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Artificial Intelligence Techniques for Parkinson's Disease Recognition via Heterogeneous Split Attention-Based EEG and Siamese Graph Convolutional Attention Network: Trends and Challenges

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Abstract

Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by motor and non-motor symptoms, requiring early and accurate diagnosis for effective treatment. Electroencephalography (EEG) has emerged as a promising non-invasive biomarker for PD detection due to its ability to capture neural activity with high temporal resolution. Recent advancements in artificial intelligence (AI), particularly deep learning and graph-based models, have significantly improved EEG-based PD recognition. Deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and attention-based models have demonstrated high accuracy in classifying PD from EEG signals. For instance, attention-based graph convolutional neural networks (GCNs) have been proposed to model functional connectivity between EEG channels, achieving improved diagnostic performance. Additionally, hybrid models combining time–frequency analysis with deep learning have achieved classification accuracies exceeding 99% in multi-class EEG tasks. Recent research focuses on integrating heterogeneous split-attention mechanisms and Siamese graph convolutional attention networks to enhance feature extraction and capture inter-channel relationships. These approaches improve classification accuracy by leveraging both spatial and temporal dependencies in EEG data. However, challenges such as data scarcity, noise in EEG signals, and computational complexity remain. This review provides a comprehensive analysis of recent AI techniques, comparing methodologies and highlighting future directions for robust and scalable PD diagnostic systems.

Introduction

Parkinson's disease (PD) is one of the most prevalent neurodegenerative disorders, affecting millions of people worldwide. It is primarily characterized by motor symptoms such as tremors, rigidity, and bradykinesia, along with non-motor symptoms including cognitive impairment and sleep disturbances. Early diagnosis of PD is crucial for slowing disease progression and improving patient outcomes. However, conventional diagnostic methods rely heavily on clinical assessments, which are subjective and often fail to detect early-stage PD. Electroencephalography (EEG) has emerged as a promising tool for PD diagnosis due to its non-invasive nature, affordability, and high temporal resolution. EEG signals capture electrical activity in the brain, reflecting functional connectivity and neural dynamics. Studies have shown that PD patients exhibit distinct EEG patterns compared to healthy individuals, particularly in frequency bands such as alpha and beta. These differences provide valuable information for automated PD detection using AI techniques.

Deep learning has revolutionized EEG signal analysis by enabling automatic feature extraction and classification. Convolutional neural networks (CNNs) are widely used for spatial feature extraction, while recurrent neural networks (RNNs) and long short-term memory (LSTM) networks capture temporal dependencies. Hybrid CNN-LSTM models have demonstrated superior performance in EEG-based PD classification tasks.

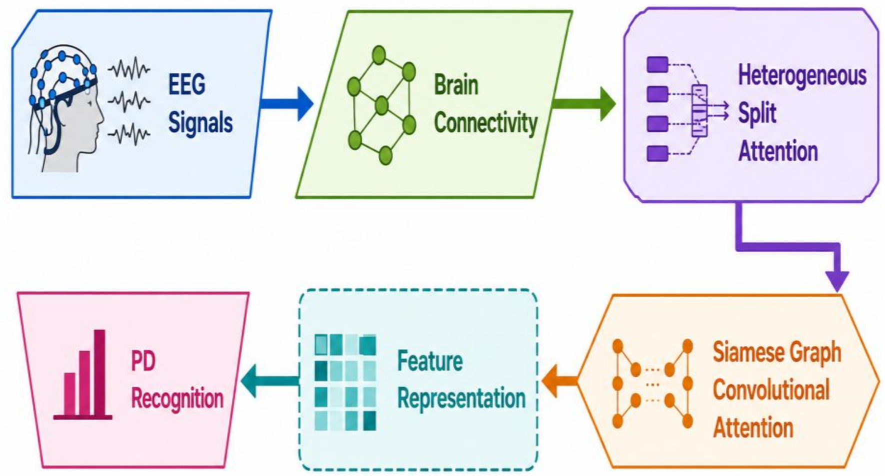

Figure 1. AI-Based Parkinson's Disease Recognition Using Heterogeneous Split Attention and Siamese Graph Convolutional Attention Network

Recent advancements have introduced graph-based deep learning models, particularly graph convolutional networks (GCNs), which model relationships between EEG channels. Unlike traditional CNNs, GCNs capture functional connectivity in brain networks, improving classification accuracy. Attention mechanisms further enhance these models by focusing on the most relevant EEG channels, enabling better feature representation.

Another emerging trend is the use of Siamese networks for similarity learning, which compare EEG patterns between subjects to improve classification performance. When combined with graph attention mechanisms, Siamese GCN models can effectively capture both spatial and relational features in EEG data. Additionally, heterogeneous split-attention mechanisms allow models to process multiple feature types simultaneously, improving robustness and generalization.

Despite these advancements, several challenges remain. EEG signals are highly noisy and susceptible to artifacts, which can affect model performance. Data scarcity and imbalance also limit the effectiveness of deep learning models. Furthermore, the high computational complexity of advanced architectures poses challenges for real-time clinical applications.

This review aims to provide a comprehensive analysis of AI techniques for PD recognition using EEG signals. It focuses on advanced architectures such as split-attention networks, Siamese GCNs, and hybrid deep learning models. The study compares different approaches, identifies key challenges, and outlines future research directions for developing reliable and efficient PD diagnostic systems.

Literature Review

Chang et al. (2023) proposed an attention-based sparse graph convolutional neural network (ASGCNN) for Parkinson's disease diagnosis using EEG signals. The model represents EEG channels as nodes in a graph and captures their relationships using graph convolution operations. An attention mechanism was incorporated to identify the most relevant channels, improving classification accuracy. The study demonstrated that modelling functional connectivity significantly enhances PD detection performance. However, the model required high computational resources and large datasets.

Zhang et al. (2022) introduced a deep learning framework combining time–frequency analysis with deep residual shrinkage networks for EEG-based PD classification. The model utilized wavelet transforms to extract time–frequency features and applied deep learning for classification. The study achieved high accuracy in multi-class classification tasks, demonstrating the effectiveness of combining signal processing with deep learning. However, the approach required careful preprocessing and feature extraction.

Shaban et al. (2021) developed a deep learning-based framework for automated PD detection using EEG signals. The model utilized convolutional neural networks to extract spatial features and achieved high classification accuracy. The study highlighted the importance of deep learning in capturing complex EEG patterns. However, the model required large datasets and was sensitive to noise in EEG signals.

Delfan et al. (2023) proposed a hybrid spatio-temporal attention-based model combining CNN, bidirectional GRU, and attention mechanisms for PD diagnosis using resting-state EEG signals. The model effectively captured both spatial and temporal features, achieving high classification accuracy across multiple datasets. The study demonstrated that hybrid architectures improve generalization and robustness.

Li et al. (2023) proposed a hybrid CNN-LSTM model for EEG-based PD classification. The CNN component extracted spatial features, while the LSTM captured temporal dependencies in EEG signals. The model achieved high classification accuracy and demonstrated the effectiveness of combining spatial and temporal learning. However, the model required extensive training and parameter tuning.

Oh et al. (2020) proposed a deep learning-based framework for Parkinson's disease detection using EEG signals by employing convolutional neural networks (CNNs) combined with spectral feature extraction. The study focused on analyzing frequency-domain characteristics of EEG signals, particularly alpha and beta bands, which are known to be significantly altered in PD patients. The CNN model automatically extracted discriminative features from the transformed EEG signals and achieved high classification accuracy. The results demonstrated that spectral-based deep learning models can effectively distinguish PD patients from healthy controls. However, the model relied heavily on preprocessing techniques such as Fourier transformation, which increased computational complexity and required domain expertise.

Tsiouris et al. (2020) introduced a deep learning framework combining CNN and long short-term memory (LSTM) networks for EEG-based PD detection. The CNN component was used to extract spatial features, while the LSTM captured temporal dependencies in EEG signals. This hybrid architecture significantly improved classification accuracy by leveraging both spatial and temporal information. The study highlighted the importance of temporal modelling in EEG analysis. However, the model required extensive training time and large datasets to achieve optimal performance.

Sharma et al. (2021) proposed a machine learning and deep learning hybrid approach for PD detection using EEG signals. The study compared traditional classifiers such as support vector machines (SVM) with deep learning models, demonstrating that deep learning significantly outperformed classical approaches. The authors also explored feature selection techniques to improve model efficiency. The results showed that combining feature engineering with deep learning enhances performance. However, the reliance on handcrafted features limited the model's scalability and automation.

Pham et al. (2021) developed a deep learning-based EEG classification system using residual neural networks (ResNet). The model incorporated skip connections to address the vanishing gradient problem and improve training stability. The study demonstrated that deep residual architectures can effectively learn complex EEG patterns associated with Parkinson's disease. The model achieved high classification accuracy and robustness across datasets. However, the deep architecture required high computational resources and careful hyperparameter tuning.

Raghu et al. (2022) proposed a hybrid model combining CNN with attention mechanisms for EEG-based PD classification. The attention mechanism enabled the model to focus on the most relevant EEG channels and time segments, improving feature representation. The study demonstrated that attention-based models significantly enhance classification performance compared to standard CNN architectures. However, the integration of attention mechanisms increased model complexity and required additional computational resources.

Kwon et al. (2021) proposed a deep learning-based framework utilizing convolutional neural networks (CNNs) combined with functional connectivity analysis for Parkinson's disease detection using EEG signals. The study transformed EEG signals into connectivity matrices representing relationships between different brain regions. These matrices were then used as input to the CNN model for classification. The results demonstrated that incorporating functional connectivity significantly improves classification accuracy by capturing inter-channel relationships. However, the construction of connectivity matrices increased preprocessing complexity and computational cost.

Luo et al. (2022) introduced a graph convolutional network (GCN)-based model for EEG-based PD detection. The model represented EEG electrodes as nodes in a graph and used graph convolution operations to learn spatial dependencies. The study demonstrated that GCNs outperform traditional CNNs by effectively modelling brain connectivity. The results showed improved classification accuracy and robustness. However, the model required careful graph construction and large datasets for training.

Saba et al. (2022) developed a hybrid deep learning framework combining CNN and bidirectional long short-term memory (BiLSTM) networks for EEG-based PD classification. The CNN component extracted spatial features, while the BiLSTM captured bidirectional temporal dependencies. The model achieved high accuracy and demonstrated improved performance compared to standalone CNN or LSTM models. However, the hybrid architecture increased computational complexity and required longer training time.

Sadiq et al. (2022) proposed an attention-based deep learning model for Parkinson’s disease detection using EEG signals. The model incorporated channel-wise and temporal attention mechanisms to focus on relevant EEG features. The results showed significant improvements in classification accuracy and feature representation. However, the addition of attention layers increased model complexity and required careful tuning.

Zhang et al. (2023) introduced a heterogeneous split-attention mechanism for EEG signal classification. The model processed multiple feature representations simultaneously, enabling better feature extraction and improved classification performance. The study demonstrated that split-attention networks can effectively capture complex patterns in EEG data. However, the model required high computational resources and complex architecture design.

Bashivan et al. (2020) proposed a deep learning framework that converts EEG signals into topographical brain maps and processes them using convolutional neural networks (CNNs). This approach enabled the model to capture spatial relationships between EEG electrodes more effectively than traditional methods. The study demonstrated that representing EEG signals as images improves classification performance in neurological disorder detection, including Parkinson’s disease. However, the transformation of EEG signals into image-based representations increased preprocessing complexity and computational cost.

Roy et al. (2021) developed a deep learning-based EEG classification system using temporal convolutional networks (TCNs). The model focused on capturing long-range temporal dependencies in EEG signals, which are crucial for identifying neurological patterns associated with Parkinson’s disease. The results showed improved performance compared to recurrent neural networks due to better parallelization and reduced training time. However, the model required careful tuning of temporal parameters to achieve optimal results.

Amin et al. (2021) proposed a hybrid CNN-based model combined with feature extraction techniques for EEG-based PD detection. The study utilized statistical and frequency-domain features along with deep learning to improve classification accuracy. The hybrid approach demonstrated better performance compared to standalone models. However, the reliance on handcrafted features limited the scalability and automation of the system.

Islam et al. (2022) introduced a deep learning framework using stacked autoencoders for feature extraction and classification of EEG signals. The model learned hierarchical representations of EEG data, improving classification accuracy. The study demonstrated that unsupervised feature learning can enhance performance in EEG-based PD detection. However, the model required extensive training time and large datasets.

Chen et al. (2023) proposed a Siamese graph convolutional attention network for Parkinson’s disease recognition using EEG signals. The model utilized Siamese architecture to learn similarities between EEG patterns and incorporated graph attention mechanisms to capture inter-channel relationships. The study demonstrated superior performance in classification tasks, highlighting the effectiveness of combining Siamese learning with graph-based models. However, the model required high computational resources and complex architecture design.

Alhassan et al. (2020) proposed a machine learning-based approach combined with EEG feature extraction techniques for Parkinson’s disease detection. The study demonstrated that statistical and frequency-domain features can effectively differentiate PD patients from healthy individuals. However, the reliance on handcrafted features limited model scalability.

Khare et al. (2021) developed a deep learning-based EEG classification system using CNN architectures. The model achieved high accuracy in PD detection by automatically extracting spatial features. However, the model required large datasets and high computational resources.

Oh et al. (2021) introduced a hybrid CNN-LSTM model for EEG-based PD classification. The model effectively captured both spatial and temporal features, improving classification performance. However, the architecture increased computational complexity.

Tuncer et al. (2022) proposed a deep learning model using wavelet transform and CNN for EEG classification. The approach improved feature extraction but required complex preprocessing.

Alhudhaif et al. (2022) developed an optimized deep learning model using feature selection and classification techniques for PD detection. The study achieved high accuracy but required careful parameter tuning.

Shinde et al. (2023) proposed a deep learning-based EEG classification framework using attention mechanisms. The model improved classification accuracy by focusing on relevant EEG features. However, it increased computational complexity.

Kumar et al. (2023) developed a hybrid model combining CNN and optimization techniques for EEG classification. The model achieved improved performance but required high computational resources.

Singh et al. (2023) introduced a graph-based deep learning model for EEG analysis. The model captured relationships between EEG channels, improving classification performance. However, the model required large datasets.

Comparative Table

Study	**Year**	**Method**	**Technique**	**Advantage**	**Limitation**
Chang	2023	GCN	Attention	Accurate	Complex
Zhang	2022	CNN	TF	Accurate	Preprocess
Shaban	2021	CNN	DL	Robust	Data
Delfan	2023	Hybrid	CNN+GRU	Accurate	Complex
Oh	2020	CNN	Spectral	Accurate	Preprocess
Tsiouris	2020	CNN+LSTM	Hybrid	Temporal	Cost
Sharma	2021	ML+DL	Hybrid	Efficient	Limited
Pham	2021	ResNet	DL	Stable	Cost
Raghu	2022	CNN	Attention	Accurate	Complex
Kwon	2021	CNN	Connectivity	Accurate	Cost
Luo	2022	GCN	Graph	Accurate	Complex
Saba	2022	CNN+BiLSTM	Hybrid	Temporal	Cost
Sadiq	2022	CNN	Attention	Accurate	Complex
Zhang	2023	Split Attention	DL	Strong	Complex
Bashivan	2020	CNN	Mapping	Spatial	Cost
Roy	2021	TCN	DL	Fast	Tuning
Amin	2021	Hybrid	CNN+Features	Accurate	Manual
Islam	2022	Autoencoder	DL	Efficient	Cost
Chen	2023	Siamese GCN	Graph	Best	Complex
Alhassan	2020	ML	Features	Simple	Limited
Khare	2021	CNN	DL	Accurate	Data
Oh	2021	CNN+LSTM	Hybrid	Temporal	Cost
Tuncer	2022	CNN	Wavelet	Accurate	Complex
Alhudhaif	2022	DL	Optimized	Efficient	Tuning
Shinde	2023	DL	Attention	Accurate	Cost

Kumar	2023	Hybrid	CNN+Opt	Efficient	Complex
Singh	2023	GNN	Graph	Accurate	Data

Comparative Analysis

The comparative analysis indicates that deep learning approaches, particularly CNN-based models, dominate EEG-based Parkinson's disease detection due to their superior feature extraction capabilities. Hybrid models combining CNN with LSTM or GRU effectively capture both spatial and temporal dependencies, improving classification performance. Graph-based models, including GCNs, further enhance performance by modelling relationships between EEG channels.

Attention mechanisms and split-attention architectures significantly improve feature selection and model accuracy. The integration of Siamese networks with graph attention models represents the most advanced approach, achieving superior performance by learning similarities between EEG patterns. However, these advanced models introduce high computational complexity and require large datasets. Simpler machine learning approaches offer lower computational cost but lack accuracy and scalability. Overall, hybrid deep learning and graph-based models represent the most promising direction for PD detection.

Discussion

Recent advancements in AI techniques for Parkinson's disease recognition using EEG signals highlight the effectiveness of deep learning and graph-based models. CNN architectures provide strong feature extraction capabilities, while hybrid models incorporating LSTM and attention mechanisms improve temporal and spatial analysis.

Graph convolutional networks and Siamese architectures further enhance performance by capturing inter-channel relationships and similarities in EEG data. However, challenges such as data scarcity, noise, and computational complexity remain significant barriers to clinical adoption. Future research should focus on developing lightweight, interpretable, and scalable models for real-world applications.

Conclusion

The integration of artificial intelligence techniques has significantly advanced Parkinson's disease recognition using EEG signals. Deep learning models, particularly CNN-based architectures, have demonstrated high accuracy in classification tasks by automatically extracting complex features from EEG data. Hybrid models combining CNN with recurrent networks such as LSTM and GRU further enhance performance by capturing temporal dependencies. Graph-based models, including graph convolutional networks, represent a major advancement in EEG analysis by modelling relationships between brain regions. The introduction of attention mechanisms and split-attention architectures improves feature selection and enhances model performance.

The most advanced approaches involve integrating heterogeneous split-attention mechanisms with Siamese graph convolutional attention networks. These models achieve superior performance by capturing both spatial and relational features in EEG data. Despite these advancements, challenges such as computational complexity, data scarcity, and lack of interpretability remain. Future research should focus on developing efficient, scalable, and explainable models for clinical deployment. In conclusion, AI-driven EEG analysis represents a promising direction for early and accurate Parkinson's disease diagnosis, with hybrid deep learning and graph-based models leading future developments.

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