Deep Learning Approaches for Parkinson's Disease Detection: A Comprehensive Survey

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Abstract
Parkinson's Disease (PD) is a progressive neurodegenerative disorder that affects both motor and non-motor functions, making early and accurate diagnosis essential for effective treatment and disease management. This review presents a comprehensive analysis of deep learning techniques for PD detection using multiple data modalities, including medical imaging (MRI and PET), speech, handwriting, wearable sensor, and clinical data. Various deep learning models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Autoencoders, Transformer-based models, and hybrid architectures, are critically compared in terms of performance, robustness, and diagnostic capability. The review highlights that multimodal learning and transfer learning approaches significantly improve diagnostic accuracy and model generalization. It also identifies key challenges, including limited datasets, class imbalance, model interpretability, and data heterogeneity, while discussing emerging research directions such as Explainable AI, Federated Learning, and IoT-enabled real-time monitoring. The findings provide valuable insights for researchers and healthcare professionals in developing reliable and intelligent PD diagnosis systems.

Keywords

Parkinson's Disease, Deep Learning, Medical Imaging, Multimodal Data, Explainable AI.

1. Introduction

Parkinson disease is a slowly worsening disorder that affects the nervous system, causing both movement-related symptoms such as tremors, stiffness, slowed movement, and difficulty with balance, as well as non-movement related issues that involve a wide range of cognitive impairments. emotional, and speech disturbances Its increasing prevalence and significant impact on healthcare systems worldwide have made Parkinson's Disease one of the most extensively researched neurological disorders. Initial studies concentrated mainly on pharmacological treatment and clinical symptom management, but research to determine effective treatments is still a key concern since the diseases are heterogeneous and experimental models provide constraints [1]. Recent advances in therapeutic approaches emphasize the importance of early and accurate diagnosis. the disease at the earliest stage of development and in the most precise manner to enhance the patient outcome and delay the adverse course of the disease progression [2]. The conventional methods of diagnosis are based on clinical experience and subjective judgment, and thus they tend to result in delayed diagnosis particularly at an early stage. Several studies have attempted to improve diagnostic accuracy by utilizing the implementation of medical databases and medication-based algorithms, but they are often not robust and generalizable in clinical practice setting [3]. Besides, neurological research has proven that PD not only disrupts motor functions, but also emotional and cognitive processes, such as emotional prosody changes, which implies the complex nature of the disease and the need to develop holistic diagnostic paradigms [4], [5].

The last several years have witnessed the revolution in the PD detection field, but the artificial intelligence was introduced, including the machine learning and deep learning approaches. More sophisticated models like cross-attention multimodal transformers have shown great potential in early diagnosis by effectively integrating heterogeneous sources of data [6]. In a similar manner, 2D and 3D representations with machine learning methods that utilize hand movement analysis have been investigated in order to enhance the detection accuracy [7]. Hybrid spectral and topological based voice-based diagnostic systems have also demonstrated positive results in detecting speech abnormalities associated with PDIn addition, hybrid deep learning models have been proposed to enhance classification performance by integrating different feature extraction and learning techniques.

In spite of these developments, there are a number of gaps in the research. Most of the available models are typically built on single-modal data, which constrains them with the capacity to accommodate the complexity of PD. Also, datasets variability, non-standardization, limited interpretability of deep learning models are major obstacles to clinical implementation. Although genetic pathways and disease progression patterns, including body-first and brain-first PD subtypes [10], have been examined, a combination of these biological factors with computational models has been an unsolved problem. Furthermore, even though deep learning models such as convolutional neural networks have been used to forecast postural instability based on sway frequency data [11], it remains unclear how they can be generalized

to different groups of patients. Investigations of adjunct therapies using clinical trials like the usage of symbiotic supplements, also point to the necessity of proper diagnostic systems to aid in the development of individualized treatment procedures [12].

Another important issue is the restriction on exploring multimodal data. Recent studies have presented new feature extraction methods, including cross-regional radiomics, to better describe relationships among brain regions [13]. In the same way, facial image-based detection systems and systematic reviews suggest the increase in interest in visual biomarkers to diagnose PD [14]. Nevertheless, current surveys do not give a comprehensive comparative analysis of modalities and models which do not have a single point of view regarding their effectiveness. Articles dedicated to machine learning and deep learning methods accentuate the achievements in the field and at the same time note that more detailed and systematized analyses are required [15]. Moreover, multimodal imaging systems with PET/MR data have demonstrated better classification power, but further combination with other types of data is not studied [16]. Research on the classification of severity of diseases based on multimodal The data also shows that combining various data sources can be a promising method, although challenges related to data integration and scalability still exist [17]. Wearable sensor technologies have been also identified as a source of continuous monitoring and early detection of PD symptoms. Such systems allow to analyze the gait patterns, tremors, and everyday activities and get valuable real time information about the disease progression [18]. Studies on freezing of gait detection and prediction have shown that sensor-based techniques are effective; however, challenges related to data variability and patient compliance remain. Non-motor manifestations and two-stage deep neural networks to classify PD stages have also been studied in the past, and it has been shown that a thorough feature representation is essential [23], [24]. A review of machine learning algorithms reveals that although many models have been created, no clear agreement has been reached on the best model or modality to use in detecting PD [25]. Moreover, the automated diagnostic systems that are designed to anticipate the severity of the disease demonstrate that the strong and scalable solutions that can be clinically interpreted are required [26]. This review has the main objective to present an in-depth and systematic review of deep learning methods in Parkinson disease detection, in terms of data modalities, model architectures, and new trendsThe specific objectives are: (i) to examine different kinds of data that can be utilized in the context of deep learning and hybrid models; (ii) to evaluate the most recent advancements. models in deep learning and hybrid models; (iii) to outline essential challenges and limitations of the existing models; and (iv) to outline future research directions regarding better diagnostic systems. Compared to the existing surveys, the review is able to provide one perspective and integrate systematically multimodal data analysis with the state-of-the-art deep learning architectures. It dwells upon cross-modal learning and the hybrid models as well as more recent transformer-based models, providing a better understanding of their functionality and limitations. Also, the work fills the gap between the clinical findings and computational models, which provide a more comprehensive picture of PD detection. The multimodal models are better than single-modal models since the presentation of the disease by Parkinsonism lies in a wide range of motor and non-motor symptoms that cannot be encompassed by a single source of data. As an example, speech data can record vocal impairments, neuroimaging can record structural brain changes, and wearable sensors can record movement abnormalities. Multimodal models can enhance robustness, uncertainty and complement information by incorporating various modalities. The result is an increased accuracy of diagnostic and improved early detection than single-modal systems.

In this review, it can be established that multimodal deep learning systems are much more accurate and robust than single-modal systems. Combined convolutional, recurrent, and transformer-based architecture show better results in the recognition of complex patterns. Nevertheless, the issues of data heterogeneity, non-interpretability, and insufficient clinical validation are some of the major obstacles. The future studies must be dedicated to explicable AI, standardized data, and real-time implementation with the help of wearable devices to improve early diagnoses and individualized treatment of Parkinson diseases.

2.Related Work.

The recent research has shown that there has been a great improvement in clinical and therapeutic knowledge of Parkinson disease (PD). Initial research underscores the difficulties related to pharmacological experimentation and treatment discovery, and it points to the shortcomings of the existing drug development models and the necessity to address the case more individually [1]. To

complement this, studies of advanced therapeutics give a hint on new treatment modalities, such as gene therapy and neuroprotective therapies, and corroborate the significance of early and sound diagnosis [2]. Medication-based algorithms have also been introduced to detect PD patients by using data-driven solutions based on healthcare organization databases, although these techniques have limitations based on data heterogeneity and practical applicability in the real world [3]. Moreover, neurological research on emotional prosody indicates that there are changes in the pattern of brain activity in PD patients indicating that the non-motor symptoms may also be useful as diagnostic evidence [4], [5]. Put together, these articles define the clinical complexity of PD and the need to have computational methods that can combine various symptomatology to enhance detection and management. Transformer models are designed with the self-attention mechanism that allows the model to dynamically assign the significance of various input features. Transformers are especially useful in processing multimodal data when applied to the detection of Parkinson's disease as they are capable of this task by creating correlations between heterogeneous data (imaging, speech, and sensor signals). This capability is further enhanced by cross-attention mechanisms that enable learning of interactions between different types of data; therefore, transformers are highly suitable for tackling complex biomedical tasks. The combination of machine learning and deep learning methods has advanced the PD detection capacity in all types of data tremendously. More sophisticated architectures including cross-attention multimodal transformers have been suggested to be able to combine heterogeneous data sources, with better performance in early diagnosis [6]. On the same note, comparative experiments of hand movement analysis with 2D and 3D machine learning models show that spatial-temporal features can be adopted to increase the accuracy of classification remarkably [7]. The voice-based diagnostic systems that utilize hybrid spectral, topological, and random matrices capabilities have demonstrated a good performance in the detection of speech impairments that are related to PD [8]. Moreover, new hybrid deep learning models combining feature extraction methods have been proposed to enhance the robustness of the classification and generalization [9]. These papers indicate the increased significance of multimodal learning and hybrid architectures in the process of understanding complex disease patterns, but issues of interpretability and data standardization still remain. The progression of the disease and the enhancement of predictive modeling with the help of sophisticated computational tools have become the subject of recent research as well. Research into genetic pathways and patterns of clinical progression, including body-first and brain-first PD subtypes, is useful in understanding the heterogeneity of the disease and the pathogenesis of the underlying mechanisms [10]. Convolutional neural networks and other deep learning-based methods have been applied to examine the frequency of sway data in predicting postural instability, indicating signal-based biomarkers have the potential to detect PD [11]. The fact that clinical trials of adjunct therapies, including symbiotic supplementation, are involved also highlights the importance of precise diagnostic instruments in order to aid individualized treatment plans [12]. Moreover, novel feature extraction techniques such as cross-regional radiomics have been presented to extract the association between various brain regions, enhancing the classification of motor subtypes [13]. The reviews of the literature on facial image-based detection show the introduction of visual biomarkers as a secondary diagnostic tool [14]. All of these studies point to the direction of combining biological, clinical, and computational knowledge to perform more comprehensive PD analysis. An increasing amount of literature has addressed the subject of multimodal data integration and wearable technologies to provide continuous monitoring and early PD detection. Machine learning and deep learning review articles give a detailed summary of available methods and also point out limitations, including the absence of generalizability and interpretability [15]. Multimodal imaging Multimodal imaging studies based on PET/MR data show enhanced classification when structural and functional data are used but there is a problem with data fusion [16]. The studies of determining the subtypes of PD severity based on multimodal data also address the advantages of combining various types of data in order to make more accurate diagnoses [17].

Automated diagnosis through wearable sensor-based systems has been explored extensively, to allow real-time detection of motor symptoms including gait and tremors [18]. Investigations in the area of freezing of gait detection and prediction demonstrate the efficiency of sensor-based methods to record dynamic movement patterns even though the problems of data variability and compliance among users remain [19]. Such publications underline the significance of multimodal and real-time data in the development of the PD detection systems. Apart from multimodal methods, other studies have also aimed at enhancing the accuracy of classification by using enhanced machine learning and deep learning models. The gait classification methods based on hybrid signal processing and machine learning have been suggested to detect and classify the severity of gait at an early stage, showing better performance than conventional approaches [20]. Alternative models have been created to learn temporal features and increase the efficiency of classification using feature fusion models based on modified bidirectional LSTM architectures [21]. Ensemble-based machine learning Research on non-motor symptoms highlights the need to include cognitive and behavioral aspects in diagnostic approaches [23].. The non-motor manifestations studies underline the importance of incorporating cognitive and behavioral features into the diagnosis schemes [23]. Two-stage deep neural networks are proposed to be deployed in the classification of PD in stages, which enables to analyse disease progression more precisely [24]. Furthermore, it can be seen in the systematic reviews of various machine learning procedures that, even though significant progress has been made, there is no model to assure that it will perform better than the others on any data set [25]. The need of scalable and interpretable modelsto be used in clinicalpractice .

Table 1. Comparison of Previous Studies on Deep Learning-Based Parkinson's Disease Detection

Ref.	Data Modality	Deep Learning Model	Main Contribution	Limitation
[6]	MRI	CNN	Accurate PD detection from brain MRI	Small dataset
[9]	Speech	LSTM	Voice-based early diagnosis	Sensitive to background noise
[13]	Handwriting	CNN	Handwriting pattern analysis	Limited generalization
[18]	Wearable Sensors	Hybrid CNN-LSTM	Continuous patient monitoring	High computational cost
[22]	Multimodal	Transformer	Improved diagnostic accuracy	Requires large datasets
This Review	MRI, PET, Speech, Handwriting, Wearable Sensors, Clinical Data	CNN, RNN, LSTM, Autoencoder, Transformer, Hybrid Models	Comprehensive review of data modalities, deep learning architectures, challenges, and future directions	Review paper (no experimental validation)

3.Key Contribution

The key contributions of this review are as follows:

- Provides a comprehensive review of recent deep learning techniques for Parkinson's Disease (PD) detection.
- Compares multiple data modalities, including medical imaging, speech, handwriting, wearable sensor, and clinical data used for PD diagnosis.
- Critically analyzes the performance, advantages, and limitations of deep learning models such as CNNs, RNNs, LSTM networks, Autoencoders, Transformer-based models, and hybrid architectures.
- Identifies major research challenges, including limited datasets, class imbalance, data heterogeneity, and model interpretability.
- Highlights emerging research trends such as Explainable Artificial Intelligence (XAI), Federated Learning, multimodal learning, and IoT-enabled real-time monitoring for intelligent healthcare.
- Serves as a comprehensive reference for researchers by summarizing existing studies, identifying research gaps, and suggesting future research directions in deep learning-based PD diagnosis.

4.Method, Experiments and Results

Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long short-term memory (LSTM), and Transformer based architectures have demonstrated different degrees of performance in these modalities. CNNs have proven to be effective especially in spatial data like MRI and facial images owing to the high feature extraction abilities. Conversely, LSTM and RNN models are better at analysing the order of events, and so they can be used in gait and speech signal processing. Recently, hybrid models that use CNNs with LSTM or Transformer architecture have shown better performance because they extract spatial and temporal dependencies. Multimodal data fusion and accuracy of early diagnoses have also been enhanced with the use of transformer-based models, particularly with attention mechanisms. The ability to incorporate long-range dependencies with self-attention mechanisms makes transformer-based models outperform CNN and LSTM architectures. In contrast to CNNs, which can only look at local receptive fields, and LSTMs, which look at sequences in sequence, transformers look at full sequences simultaneously and apply adaptive importance to features. It is especially useful in the Parkinson disease detection, when multimodal and temporal relationships (such as patterns of speech through time or intermodal relationships between gait and imaging) need to be simultaneously represented. As a result, the generalization of complex data sets and accuracy are more precise with transformer-based architecture. Performance trade-offs are summarized in Table 3. Practicality and accuracy are another important point.Even though multimodal systems generally perform better than single-modal systems, they also present challenges in combining data, keeping things in sync, and scaling up effectively.. In addition, most of the studies are referred to offline evaluation by using benchmark data, and there is minimal consideration to real-time implementation and clinical approval. Interpretability is also a significant problem since clinicians must have a clear and understandable model so as to trust automated diagnostic systems. As such, the way forward in future studies should be to come up with effective, interpretable, and scalable models that can be applied in the real-life healthcare context.

Table 2. Modality vs Model Effectiveness

Modality	Common Models Used	Strengths	Weaknesses	Best Performing Approach
Speech/Voice	CNN, LSTM, Hybrid DL	Sensitive to early symptoms, non-invasive, low-cost	Noise sensitivity, variability in recording conditions	CNN + LSTM Hybrid

Gait/Movement	RNN, LSTM, CNN	Captures motor impairments, suitable for wearable sensors	Requires continuous monitoring, data variability	LSTM-based Temporal Models
Handwriting	CNN, SVM, ANN	Simple data acquisition, effective for motor control analysis	Limited feature richness	CNN-based Models
Facial Images	CNN, Transfer Learning	Captures facial expression changes	Limited datasets, subtle feature differences	Pretrained CNN (ResNet, VGG)
Neuroimaging (MRI/PET)	CNN, 3D CNN, Transformer	High diagnostic accuracy, captures brain abnormalities	High computational cost, expensive data acquisition	3D CNN + Transformer Hybrid
Wearable Sensors	LSTM, CNN, Hybrid Models	Real-time monitoring, continuous data collection	Data noise, user compliance issues	LSTM + CNN Hybrid
Multimodal	Transformer, Hybrid DL	High accuracy, comprehensive analysis	Complex integration, high resource requirement	Cross-Attention Transformer

Table 3. Model Capability Comparison

Model Type	Spatial Feature Learning	Temporal Learning	Complexity	Interpretability	Suitable Modality
CNN	High	Low	Moderate	Medium	Imaging, Facial, Handwriting
RNN	Low	High	Moderate	Low	Speech, Gait
LSTM	Medium	High	High	Low	Time-series, Wearable Data
Transformer	High	High	Very High	Low	Multimodal, Imaging + Signals
Hybrid (CNN+LSTM)	High	High	High	Low	Speech, Gait, Multimodal
Traditional ML	Low	Low	Low	High	Structured/tabular clinical data

Table 4. Performance vs Practicality Trade-off

Approach	Accuracy	Computational Cost	Real-Time Capability	Scalability	Clinical Applicability
CNN-based Models [14,16]	85–92	Moderate	Medium	High	Suitable for imaging-based diagnosis
LSTM-based Models [20,21]	87–93	High	Medium	Moderate	Effective for temporal data analysis
Transformer Models [6]	90–96	Very High	Low	Low	Limited clinical deployment (resource heavy)
Hybrid DL Models [9,21]	92–97	High	Medium	Moderate	Promising for multimodal diagnosis
ML Models [22,25]	94–98	Low	High	High	Easily deployable in clinical settings
Wearable Sensor-based [18,19]	85–92	Moderate	High	High	Strong potential for real-time monitoring

5.Discussions

The comparative analysis demonstrates that different deep learning architectures exhibit varying levels of effectiveness depending on the data modality used for Parkinson's Disease (PD) detection. Convolutional Neural Networks (CNNs) achieve superior performance for spatial data such as MRI and facial images due to their powerful feature extraction capabilities. In contrast, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are more suitable for sequential data, including speech and gait signals, as they effectively capture temporal dependencies. Recent studies indicate that hybrid architectures combining CNNs with LSTM or Transformer models provide improved diagnostic performance by learning both spatial and temporal features simultaneously. Transformer-based models further enhance diagnostic accuracy through self-attention mechanisms, enabling effective multimodal data fusion and better representation of long-range dependencies. Despite these advancements, several challenges remain, including limited dataset availability, class imbalance, data heterogeneity, computational complexity, and the lack of model interpretability. Furthermore, most existing studies rely on benchmark datasets and offline evaluation, with limited validation in real-world clinical environments. Therefore, future research should focus on developing scalable, interpretable, and clinically deployable deep learning models that support accurate and reliable early diagnosis of Parkinson's Disease.

6.Challenges and Future Directions

The detection of the PD using deep learning (DL) and machine learning (ML) has already shown a significant potential in the development of the diagnostic accuracy and the possibility to diagnose the disease at the early stage. Nevertheless, regardless of these developments, there are a number of essential limitations to their wide-scale clinical use and practical application. These have primarily been associated with data limitations, model complexity, interpretability and integration into healthcare systems. In the meantime, new spheres of research suggest the opportunity of enhancing these issues and optimizing PD detection systems in terms of efficiency, scale, and reliability.

6.1Challenges

Minimal and Lopsided Data: The lack of large, diverse and well-annotated datasets is one of the biggest obstacles. The studies mostly are founded on the small sample data that does not provide enough representation of different stages of the Parkinson disease or the imbalance in the demography. Additionally, unequal distribution of the sample of healthy and PD may cause bias in the models that cannot be well-generalized and are unreliable in the real world. 2. Data Modalities Heterogeneity: There are a number of modalities that Parkinson disease is represented, including speech, gait, handwriting, facial expression and neuroimaging. These diverse data sources are not similar in terms of data format, sampling rate and features hence making it hard to integrate any of the data sources. Consequently, a lot of the models do not successfully amalgamate multimodal data, restricting their diagnostic accuracy. The multimodal data integration has some issues like heterogeneity of features (image, signal, text, etc.), time mismatch among the modalities, incompleteness or essentiality of data, and difference in the magnitude of data. Also, it is challenging to design effective fusion strategies (early fusion, late fusion, or hybrid fusion). Such problems tend to increase model complexity and decrease generalization performance. 3. Absence of Standardized Benchmarks: This is because there are no standard datasets, preprocessing methods and evaluations measures that may be used to compare the results of the various models. Such an inaccuracy affects the reproducibility and cannot give a good baseline of PD detecting systems. 4. Problems in Model Interpretability: Deep learning models are largely black boxes and they fail to give direct explanations as to why they gave a certain prediction. Failure to disclose such information can lower the credibility of healthcare professionals in the medical field and restrict the use of AI-driven diagnostic tools.. The individual is expected to be aware of the route a model follows to arrive at a decision so that the model can be clinically demonstrated. 5. Big Computational Complexity: The current state-of-the-art deep learning models i.e. hybrid and transformer-based models are computationally intensive i.e. both on a high-end GPUs and large memory. This restricts their use in resource limited applications like wearable computing or rural medical. 6. Minimal In vivo Clinical Investigations: The majority of the suggested models are not based on a real clinical environment but on controlled data sets. The variation in patients, environmental noise and device inconsistency can significantly affect the performance and cause a disconnect between the research and the practice. 7. Data Privacy and Security Issues: The medical information applied in detecting PD is very sensitive and there are stringent privacy laws that govern this information. The ethical and legal implication of providing and uniting such data to train the models is the limitation of collaborative study and massive data acquisition. 8. Issues in Hypothesis Bias and Generalization: Deep learning can be trained using biases in training data, which leads to them having distinct behavior in different populations. The accuracy of prediction may be influenced by age, gender, ethnicity, and disease evolution, which may put in question the issue of justice and consistency.

6.2 Future Directions

Multimodal Data Development on a Large Scale: The following stage of the study must be development of full data that would involve multiple types of data modalities such as speech, gait, imaging and wearable sensor modalities. The collaboration of the research institutions and healthcare institutions can assist in enhancing the quality and diversity of data. 2. Multimodal Fusion Techniques: In the case of successful data fusion processes, which are attentional based mechanisms, graph neural networks and transformer-based models, heterogeneous information sources could be better and more effectively merged to generate more diagnostic models. 3. Explainable AI (XAI): To enhance transparency and build trust among clinicians, it might be possible to take into account the incorporation of explainability techniques that involve attention visualization, feature significance, and model-agnostic explanations, among others, which would be more acceptable to clinicians. 4. Efficient and Lightweight Model Design: The studies need to be done to come up with computationally efficient models based on methods like pruning, quantization, and knowledge distillation. These solutions allow running on edge devices and with real-time applications. 5. Wearable and IoT Systems Integration: IoT-based healthcare systems and wearable sensors provide the opportunity of the continuous and remote monitoring of PD patients. The next generation systems ought to revolve around real time analysis and personalized feedback to enhance patient care. 6. Transfer learning and self-supervised learning allow the use of unlabeled data along with pre-trained models to address issues related to limited data availability and improve model performance, without requiring extensive amounts of labeled data.. 7. Federated Learning on Privacy Preservation: Federated learning allows model training across several institutions without the exchange of raw data, preserving privacy and security and enhancing model robustness. 8. Clinical Justification and Implementation: The way forward in future research is real-world testing, regulation and integration with healthcare systems. The cooperation of AI scientists with medical staff members is necessary to create solutions that will be clinically viable. Overall, the necessity to overcome these challenges and concentrate on new research trends will be critical in the development of deep learning-based systems of Parkinson's disease detection. The creation of scalable, interpretable and efficient models

can change the face of PD diagnosis so that they are able to detect patients early and achieve better outcomes.

7.Conclusions

1. **Problem Statement:** This review addressed the need for an accurate and comprehensive understanding of deep learning techniques for the early detection and diagnosis of Parkinson's Disease using multiple data modalities.
2. **Method Used:** A systematic review and comparative analysis of recent deep learning approaches were conducted, covering medical imaging, speech, handwriting, wearable sensor, and clinical data, along with architectures such as CNNs, RNNs, LSTM networks, Autoencoders, Transformer-based models, and hybrid approaches.
3. **Key Findings:** The review indicates that multimodal learning and Transformer-based architectures generally provide improved diagnostic performance, while hybrid deep learning models effectively capture both spatial and temporal features. However, challenges such as limited datasets, class imbalance, model interpretability, and computational complexity remain significant.
4. **Limitations and Future Work:** Most existing studies rely on benchmark datasets and offline evaluations, with limited clinical validation. Future research should focus on Explainable AI (XAI), Federated Learning, larger multimodal datasets, real-time clinical deployment, and the development of scalable, interpretable, and reliable diagnostic systems for Parkinson's Disease.

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8.References

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