A Comprehensive Literature Review on Multimodal Explainable AI Techniques for Early Detection of Parkinson’s Disease

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Abstract: Parkinson's Disease (PD) is a neurodegenerative disease characterized by its progressive nature and difficulties associated with the early diagnosis due to subjective neurological examinations and motor symptom presentation only during later stages of the disease. Advances in the fields of Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) now allow for automated and objective detection of PD through analysis of biomedical signals, specifically speech, handwriting, and gait measurements. This paper offers an overview of the existing AI-driven multimodal approaches used for early PD diagnosis paying special attention to the role played by explainability methods in creating reliable and transparent algorithms. The recent scientific developments in multimodal analysis of speech, handwriting dynamics, and gait as well as feature fusion strategies and interpretable deep learning architectures are analyzed. CNNs, RNNs, Transformer Models, Siamese Networks and various self-supervised methods are considered in detail. Moreover, the increasing use of multimodal systems which integrate different biomedical data sources into one model is highlighted. Research gaps in this domain include the lack of practical validation of approaches in real-world conditions, vulnerability to absence of some modality, high complexity, potential data bias and lack of inherently interpretable models. Finally, perspectives for future studies in the area of multimodal AI-driven PD detection are discussed.

Keywords: Parkinson’s Disease, Multimodal Artificial Intelligence, Early Diagnosis, Explainable Artificial Intelligence, Deep Learning Models

1. INTRODUCTION

Parkinson's Disease (PD) is among the commonest types of neurodegenerative conditions that are prevalent among old people globally. The cause of Parkinson's disease is the continuous deterioration of neurons responsible for producing dopamine in the substantia nigra section of the brain. Consequently, there is insufficient dopamine production, which triggers several motor impairments because dopamine plays a significant role in motor function. An early diagnosis of Parkinson's is important for treating and managing this condition effectively. Nevertheless, conventional methods of diagnosis of PD usually depend on neurological and physical examinations, which detect the disease at a stage when substantial neuronal deterioration has occurred.The diagnosis of early stage Parkinson's Disease can be detected through speech signal analysis, handwriting analysis, gait analysis or a combination of these. Because of its non-invasive and non-obtrusive data collection methods, these modalities can provide a set of specific traits and patterns to detect symptoms related to PD.

2. LITERATURE REVIEW

A. Overview of AI-Based Parkinson’s Disease Detection

Nowadays, Parkinson's Disease (PD) is one of the main subjects of investigation in the field of using AI in diagnosing diseases, since there is a rising need for objective, non-invasive, and accurate early diagnostic approaches. Typically, standard clinical tests rely on subjective measurements, and therefore cannot provide an early diagnosis.

However, due to advances in ML and DL, it has become possible to create digital biomarkers for early diagnosis by processing physiological and behavioral data. Previous literature showed that dysphonia biomarkers were highly effective at identifying Parkinson's disease, especially when using methods of speech signal processing analysis. This allowed us to verify the importance of specific biomarkers such as jitter, shimmer, and harmonic-to-noise ratio. The development of deep learning led to more advanced and reliable models that can automatically discover complicated representations.

B. Speech-Based Parkinson's Disease Detection

Loss of speech is usually the first sign of PD and is characterized in the form of reduced volume of speech and monotonous delivery. Traditional approaches to signal processing introduced by Little et al.,2009 and Tsanas et al.,2010 successfully proved that dysphonia measurements can serve as an efficient tool for remote monitoring of PD. Orozco-Arroyave et al.,2016 continued this trend proving that the measurement of speech is not language-dependent and therefore provides a universal physiological biomarker. The step from manual to automatic speech feature extraction was made by Gunduz,2019 and Zhang et al.,2020, introducing CNN models capable of generating complicated features based on spectrograms of voices. The most recent developments have been devoted to temporal modeling of speech. Using Transformer-based architecture and self-supervised contrastive predictive coding, Tougui et al.,2014 and Dodda et al.,2026 captured long-term dependencies in acoustic signal, thus improving the performance of RNN models. Shen et al.,2025 and Lim et al.,2025 extended the investigation to deep feature fusion and multi-task learning, where models share the representations for detection and severity assessment of the disease.

C. Handwriting-Based Parkinson's Disease Detection

Handwriting features such as micrographia and tremor serve as a unique biomarker since they involve both cognitive planning and fine motor skills of writing. In early studies done by Drotár et al.,2016, the concept of air-stroke (pen movement between letters) was found to be more informative than pressure exerted on writing. However, performance of handwriting recognition through deep learning was constrained by the lack of sufficient datasets. In response to this limitation, Kaur et al.,2021 developed a method that employed generative adversarial networks to generate artificial handwriting data, which worked well for training deep models and preventing overfitting. Saravanan et al.,2023 and Pandey et al.,2025 adopted deeper neural network architecture, specifically Siamese networks, allowing comparing the present handwriting with historical handwriting of the patients and therefore enabling a better and tailor-made diagnosis of PD.

D. Gait Analysis-Based Parkinson's Disease Detection

The non-invasive assessment of PD severity can be done by gait analysis based on IMU-acquired signals. Del Din et al.,2016 pointed out an unaddressed research problem relating to the "white-coat effect." It means that it would make sense to study discrepancies in gait features recorded during laboratory sessions and in natural settings. For this reason, more robust models that are capable of processing noisy data should be created. Modern architectures such as PD-ResNet presented by Yang et al.,2022 employed deep residual networks in order to detect PD biomarkers within raw vertical ground reaction force. At present, the task of binary classification can no longer be considered innovative. Esan et al.,2025 developed interpretable methods in gait analysis allowing medical experts to determine the phase of the gait cycle having the most significant impact on the final decision made by the algorithm. Dahiya et al.,2026] predicted FOG events using Spatiotemporal Transformers.

E. Multimodal AI and Feature Fusion Strategies

According to recent literature, it is evident that due to heterogeneity of the symptoms in PD, it becomes difficult to achieve proper diagnosis using just one kind of information. Makarious et al.,2022 and Park et al.,2022 were pioneers in the implementation of a population-based approach to the problem of PD using the multimodal machine learning approach with integration of genomic information, clinical history, and digital biomarkers. Currently, the advanced models that utilize advanced Fusion Networks became very popular. In particular, Attention-based Fusion has already replaced simple feature concatenation. In fact, such models successfully eliminate noise from audio signals and select stable gait data that becomes crucial for proper signal processing. Balaha et al.,2025 and Tasyurek et al.,2026 proposed frameworks that integrate speech, gait, and handwriting using Siamese Deep Learning.

F. Explainable AI (XAI) and the Path to Clinical Adoption

Transparency issues in deep learning continue to hinder its integration into clinical practice. Band et al.,2023 carried out a review that emphasized the need for a clinician to understand the reasons behind a diagnosis apart from probability scores. As a result of this, recent research in PD has been including SHAP and LIME into their analysis pipelines. Priyadharshini et al.,2024 and Shen et al.,2025 have demonstrated how XAI can link conclusions drawn by AI algorithms with the existing clinical measures such as dysphonia or kinesiology. It ensures that any AI diagnosis matches clinical criteria such as the EFNS/MDS-ES criteria.

3. RESEARCH GAPS

Though much progress has been made in applying machine learning methods to diagnose Parkinson's Disease (PD), there still exist numerous gaps in current research:

- Lack of Robustness to Missing Modalities
- No Longitudinal Study of Disease Progression
- High Memory and Energy Costs of New Models
- Focus on Post-Hoc Interpretability Methods
- Data Scarcity and Bias

4. CONCLUSION

Significant progresses were recently made in the area of artificial intelligence and deep learning that allow the development of automatic diagnostic solutions in which patterns can be detected in high-dimensional, biomedically relevant data. In such a context, architectures such as CNNs, RNNs or transformer-like models have achieved remarkable results. By combining several modalities, including voice, handwriting, and gait, more accurate predictions has been generated. However, the main obstacle to employing AI in the clinical setting is the lack of interpretability. Deep learning algorithms represent the black box nature of decisions made by models. To address this problem, explainable artificial intelligence (XAI) techniques have been devised, such as SHAP, LIME, or saliency maps. Therefore, the approach of utilizing multimodal and explainable AI could lead to a promising solution for early diagnosis of Parkinson's disease.

While a considerable progress has been made, there are still numerous challenges related to PD diagnostics that need to be addressed. First, longitudinal stability of contemporary models is quite low and, at the same time, computation of multimodal fusion deep nets requires substantial resources.

It is vital for future research to concentrate on designing "dropout-robust" and "edge-deployable" structures which would help achieve continuous monitoring as suggested by pioneering scientists in this field. Thus, focusing not only on the quality of results but also on scalability and robustness may prove critical for the integration of AI into routine practice.

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