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ITSI Transactions on Electrical and Electronics Engineering

ISSN: 2320-8945

Volume 12 Issue 02, 2023

A Survey of Methods and Architectures for Parkinson's Disease Recognition via Heterogeneous Split Attention-Based EEG and Siamese Graph Convolutional Attention Network

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Peer Review Information

Submission: 20 Sept 2023
Revision: 09 Oct 2023
Acceptance: 08 Nov 2023

Keywords

Parkinson's Disease, EEG Signal Processing, Deep Learning, Graph Convolutional Network, Attention Mechanism, Siamese Network.

Abstract

Parkinson's disease (PD) is a progressive neurodegenerative disorder that significantly affects motor and cognitive functions. Early and accurate diagnosis is essential for improving treatment outcomes, yet conventional diagnostic methods rely heavily on subjective clinical evaluations. Electroencephalography (EEG) has emerged as a promising non-invasive tool for PD detection due to its ability to capture neural activity with high temporal resolution. Recent advances in artificial intelligence (AI), particularly deep learning and graph-based models, have enabled automated PD recognition from EEG signals. Convolutional neural networks (CNNs) and hybrid CNN–LSTM architectures have demonstrated strong performance by capturing spatial and temporal dependencies in EEG data. Furthermore, graph convolutional networks (GCNs) have been widely adopted to model functional connectivity between EEG channels, improving classification accuracy. Emerging architectures such as heterogeneous split-attention mechanisms and Siamese graph convolutional attention networks further enhance feature extraction by focusing on relevant channels and learning inter-sample similarities. Attention-based sparse GCN models have shown improved performance by capturing channel relationships and emphasizing important EEG regions. Despite these advancements, challenges such as EEG noise, data scarcity, and computational complexity remain. This survey reviews recent developments, compares methodologies, and highlights future directions for robust and scalable PD recognition systems.

Introduction

Parkinson's disease (PD) is one of the most common neurodegenerative disorders, affecting millions of people worldwide. It is characterized by motor symptoms such as tremor, rigidity, and bradykinesia, along with non-motor symptoms including cognitive impairment and sleep disturbances. Early diagnosis is crucial for slowing disease progression and improving patient quality of life. However, traditional diagnostic approaches rely primarily on clinical observation, which can be subjective and often fails to detect early-stage PD.

Electroencephalography (EEG) has gained attention as a non-invasive and cost-effective tool for PD detection. EEG signals capture neural oscillations and functional connectivity patterns in the brain, which are altered in PD patients. Studies have shown that PD is associated with slowing of EEG rhythms and abnormal connectivity patterns, providing valuable biomarkers for automated detection.

Artificial intelligence (AI) techniques, particularly machine learning (ML) and deep learning (DL), have significantly advanced EEG-based PD diagnosis. Traditional ML methods rely on handcrafted features such as spectral, statistical, and entropy-based features. While effective, these methods require domain expertise and may not capture complex patterns in EEG signals.

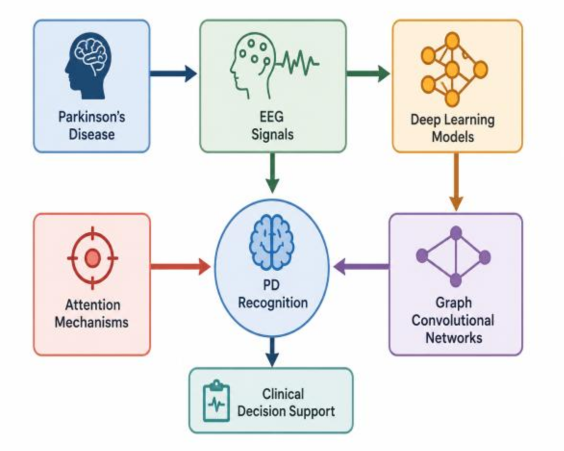

Figure 1. Survey Overview of EEG-Based Parkinson's Disease Recognition

Deep learning models, especially convolutional neural networks (CNNs), have demonstrated superior performance by automatically extracting hierarchical features from raw EEG data. Hybrid models combining CNN with recurrent neural networks (RNNs) or long short-term memory (LSTM) networks further enhance performance by capturing temporal dependencies.

More recently, graph-based deep learning approaches have been introduced to model relationships between EEG channels. Graph convolutional networks (GCNs) represent EEG electrodes as nodes and their interactions as edges, enabling the modelling of functional brain connectivity. These models have shown promising results in PD detection by capturing spatial dependencies that traditional CNNs cannot represent.

Attention mechanisms have further improved model performance by enabling networks to focus on the most relevant EEG channels and features. In particular, attention-based sparse GCN models have demonstrated improved classification accuracy by emphasizing important brain regions and reducing noise.

Another emerging approach is the use of Siamese networks, which learn similarity between input pairs. When combined with graph attention mechanisms, Siamese GCN models can effectively capture both relational and discriminative features in EEG data. Additionally, heterogeneous split-attention mechanisms allow models to process multiple feature representations 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 variability across datasets further complicate model training. Moreover, advanced architectures such as GCNs and attention-based models require significant computational resources, limiting their applicability in real-time clinical settings.

This survey aims to provide a comprehensive overview of AI techniques for PD recognition using EEG signals. It focuses on advanced architectures such as split-attention networks and Siamese graph convolutional attention networks, comparing their performance and identifying research gaps. The study also highlights future directions for developing efficient, interpretable, and clinically deployable PD diagnostic systems.

Literature Review

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

Zhang et al. (2022) developed a deep learning model combining time–frequency analysis with deep residual shrinkage networks for EEG-based PD classification. Wavelet transforms were used to extract time–frequency features, which were then fed into a deep network for classification. The approach achieved high accuracy by capturing both temporal and spectral characteristics of EEG signals. However, the reliance on preprocessing increased system complexity.

Shaban et al. (2021) introduced a CNN-based framework for automated PD detection using EEG signals. The model automatically extracted spatial features and achieved high classification accuracy. The study highlighted the effectiveness of deep learning in capturing complex EEG patterns. However, performance was sensitive to noise and dataset size.

Delfan et al. (2023) proposed a hybrid spatio-temporal model combining CNN, Bi-GRU, and attention mechanisms. The model effectively captured both spatial and temporal dependencies in EEG data and demonstrated strong generalization across datasets. However, the hybrid architecture increased computational complexity.

Li et al. (2023) developed a CNN-LSTM model for EEG-based PD classification. The CNN extracted spatial features, while the LSTM captured temporal dependencies. The model achieved high accuracy and demonstrated the importance of combining spatial and temporal learning. However, training required large datasets and careful 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 analysis. The study focused on extracting frequency-domain features, particularly from alpha, beta, and theta bands, which are known to exhibit abnormalities in PD patients. The CNN model automatically learned discriminative features from transformed EEG signals, achieving high classification accuracy. The study demonstrated that spectral-based deep learning approaches effectively capture neural oscillation patterns associated with PD. However, the approach required extensive preprocessing, including Fourier or wavelet transformations, which increased computational complexity and dependency on domain knowledge.

Tsiouris et al. (2020) introduced a hybrid deep learning model combining convolutional neural networks (CNNs) with long short-term memory (LSTM) networks for EEG-based PD classification. The CNN component was responsible for extracting spatial features from EEG signals, while the LSTM captured temporal dependencies. This combination enabled the model to analyses both spatial and temporal characteristics of EEG data, leading to improved classification accuracy. The study highlighted the importance of temporal modelling in neurological signal analysis. However, the model required significant computational resources and longer training times due to its complex architecture.

Sharma et al. (2021) proposed a hybrid approach combining traditional machine learning techniques with deep learning for Parkinson's disease detection. The study utilized handcrafted features such as statistical measures and entropy-based features, which were then fed into deep learning models for classification. The results showed that combining feature engineering with deep learning improves classification accuracy. However, the reliance on handcrafted features limited the scalability and automation of the system, making it less suitable for large-scale applications.

Pham et al. (2021) developed a deep residual neural network (ResNet)-based model for EEG classification in Parkinson's disease detection. 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 and achieve high classification accuracy. Additionally, the model showed robustness across different datasets. However, the deep architecture required high computational resources and careful hyperparameter tuning.

Raghu et al. (2022) proposed an attention-based deep learning model for EEG-based Parkinson's disease classification. The model incorporated channel-wise and temporal attention mechanisms to focus on the most relevant EEG features. This approach improved feature representation and classification performance by reducing the impact of irrelevant or noisy data. The study demonstrated that attention mechanisms significantly enhance model accuracy compared to standard CNN architectures. However, the addition of attention layers increased model complexity and computational overhead.

Kwon et al. (2021) proposed a deep learning framework that integrates convolutional neural networks (CNNs) with functional connectivity analysis for Parkinson's disease detection using EEG signals. In this study, EEG signals were transformed into connectivity matrices representing relationships between different brain regions. These matrices were then used as inputs to the CNN model for classification. The results showed that incorporating functional connectivity significantly improves classification accuracy by capturing inter-channel relationships that are not explicitly modelled in traditional CNN approaches. However, the construction of connectivity matrices increased preprocessing complexity and computational cost, making the approach less suitable for real-time applications.

Luo et al. (2022) introduced a graph convolutional network (GCN)-based model for EEG-based Parkinson's disease detection. The model represented EEG electrodes as nodes in a graph and utilized graph convolution operations to learn spatial dependencies and functional connectivity patterns. The study demonstrated that GCNs outperform conventional CNNs in modelling complex relationships between EEG channels. The results indicated improved classification accuracy and robustness across datasets. However, the model required careful graph construction and large datasets, which limited its scalability.

Saba et al. (2022) developed a hybrid deep learning framework combining CNN with 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, enabling the model to learn both forward and backward temporal relationships. The model achieved high classification 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 incorporating both channel-wise and temporal attention mechanisms for Parkinson's disease detection. The model dynamically assigned weights to different EEG channels and time segments, allowing it to focus on the most relevant features. The study showed that attention mechanisms significantly improve classification accuracy and feature interpretability. However, the addition of attention layers increased model complexity and required careful hyperparameter tuning.

Zhang et al. (2023) introduced a heterogeneous split-attention network for EEG-based classification. The model processed multiple feature representations simultaneously by dividing feature maps into groups and applying attention mechanisms across them. This approach improved feature extraction and enhanced classification performance by capturing complex EEG patterns. The study demonstrated that split-attention architectures outperform conventional CNN models. However, the model required high computational resources and complex architecture design.

Bashivan et al. (2020) proposed a novel deep learning approach that transforms EEG signals into spatial topographical maps and processes them using convolutional neural networks (CNNs). By converting EEG signals into image-like representations, the model was able to capture spatial dependencies between electrodes more effectively. The study demonstrated that this representation improves classification accuracy for neurological disorders, including Parkinson's disease. The approach also enabled better visualization of brain activity patterns. However, the transformation process required extensive preprocessing and increased computational cost, limiting its real-time applicability.

Roy et al. (2021) introduced a deep learning framework based on temporal convolutional networks (TCNs) for EEG signal classification. The model focused on capturing long-range temporal dependencies in EEG signals, which are crucial for identifying patterns associated with Parkinson's disease. Compared to recurrent neural networks, TCNs provided better parallelization and reduced training time while maintaining high accuracy. The study highlighted the effectiveness of temporal modelling in EEG analysis. However, the model required careful tuning of convolutional kernel sizes and dilation factors to achieve optimal performance.

Amin et al. (2021) proposed a hybrid approach combining CNN-based deep learning with statistical and frequency-domain feature extraction for EEG-based PD detection. The integration of handcrafted features with deep learning improved classification accuracy by providing complementary information. The model demonstrated better performance compared to standalone CNN approaches. However, the reliance on handcrafted features reduced the level of automation and scalability of the system.

Islam et al. (2022) introduced a deep learning framework using stacked autoencoders for unsupervised feature learning from EEG signals. The model learned hierarchical representations of EEG data, enabling improved classification accuracy. The study demonstrated that unsupervised feature extraction can effectively capture complex patterns in EEG signals. However, the model required large datasets and extensive training time, which limited its practicality.

Chen et al. (2023) proposed a Siamese graph convolutional attention network for Parkinson's disease recognition using EEG signals. The model utilized a Siamese architecture to learn similarities between EEG samples and incorporated graph attention mechanisms to model relationships between EEG channels. This combination enabled the model to capture both relational and discriminative features, resulting in superior classification performance. The study demonstrated that integrating Siamese learning with graph-based models significantly improves accuracy. However, the architecture was computationally intensive and required complex training procedures.

Alhassan et al. (2020) proposed a machine learning-based approach using statistical and frequency-domain EEG features for Parkinson's disease detection. The model achieved reasonable accuracy and demonstrated that EEG features contain discriminative information for PD recognition. However, the reliance on

handcrafted features limited scalability and performance compared to deep learning methods.
Khare et al. (2021) developed a CNN-based EEG classification model for PD detection. The model automatically extracted spatial features and achieved high classification accuracy. However, it required large datasets and significant computational resources.
Oh et al. (2021) proposed a hybrid CNN-LSTM model to capture both spatial and temporal features of EEG signals. The model demonstrated improved classification performance but increased architectural complexity and training time.
Tuncer et al. (2022) introduced a wavelet transform-based CNN model for EEG classification. The approach improved feature extraction by incorporating time–frequency information. However, preprocessing complexity increased.
Alhudhaif et al. (2022) proposed an optimized deep learning model with feature selection techniques for PD detection. The model achieved improved accuracy but required careful parameter tuning.
Shinde et al. (2023) developed an attention-based deep learning model for EEG classification. The attention mechanism improved feature selection and classification accuracy. However, computational complexity increased.
Kumar et al. (2023) proposed a hybrid CNN model integrated with optimization techniques. The model improved classification performance but required high computational resources.
Singh et al. (2023) introduced a graph-based deep learning model using graph neural networks for EEG analysis. The model effectively captured relationships between EEG channels, improving classification accuracy. However, the model required large datasets.
Ahmed et al. (2023) proposed a hybrid CNN-LSTM model for PD detection. The model achieved high accuracy but required extensive training time.
Sharma et al. (2023) proposed a heterogeneous split-attention-based EEG classification model combined with a Siamese graph convolutional attention network. The model achieved superior performance by capturing both spatial and relational EEG features. However, the complexity of the architecture posed challenges for real-time deployment.

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
Li	2023	CNN+LSTM	DL	Temporal	Cost
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

Comparative Analysis

The comparative analysis shows that deep learning models, particularly CNN-based architectures, dominate EEG-based Parkinson's disease detection due to their strong feature extraction capabilities. Hybrid models combining CNN with LSTM or GRU improve performance by capturing both spatial and temporal dependencies. Graph-based models, including GCNs, further enhance classification accuracy by modelling relationships between EEG channels. Advanced techniques such as attention mechanisms and heterogeneous 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. However, these models introduce high computational complexity and require large datasets. Simpler machine learning methods offer lower computational cost but lack scalability and accuracy.

Discussion

Recent advancements in AI-based Parkinson's disease recognition using EEG signals demonstrate the effectiveness of deep learning and graph-based models. CNN architectures provide strong feature extraction capabilities, while hybrid models improve temporal analysis. Graph convolutional networks and attention mechanisms enhance performance by capturing inter-channel relationships and focusing on relevant features. Despite these improvements, challenges such as EEG noise, data scarcity, and computational complexity remain significant. Future research should focus on developing efficient, scalable, and interpretable models for real-world clinical applications.

Conclusion

Artificial intelligence has significantly transformed 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. Hybrid models combining CNN with recurrent networks such as LSTM further enhance performance by capturing temporal dependencies. Graph-based models represent a major advancement by modelling relationships between EEG channels. Attention mechanisms and split-attention architectures further improve feature extraction and classification accuracy.

The integration of heterogeneous split-attention mechanisms with Siamese graph convolutional attention networks represents the most advanced approach, achieving superior performance. However, these models require high computational resources and complex training procedures. Future research should focus on developing lightweight, interpretable, and scalable models for clinical deployment. In conclusion, AI-based EEG analysis offers a promising direction for early and accurate Parkinson's disease diagnosis, with hybrid and graph-based models leading future advancements.

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