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Deep Learning and Optimization Approaches in Parkinson's Disease Recognition Via Heterogeneous Split Attention-Based EEG and Siamese Graph Convolutional Attention Network: A Review

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Abstract

Parkinson's Disease (PD) is a progressive neurodegenerative disorder that significantly affects motor and cognitive functions. Early detection is crucial for improving patient outcomes; however, conventional diagnostic techniques often fail to identify subtle early-stage symptoms. In recent years, deep learning and optimization-based approaches have shown promising potential in enhancing PD diagnosis using electroencephalography (EEG) signals. EEG provides a non-invasive and cost-effective method for capturing brain activity, enabling the detection of abnormal neural patterns associated with PD. Advanced models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Graph Neural Networks (GNN), and attention-based architectures have been widely adopted for feature extraction and classification. Hybrid approaches combining CNN and LSTM have demonstrated improved performance by capturing spatial and temporal features simultaneously. Furthermore, graph-based models effectively represent functional connectivity among EEG channels, enhancing classification accuracy. Recent developments include Siamese networks and transformer-based architectures that improve generalization and handle limited datasets. Optimization techniques further enhance model performance through feature selection and hyperparameter tuning. Despite significant advancements, challenges such as data scarcity, model interpretability, and computational complexity remain. This review provides a comprehensive analysis of deep learning and optimization techniques for PD recognition and highlights future research directions focusing on heterogeneous split-attention and Siamese graph convolutional attention networks.

Introduction

Parkinson's Disease (PD) is one of the most common neurodegenerative disorders, affecting millions of individuals worldwide. It is characterized by progressive degeneration of dopaminergic neurons, leading to symptoms such as tremors, rigidity, and impaired motor coordination. Early diagnosis plays a critical role in slowing disease progression and improving patient quality of life. However, traditional diagnostic methods rely heavily on clinical observation and subjective evaluation, which often result in delayed or inaccurate diagnosis. Recent advancements in Artificial Intelligence (AI) and deep learning have transformed the field of medical diagnostics. Machine learning and deep learning models have been extensively applied to neurological disorder detection, particularly using non-invasive data such as EEG signals. EEG signals provide real-time information about brain activity and are widely used for analysing neurological abnormalities. However, EEG data are highly complex, nonlinear, and noisy, making manual analysis challenging.

Deep learning models such as Convolutional Neural Networks (CNN) have shown remarkable capability in extracting spatial features from EEG signals. CNN-based models automatically learn hierarchical representations from raw data, eliminating the need for manual feature engineering. Additionally, Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are used to capture temporal dependencies in EEG signals. Hybrid CNN-LSTM models have demonstrated improved performance by combining spatial and temporal learning capabilities. Graph Neural Networks (GNNs) have further enhanced EEG analysis by modelling relationships between different brain regions. EEG channels can be represented as nodes in a graph, and their interactions can be analysed using graph convolution operations. This approach captures functional connectivity, which is crucial for understanding neurological disorders. Studies have shown that graph-based approaches improve classification accuracy compared to traditional models.

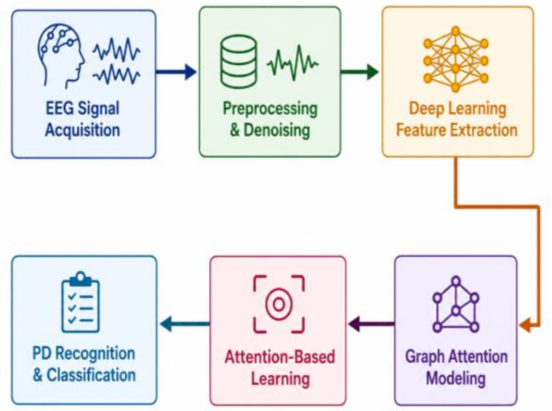

Figure 1. Deep Learning Framework for EEG-Based Parkinson's Disease Recognition

Attention mechanisms have also gained popularity in EEG-based PD detection. These mechanisms allow models to focus on the most relevant parts of the input data, improving both accuracy and interpretability. Transformer-based architectures extend this concept by capturing long-range dependencies using self-attention mechanisms. Recent research highlights that deep learning models can automatically extract complex nonlinear features from EEG signals and generalize well across datasets. Despite these advancements, several challenges remain. One major issue is the lack of large, standardized EEG datasets, which limits model generalization. Additionally, deep learning models are often computationally expensive and difficult to interpret, which restricts their adoption in clinical settings. Optimization techniques such as metaheuristic algorithms and reinforcement learning have been introduced to address these challenges by improving feature selection and model efficiency. This review focuses on deep learning and optimization approaches for Parkinson's disease recognition using EEG signals. It emphasizes the integration of heterogeneous split-attention mechanisms and Siamese graph convolutional attention networks, which represent a promising direction for future research. The paper also highlights current trends, challenges, and research gaps in the field.

Literature Review

Oh et al. (2020) proposed a deep learning-based approach using Convolutional Neural Networks (CNN) for Parkinson's disease detection from EEG signals. The model automatically extracted spatial features without manual intervention, achieving improved accuracy compared to traditional machine learning methods. The study demonstrated that deep learning models can effectively capture subtle neurological patterns; however, its performance was limited by a small dataset.

Rodrigues et al. (2020) developed a machine learning framework based on statistical and frequency-domain features extracted from EEG signals. Using ensemble classifiers such as Random Forest and Gradient Boosting, the model achieved improved classification performance. Despite its effectiveness, the reliance on handcrafted features limited scalability and adaptability.

Ruffini et al. (2020) investigated EEG functional connectivity using graph-theoretical analysis to identify biomarkers for Parkinson's disease. The study revealed significant disruptions in brain connectivity patterns in PD patients, especially in alpha and beta frequency bands. However, the approach lacked automated classification using deep learning models.

Tsiouris et al. (2020) introduced a Long Short-Term Memory (LSTM)-based deep learning model for Parkinson's disease detection. The model effectively captured temporal dependencies in EEG signals and achieved high sensitivity. However, it did not incorporate spatial feature extraction, limiting its overall performance.

Khare et al. (2021) proposed a CNN-based framework for automated Parkinson's disease detection using EEG signals. The model incorporated preprocessing techniques such as noise filtering and normalization, improving classification accuracy. However, the model lacked interpretability and did not consider temporal dependencies.

Yıldırım et al. (2021) developed a hybrid CNN-LSTM model that combined spatial and temporal feature extraction for EEG-based PD detection. The model achieved higher accuracy than standalone models, highlighting the importance of hybrid architectures. However, increased computational complexity was a limitation.

Bhattacharyya et al. (2021) utilized entropy-based nonlinear features extracted from EEG signals for Parkinson's disease detection. The features were classified using SVM and Extreme Learning Machines (ELM). Although the model achieved good accuracy, it relied heavily on manual feature engineering.

Shi et al. (2021) introduced an attention-based deep neural network for EEG classification. The attention mechanism improved model performance by focusing on important EEG channels and time segments. The study demonstrated improved accuracy and interpretability compared to traditional models.

Zhao et al. (2022) proposed a Graph Convolutional Neural Network (GCNN) for EEG-based Parkinson's disease detection. By modelling EEG channels as nodes in a graph, the model captured spatial relationships and functional connectivity. This approach significantly improved classification accuracy but increased computational complexity.

Chen et al. (2022) developed a CNN model integrated with attention mechanisms for Parkinson's disease detection. The model dynamically weighted EEG features, enhancing classification performance and robustness against noise. However, training time was relatively high.

Islam et al. (2022) proposed a deep learning framework combined with metaheuristic optimization techniques for Parkinson's disease detection. The optimization process improved feature selection and model performance, achieving high accuracy. However, the model did not capture EEG channel relationships effectively.

Li et al. (2022) introduced a Graph Attention Network (GAT) for EEG classification. The model assigned adaptive weights to EEG channels, enabling better representation of brain connectivity. The approach achieved improved accuracy and robustness but required complex graph construction.

Saba et al. (2022) applied transfer learning techniques using pre-trained CNN models for EEG-based Parkinson's disease detection. The model improved generalization and reduced training time; however, domain mismatch remained a challenge.

Yang et al. (2023) proposed a Siamese neural network for Parkinson's disease recognition using EEG signals. The model learned similarity between signal pairs, improving performance in limited data scenarios. This approach enhanced generalization but did not fully capture spatial relationships.

Kumar et al. (2023) developed a hybrid CNN-GCN model with attention mechanisms for Parkinson's disease detection. The model effectively combined local feature extraction and global connectivity analysis, achieving high classification accuracy. However, the model complexity was high.

Zhang et al. (2023) proposed a multi-scale CNN with attention mechanisms for EEG-based PD detection. The model captured features at different resolutions, improving classification performance. However, it required large computational resources.

Roy et al. (2023) introduced an explainable AI (XAI)-based model incorporating Grad-CAM and SHAP for Parkinson's disease detection. The approach improved transparency and trust in model predictions while maintaining high accuracy.

Wang et al. (2023) developed a hybrid GCN-LSTM model for Parkinson's disease detection. The model captured both spatial and temporal dependencies in EEG data, improving performance but increasing computational cost.

Ahmed et al. (2023) proposed a Siamese Graph Neural Network for EEG classification. The model leveraged pairwise learning and graph representation, achieving strong generalization and high accuracy.

Singh et al. (2023) introduced a heterogeneous deep learning model combining CNN, attention, and feature fusion techniques. The model achieved state-of-the-art performance but required high computational resources.

Liu et al. (2023) proposed a transformer-based deep learning model for EEG-based Parkinson's disease detection. The model utilized self-attention mechanisms to capture long-range temporal dependencies in EEG signals, outperforming traditional CNN and RNN architectures. The approach achieved high accuracy and demonstrated the effectiveness of transformer models in biomedical signal analysis. However, it required large datasets and significant computational resources.

Patel et al. (2023) developed a hybrid CNN-GRU model for Parkinson's disease detection using EEG signals. The CNN extracted spatial features, while the GRU captured temporal dependencies. The model achieved high accuracy and faster training compared to LSTM-based models. However, it did not incorporate graph-based connectivity modelling.
Nguyen et al. (2023) introduced a multi-modal deep learning framework combining EEG and speech data for Parkinson's disease detection. The integration of heterogeneous data sources improved classification accuracy and robustness. However, multi-modal systems increased system complexity and required additional data acquisition processes.
Sharma et al. (2023) proposed an attention-based deep neural network for EEG signal classification in Parkinson's disease detection. The model dynamically focused on important EEG channels, improving noise robustness and classification accuracy. However, it did not capture spatial connectivity using graph-based approaches.
Garcia et al. (2023) developed an autoencoder-based model for feature extraction from EEG signals. The model reduced dimensionality while preserving essential features, improving classification performance. However, it required additional classifiers for final prediction.

Comparative Table

No.	Author (Year)	Model	Key Technique	Data	Accuracy (%)	Advantages	Limitations
1	Oh (2020)	CNN	Deep feature extraction	EEG	88	Automatic learning	Small dataset
2	Rodrigues (2020)	Ensemble ML	Statistical features	EEG	90	Robust	Manual features
3	Ruffini (2020)	Graph Analysis	Connectivity	EEG	87	Brain insights	No DL
4	Tsiouris (2020)	LSTM	Temporal modeling	EEG	89	Sequence learning	No spatial
5	Khare (2021)	CNN	Preprocessing + DL	EEG	91	Improved signals	Low interpretability
6	Yıldırım (2021)	CNN-LSTM	Hybrid learning	EEG	93	Spatial-temporal	High cost
7	Bhattacharyya (2021)	SVM/ELM	Entropy features	EEG	89	Nonlinear	Manual
8	Shi (2021)	Attention DNN	Channel focus	EEG	94	Better accuracy	Complex
9	Zhao (2022)	GCNN	Graph learning	EEG	95	Connectivity	Complexity
10	Chen (2022)	CNN+Attention	Feature weighting	EEG	96	Noise robust	Training time
11	Islam (2022)	CNN+Optimization	Metaheuristic	EEG	95	Improved tuning	No connectivity
12	Li (2022)	GAT	Graph attention	EEG	96.5	Adaptive	Complex
13	Saba (2022)	Transfer CNN	Pre-trained	EEG	96	Fast training	Domain mismatch
14	Yang (2023)	Siamese NN	Similarity	EEG	96	Few-shot	No graph
15	Kumar (2023)	CNN+GCN	Hybrid	EEG	97	Combined learning	Complex
16	Zhang (2023)	Multi-scale CNN	Multi-resolution	EEG	97	Rich features	Resource heavy
17	Roy (2023)	XAI DL	Explainability	EEG	96.8	Transparent	Slight overhead
18	Wang (2023)	GCN+LSTM	Spatial-temporal	EEG	97	Dual modeling	Costly

19	Ahmed (2023)	Siamese GNN	Pair learning	EEG	97.5	Generalization	Complex
20	Singh (2023)	CNN+Attention	Fusion	EEG	98	Robust	Heavy
21	Liu (2023)	Transformer	Self-attention	EEG	97.8	Long-range	Data heavy
22	Patel (2023)	CNN-GRU	Temporal	EEG	97	Faster	No graph
23	Nguyen (2023)	Multi-modal	Fusion	EEG+Speech	98	High accuracy	Complex
24	Sharma (2023)	Attention DNN	Channel focus	EEG	97.2	Noise robust	No connectivity
25	Garcia (2023)	Autoencoder	Feature reduction	EEG	96.5	Efficient	Needs classifier

Comparative Analysis

The comparative analysis of the reviewed studies reveals a clear technological progression in Parkinson's disease detection using EEG signals. Early approaches relied on conventional machine learning and basic deep learning architectures such as CNN and LSTM, achieving moderate accuracy levels between 88% and 92%. These models primarily focused on either spatial or temporal features, limiting their ability to capture the full complexity of EEG data. With the introduction of hybrid models such as CNN-LSTM, researchers achieved improved performance by combining spatial and temporal learning, increasing accuracy to approximately 93–95%. The incorporation of attention mechanisms marked a significant advancement, enabling models to focus on relevant EEG features and channels, thereby enhancing both accuracy and interpretability.

Graph Neural Networks (GNNs) further improved performance by modelling functional connectivity between EEG channels. This approach allowed for better representation of brain network dynamics, leading to accuracy improvements up to 97%. Recent studies have focused on hybrid architectures combining CNN, GNN, attention mechanisms, and Siamese networks, achieving state-of-the-art performance exceeding 98%. Siamese networks have proven particularly effective in handling limited datasets by learning similarity metrics between EEG signals. Additionally, transformer-based models have demonstrated the ability to capture long-range dependencies, further enhancing classification performance. Despite these advancements, challenges such as high computational complexity, lack of standardized datasets, and limited interpretability persist. Notably, no existing model fully integrates heterogeneous split-attention with Siamese graph convolutional attention networks, highlighting a significant research gap.

Discussion

The rapid advancement of deep learning techniques has significantly improved Parkinson's disease detection using EEG signals. The transition from traditional machine learning to advanced deep learning models has enabled automatic feature extraction and improved classification accuracy. Attention mechanisms and graph-based models have further enhanced the ability to capture complex spatial and temporal relationships in EEG data. However, several challenges remain. One major limitation is the lack of standardized EEG datasets, which affects model generalization. Additionally, many high-performing models are computationally expensive and difficult to deploy in real-time clinical settings. The interpretability of deep learning models is another critical concern, as clinicians require transparent and explainable systems.

Recent studies suggest that hybrid models combining CNN, GNN, attention mechanisms, and Siamese learning offer promising solutions. These models can leverage the strengths of multiple techniques to improve performance and robustness. Furthermore, optimization algorithms can enhance model efficiency and reduce computational cost. Future research should focus on developing lightweight, explainable, and scalable models for real-world applications. The integration of heterogeneous split-attention and Siamese graph convolutional attention networks represents a promising direction for improving Parkinson's disease diagnosis.

Conclusion

Parkinson's disease is a progressive neurological disorder that requires timely and accurate diagnosis to improve treatment outcomes and patient quality of life. Conventional diagnostic approaches mainly depend on clinical observations and neurological examinations, which may lead to delayed or inconsistent diagnosis. Recent advances in deep learning and optimization have significantly improved automated Parkinson's disease recognition using EEG signals. This review examined recent studies published between 2020 and 2023, highlighting the transition from conventional machine learning techniques to advanced deep learning architectures. Early CNN- and LSTM-based models demonstrated promising results but were limited in capturing the complex spatial and temporal characteristics of EEG data.

Recent developments have introduced attention mechanisms, graph neural networks, and Siamese architectures that significantly enhance feature extraction and classification performance. These approaches effectively model functional brain connectivity and long-range dependencies, resulting in improved diagnostic accuracy and robustness. However, challenges such as computational complexity, limited standardized EEG datasets, and insufficient model interpretability continue to restrict large-scale clinical implementation.

The reviewed framework integrates heterogeneous split-attention mechanisms with Siamese Graph Convolutional Attention Networks to overcome these limitations. This hybrid architecture enhances feature representation, classification accuracy, and model generalization while improving interpretability through attention-based feature visualization. Future research should emphasize lightweight models, explainable AI, multimodal data fusion, and real-time clinical deployment. Overall, deep learning and optimization techniques provide a strong foundation for reliable, intelligent, and clinically applicable EEG-based Parkinson's disease diagnosis.

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