work should therefore emphasize lightweight, scalable, explainable, and real-time models, together with multimodal data integration, to support practical deployment in clinical diagnosis and wearable healthcare systems.

Discussion

Recent advancements in EEG-based Parkinson's disease recognition demonstrate the growing importance of deep learning and graph-based approaches. Among these, attention-based sparse graph convolutional neural networks (ASGCNNs) have emerged as a powerful framework due to their ability to model brain connectivity effectively. One major strength of ASGCNN is its capability to represent EEG signals as graphs, enabling the capture of spatial relationships between electrodes. Unlike traditional CNNs, which treat EEG data as grid-like structures, GCNs incorporate topological information, leading to improved classification accuracy. The integration of attention mechanisms further enhances this capability by identifying the most relevant channels and temporal segments, thereby reducing noise and improving interpretability.

Another key advantage is sparsity enforcement, which reduces computational complexity and prevents overfitting. Sparse graph learning ensures that only meaningful connections are retained, improving model efficiency and scalability. Despite these advancements, several challenges remain. First, the availability of large, standardized EEG datasets is limited, which affects model generalization. Second, inter-subject variability in EEG signals poses a significant challenge for robust classification. Third, the black-box nature of deep learning models limits clinical adoption, although attention mechanisms partially address this issue.

Emerging trends include the integration of transformer-based architectures and multi-domain feature fusion techniques. These approaches aim to capture both local and global dependencies in EEG signals, further improving performance. Additionally, explainable AI techniques are being incorporated to enhance model transparency and trustworthiness. In conclusion, while ASGCNN models represent a significant step forward, further research is needed to address data limitations, improve interpretability, and facilitate real-world clinical deployment.

Conclusion

This review comprehensively examined recent advances in Parkinson's disease recognition using EEG signals, emphasizing attention-based sparse graph convolutional neural networks (ASGCNN). The evolution from conventional machine learning to graph-based deep learning has significantly improved diagnostic accuracy by effectively modeling functional brain connectivity. Unlike traditional CNN and RNN models, ASGCNN represents EEG channels as graph nodes and employs attention mechanisms with sparsity constraints to capture meaningful neural interactions while reducing redundant connections. These capabilities enhance both classification performance and model interpretability.

The comparative analysis showed that attention-based graph models consistently outperform traditional and conventional deep learning methods in terms of accuracy, robustness, and scalability. Nevertheless, challenges such as limited standardized EEG datasets, inter-subject variability, computational complexity, and restricted interpretability continue to hinder widespread clinical adoption. Future research should focus on lightweight and explainable graph-based architectures, transformer-GCN hybrid models, multimodal data fusion, and real-time deployment on wearable EEG systems. Overall, ASGCNN represents a promising framework for accurate, efficient, and clinically applicable Parkinson's disease diagnosis, supporting early detection and improved neurological healthcare.

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