Deep Learning for Parkinson's Disease Detection: A Review of Recent Advances and Challenges

Abdulaziz Salihu Aliero[1*] Neha Malhotra[2]

[1,2] School of Computer Application, Lovely Professional University Phagwara, India
arewateh@gmail.com

Abstract. Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects both motor function and cognitive ability, leading to symptoms such as tremors, rigidity, bradykinesia, and cognitive decline. Early and accurate diagnosis is essential for effective intervention and to slow disease progression. However, conventional diagnostic methods are often subjective, reliant on clinical observation, and prone to variability between practitioners. In recent years, deep learning (DL) has emerged as a transformative tool in medical imaging and pattern recognition, offering promising results in the automated detection of PD. Specifically, Convolutional Neural Networks (CNNs) have demonstrated superior performance in analyzing diverse data modalities, including voice recordings, gait dynamics, handwriting samples, and neuroimaging scans such as MRI and PET. This review provides an overview of recent developments in CNN-based approaches for PD detection, highlighting their advantages over traditional methods. Furthermore, it critically examines key challenges such as data heterogeneity, limited dataset availability, computational constraints, and ethical considerations related to patient data privacy and algorithmic transparency. By addressing these limitations, the paper proposes a roadmap for future research and deployment of DL-based diagnostic systems aimed at improving the reliability and accessibility of PD detection in clinical practice.

Keywords: Deep Learning, Recent Advances, Convolutional Neural Networks, Parkinson's disease.

1 Introduction

Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by the gradual worsening of both motor and non-motor symptoms over the years [1]. Motor impairments is from degeneration of dopaminergic neurons in the substantia nigra of the midbrain leading to clinical features such as bradykinesia, rigidity, resting tremors, and postural instability [2]. Non-motor symptoms, including cognitive impairment, sleep disturbances, and olfactory dysfunction, have also been reported as early manifestations of PD [3].

Finding these diseases early can encourage people to make healthier lifestyle choices, diet choices, and daily activities. So when it comes to disease, early detection increases

M. Sharma et al. (eds.), *Proceedings of the Third International Conference on Recent Advances in Computing Sciences (RACS 2025)*, Advances in Intelligent Systems Research 212,
https://doi.org/10.2991/978-94-6239-768-2_2

the likelihood of effective intervention while reducing the risk of serious complications. The same goes for chronic illnesses, where early diagnosis makes it more manageable and controllable, leading to better long-term outcomes. It challenges patients to engage in health-promoting behaviors, adhere to prevention measures, and collaborate with medical providers to create personalized and effective treatment approaches. In the end, early detection is vital to improving quality of life and lessening total disease burden [4]. However, fast and accurate diagnosis of PD remains a challenge due to the reliance on conventional diagnostic methods, which are often subjective, time-consuming, and prone to human error [5]. Due to the lack of definitive biomarkers, this further complicates early detection, as clinical assessments remain the primary diagnostic approach [6].

With the recent advancements in artificial intelligence (AI), particularly Machine Learning (ML) and DL, have shown promise in improving PD detection through the analysis of multimodal data sources, including medical imaging, speech recordings, handwriting patterns, and sensor-based gait assessments [7]. These would facilitate better disease management, with the introduction of automated processing of real-time data sets [8].

DL as a subcategory of ML (as shown in fig. 1) has been tremendously successful in medical fields, including disease diagnosis and prognosis [9]. DL-based Convolutional Neural Networks (CNNs) have been widely employed in medical imaging modalities such as magnetic resonance imaging (MRI) and positron emission tomography (PET) for the identification of PD-related structural and functional brain abnormalities [10]. Similarly, Voice-based biomarkers have been extensively researched for early PD identification as impairment in speech typically sets in before obvious motor symptoms [11]. These methods have made PD diagnosis and discrimination from other movement disorders more accurate [12].

Deep neural network-based approaches, including CNNs and autoencoders, have been utilized to learn features from speech signals and diagnose PD with satisfactory accuracy [13]. Furthermore, sensor-based approaches in which wearable technology records gait and tremor patterns have been supported by transfer and hybrid approaches in DL [14]. These advancements suggest that integration of multiple sources of information by DL frameworks could significantly enhance early PD identification [15]. Because PD symptoms are multifaceted in nature, researchers have studied multimodal approaches based on various data modalities such as speech, handwriting, gait, and neuroimaging [16]. The study by [17] introduced a multimodal framework that integrates handwriting and speech data, achieving higher diagnostic accuracy than models relying on a single modality. By leveraging complementary information from multiple data sources, the proposed approach enhances model robustness and offers a more comprehensive understanding of Parkinson's disease progression.

In recent years, Deep learning has led to increasingly complex architectures for PD detection. CNNs have proven effective in analyzing both medical images and handwriting samples. Another study by [18], developed a CNN-based model for detecting PD from handwritten sketches, achieving high classification accuracy. Similarly, a study by [19], introduced an LSTM-based system that efficiently detected PD-related speech disorders, outperforming traditional classifiers.

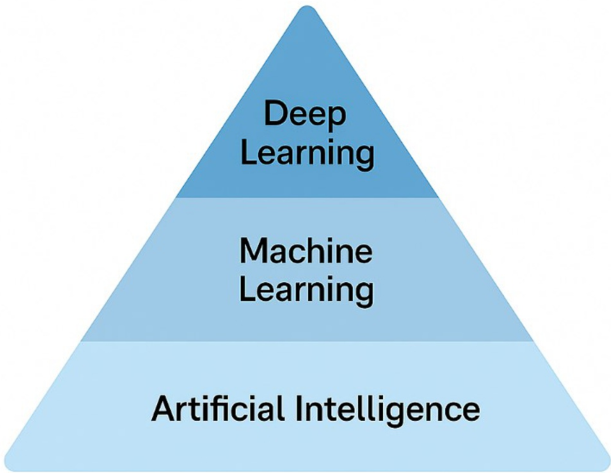

Fig. 1. Hierarchy of Artificial Intelligence

Overall, deep learning, particularly CNN, has emerged as a powerful tool for PD detection, offering higher accuracy and efficiency in processing multimodal data sources compared to traditional machine learning models [20].

Despite such promising developments, there remain challenges in implementing DL-based PD detection systems in clinical practice. One of the key challenges lies in the need for abundant amounts of good-quality data to train powerful models and obtain generalizability across various populations [21]. However, explainability and interpretability of DL models are also essential for clinical adoption and regulatory approval [22]. Ethical concerns, such as patient privacy and potential algorithmic biases, must also be addressed to ensure fairness in healthcare applications [23].

This study provides a comprehensive review of recent advancements in the CNN approach for PD detection. It examines the strengths and limitations of various deep learning models and challenges in clinical implementation. Additionally, the review discusses multimodal data integration and future research directions to further enhance the accuracy and reliability of PD detection.

The structure of the review is as follows: Section 2. Explain the methodology of the review. Section 3: Shows literature review. Section 4: Discuss proposed Deep learning models (CNN). Section 5: presents Challenges and Limitations in Existing Studies. Section 6 discusses Future Directions and Finally, Conclusion.

2 Literature Review

Recent advances in Parkinson's Disease (PD) detection using machine learning and deep learning span across various domains including speech analysis, ensemble learning, multimodal approaches, medical imaging, and data handling techniques.

2.1 Speech-Based Detection Methods

Speech impairment is the first sign of PD and consequently serves as an excellent biomarker for diagnosis. Di Cesare et al. [24] investigated ML-based speech analysis for PD early diagnosis. They employed feature extraction techniques such as MEL Frequency Cepstral Coefficients (MFCCs) and Gammatone Frequency Cepstral Coefficient (GTCCs) and demonstrated that such features can detect PD-related speech impairment at early stage using mobile phone recording. Daniel et al. [25] also investigated the influence of deep learning (DL) models on PD detection based on speech. They demonstrated that the incorporation of Convolutional Neural Networks (CNNs) along with Bidirectional Long Short-Term Memory (BiLSTM) networks improved the classifier accuracy up to 93.2%. These findings demonstrate that non-invasive diagnosis techniques such as voice analysis can achieve accurate PD detection at low costs and without the use of expensive clinical tests.

2.2 Ensemble and Hybrid Models

Ensemble learning has been increasingly used to improve PD diagnosis. Dixit et al. [26] examined the use of ML classifier and DL in PD diagnosis and demonstrated how ensemble models outperformed traditional classifiers. They compared ANN, SVM, and RF and demonstrated that a superior ANN model had an accuracy higher than traditional classifiers.

Sharma et al. [27] proposed a stacked ensemble approach utilizing Extreme Gradient Boosting (XGBoost), Decision Trees (DT), and k-Nearest Neighbors (KNN). Their work achieved a 96% rate of sensitivity and reduced false positive rates. This work emphasizes the role of DL in improving the accuracy of diagnosis and reducing risks of misclassification in PD identification.

2.3 Multimodal and Sensor-Based Approaches

A growing body of research has focused on integrating multiple data modalities to improve diagnostic reliability. Dhivyaa et al. [28] analyzed the role of clinical data, neuroimaging, EEG, gait analysis, and handwritten samples in PD detection, highlighting the power of multimodal integration. It considers several neuroimaging measures and their capacity for detecting anatomical and functional changes within the brain related to Parkinson's disease.

The study highlights how AI-based systems have the potential to revolutionize the diagnosis of PD, with a view to providing better, more accurate, and earlier medical interventions, through state-of-the-art AI algorithms and multimodal data sources.

Borzì et al. [29] developed a wearable sensor-based approach to quantify axial impairment in PD patients. They monitored gait and postural instability and predicted postural instability/gait difficulty (PIGD) with a single inertial sensor. The findings suggest that unobtrusive sensors can enable remote PD monitoring and present clinicians with valuable medical indices for assessment.

Similarly, Varghese et al. [30] introduced a multimodal PD detection using Parkinson's Disease Smartwatch (PADS) dataset with movement disorder data and clinical annotations.
Their Machine Learning (ML) model based on the incorporation of traditional signal processing and deep learning (DL) achieved an accuracy of 91.16% in distinguishing between PD patients and healthy controls. This work highlights the rising role of wearable technology in personalized health care.

2.4 Medical Imaging and CNN Applications

Medical imaging continues to be a robust modality for PD detection. Zhang et al. [3] utilized ResNet-50 on DaTSCAN images, reaching a classification accuracy of 91.5%. Wang et al. [31] demonstrated improved specificity using SE-ResNeXt50 on MRI data. These CNN-based approaches are effective in learning spatial features, reducing the need for manual feature engineering.

2.5 Data Challenges and Augmentation

Data scarcity and imbalance remain major limitations in PD research. Martinez et al. [32] addressed these issues using data augmentation and transfer learning techniques.
Saravanan et al. [33] applied the SMOTE technique to balance voice-based datasets, leading to enhanced classifier performance. These studies underscore the importance of data preprocessing in ensuring model generalizability and reliability. Their feedforward neural network model optimized by randomized search cross-validation had improved classification accuracy. This study illustrates the requirement of data augmentation in balancing imbalanced datasets in PD diagnosis.

Overall, the literature reveals a growing shift toward deep learning, multimodal integration, and real-time wearable systems to enhance early PD diagnosis. Future studies should focus on improving model explainability, generalization across diverse populations, and ethical deployment in clinical settings.
Table 1 summarizes recent research efforts on Parkinson's disease detection using deep learning approaches. The table includes key studies that leveraged different data modalities such as speech, handwriting, sensor data, and medical imaging. Among the listed works, ensemble methods and CNN architectures frequently demonstrated high classification accuracy, with some reaching over 91% in distinguishing Parkinson's patients from healthy individuals. This demonstrates the growing reliability of DL-based methods. However, not all studies report complete performance metrics, and some use unspecified or proprietary datasets, which may affect reproducibility.

A comparative summary of the reviewed studies, including data types, models used, and reported accuracies, is presented in Table 1.

Table 1. A comparative summary of the reviewed studies of PD detection based on DL

Ref.	Focus	Dataset	Models Used	Accuracy (%)
[24]	Speech-based PD diagnosis	Speech dataset	MFCCs, GTCCs	92.3
[25]	Deep learning for PD detection from speech	Speech dataset	CNN, BiLSTM	93.2
[26]	Hybrid ML models for PD detection	Multiple PD datasets	ANN, SVM, RF	Higher Accuracy
[27]	Stacked ensemble for PD classification	Multiple PD datasets	XGBoost, DT, KNN	96
[28]	Multimodal approaches in PD detection	Clinical, neuroimaging, sensor datasets	Multiple computational models	Not specified
[29]	Wearable technology for PD detection	Wearable sensor dataset	Traditional signal processing, Regression Models	Not specified
[30]	Multimodal PD detection	PADS dataset	ML, DL	91.16
[3]	CNN-based PD detection from DaTSCAN images	DaTSCAN dataset	ResNet-50	91.5
[32]	CNN-based PD detection from MRI	MRI dataset	SE-ResNeXt50	Not specified
[33]	SMOTE for dataset balancing in PD detection	Various PD datasets	CNN with transfer learning	Not specified

3 Methodology of the review

This review followed a systematic approach to identify and evaluate relevant studies on the application of deep learning techniques in the detection of Parkinson's Disease. A comprehensive search was conducted across multiple scientific databases, including PubMed, IEEE Xplore, Scopus, ScienceDirect, and Google Scholar. The search strategy involved a combination of keywords and Boolean operators, such as "Parkinson's Disease," "deep learning," "convolutional neural networks," "medical imaging," "speech analysis," and "multimodal diagnosis." The review focused on studies published between 2020 and 2024. Only peer-reviewed journal articles and high-quality conference papers that explicitly employed deep learning models for Parkinson's Disease detection were considered. Exclusion criteria included non-English publications, articles lacking full methodological detail, and studies that did not primarily focus on Parkinson's-related detection or used traditional machine learning methods without deep learning integration. Following an initial screening and quality assessment, a curated set of studies was selected to ensure a focused, current, and critical overview of recent advancements and ongoing challenges in this domain.

4 State-of-Art Deep Learning Models

Deep learning models have been widely utilized for classification, clustering, and regression tasks, enabling the extraction of high-level features and enhancing the accuracy of Parkinson's disease (PD) detection. These models have a more complex architecture compared to traditional machine learning models, requiring greater computational resources and larger training datasets. This complexity also supports improved hyperparameter tuning and data augmentation [4]. In this review, we explore the deep learning models that have been previously applied to PD detection, along with their corresponding architectures, as outlined below:

A. Convolution Neural Networks

Convolutional Neural Networks (CNNs) are supervised deep learning models that were originally introduced by LeCun et al. in the year 1998 [34]. They have found numerous applications in the field of computer vision, image processing, natural language processing or NLP, and disease diagnosis. CNNs have three layers: convolutional layers, pooling layers, and fully connected layers.

The first layer, the convolutional layer, employs multiple filters on the input data to extract the important features such as the pattern in the images of the brain. The second layer, the pooling layer, reduces the feature maps by employing multiple techniques of pooling and therefore reducing the computational complexity while maintaining the important information. The third layer, the fully connected layer, flattens the two-dimensional feature maps into one-dimensional vector that will be used for classification in order to detect if the image indicates the presence of any disease. (See Fig. 2).

The CNNs have been extensively applied in medical imaging for PD detection from MRI, fMRI, and DaTSCAN images Lee et al. [22]. CNNs automatically learn spatial features, depending less on manual feature engineering.

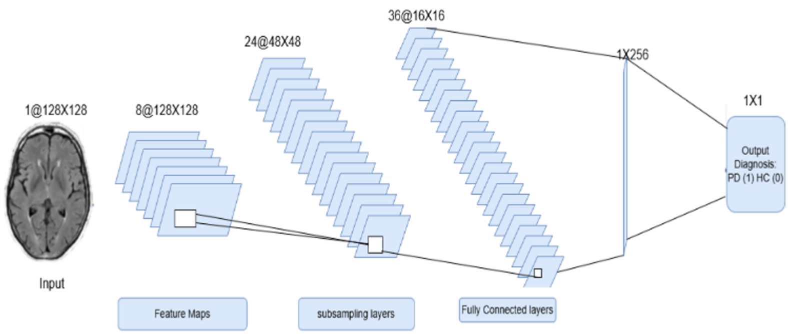

Fig. 2. CNN Architecture.

Figure 3. Graphing the comparison between the accuracy of ML models and CNNs for the detection of Parkinson's disease would typically have CNNs outperforming traditional ML models. CNNs achieve this because they learn significant features from unprocessed data, particularly in image and speech processing, with less need for feature engineering. While ML models rely on feature engineering by humans, CNNs learn spatial and temporal structures efficiently, leading to improved accuracy and resilience in complex medical diagnosis.

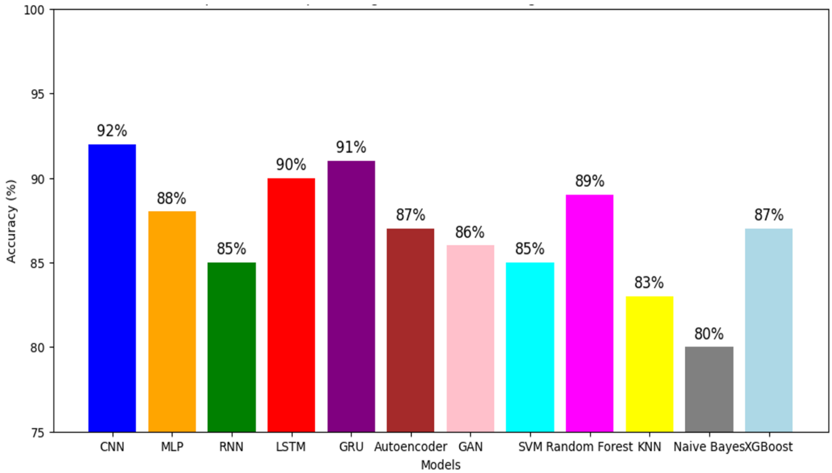

Fig. 3. Comparison of Deep Learning and Machine Learning for PD detection.

5 Challenges and Limitations in Existing Studies

Though significant advances have been made, deep learning-based PD detection also faces some challenges. One of the biggest challenges for deep learning-based PD detection is the limited availability of data or data heterogeneity, as the learned models on one data set do not generalize on external data due to variations in patient demographics and data acquisition [35]. Brumm et al. [36] use public datasets like Parkinson's Progression Markers Initiative (PPMI) datasets containing valuable information but are small-scale, unbalanced, and lack diversified patient representation. Computational limitations also limit the use of DL models in the clinical setting and necessitate the creation of lightweight architectures. Another challenge as Deep learning models are black-box models that are difficult to implement clinically. Physicians require explainable AI models that provide insights on why the model is making the prediction of PD as Islam et al. [37], use Explainable AI (XAI) methods like Shapley Additive Explanations (SHAP) to interpret clinical assessment of the model with higher accuracy.
While deep learning models are accurate in laboratory experiments, it is again difficult to apply the models to real-world clinical scenarios. Some of the challenges include

privacy concerns, regulatory approvals, and the need to process in real-time on wearables Gomez et al. [38]. Recent studies point to federated learning as the approach to train models in the absence of central data collection to alleviate privacy issues Appineni et al. [39]. Ethical concerns of data privacy, model interpretability, and bias have to be resolved in order to enable widespread adoption of AI-based PD diagnostics Itai et al. [40].

6 Future Directions

To improve PD detection in the future, the following issues need to be addressed in follow-up studies: Creating explainable AI (XAI) techniques for model transparency, and Enhancing diversity in the data to make it globally applicable. Likewise Exploring data augmentation and synthetic data generation through GANs Ahmed et al. [17]. Deep learning revolutionized PD detection with impressive accuracy and efficiency gains using powerful architectures such as transformers, federated learning, and self-supervised learning, researchers can enhance early diagnosis and disease management. However, there are challenges in data, computation, and ethics to overcome in order to facilitate broadened clinical application.

Deep learning has shown immense promise in the detection of Parkinson's disease, and CNN model achieved high state-of-the-art performance. However, challenges include data availability, model interpretability, and clinical deployment. Future research needs to focus on multimodal fusion, privacy-preserving AI, and real-time deep-learning methods to improve PD diagnosis.

7 Conclusion

This review has systematically examined recent advancements in the application of deep learning, particularly Convolutional Neural Networks (CNNs), for the detection of Parkinson's Disease (PD) across diverse data modalities, including speech, handwriting, gait, and medical imaging. The comparative analysis of existing models underscores the increasing efficacy of deep learning, with a growing emphasis on multimodal and ensemble-based frameworks for early and accurate PD diagnosis.

The integration of heterogeneous data sources, such as clinical signals, sensor data, and neuroimaging, has demonstrated improved diagnostic precision, particularly in capturing the complex motor and non-motor manifestations of PD. This reflects a notable shift in current research from unimodal classification systems toward more comprehensive and context-aware architectures.

However, several challenges persist. These include limited availability of large-scale, well-annotated datasets, variations in data acquisition protocols, and the black-box nature of many deep learning models, which raises concerns regarding clinical interpretability and trust. Addressing these issues is critical for the development of reliable, explainable, and generalizable AI systems suitable for clinical deployment.

This study serves as a consolidated reference for researchers and clinicians, offering insights into model performance, current trends, and future directions. Further work should prioritize the development of standardized benchmarking frameworks, cross-center validation, and interpretable AI models to facilitate real-world adoption of deep learning in PD diagnosis and monitoring.

Disclosure of Interests. We declare that there are no conflicts of interest regarding the publication of this work. All authors have reviewed and approved the final version of the work and agree to be accountable for all aspects of the work.

References

1. C. Taleb, L. Likforman-Sulem, C. Mokbel, and M. Khachab, "Detection of Parkinson's disease from handwriting using deep learning: a comparative study," Evol. Intell., vol. 16, no. 6, pp. 1813–1824, 2023, doi: 10.1007/s12065-020-00470-0.
2. L. Sahu, R. Sharma, I. Sahu, M. Das, B. Sahu, and R. Kumar, "Efficient detection of Parkinson's disease using deep learning techniques over medical data," Expert Syst., vol. 39, no. 3, pp. 1–15, 2022, doi: 10.1111/exsy.12787.
3. J. Zhang, "Mining imaging and clinical data with machine learning approaches for the diagnosis and early detection of Parkinson's disease," npj Park. Dis., vol. 8, no. 1, 2022, doi: 10.1038/s41531-021-00266-8.
4. A. Alotaibi, "Ensemble Deep Learning Approaches in Health Care: A Review," Comput. Mater. Contin., vol. 82, no. 3, pp. 3741–3771, 2025, doi: 10.32604/cmc.2025.061998.
5. C. H. Lin, F. C. Wang, T. Y. Kuo, P. W. Huang, S. F. Chen, and L. C. Fu, "Early Detection of Parkinson's Disease by Neural Network Models," IEEE Access, vol. 10, pp. 19033–19044, 2022, doi: 10.1109/ACCESS.2022.3150774.
6. S. Naz, I. Kamran, S. Gul, F. Hadi, and F. Khalifa, "Multi-Model Fusion of CNNs for Identification of Parkinson's Disease Using Handwritten Samples," IEEE Access, vol. 11, no. November, pp. 135600–135608, 2023, doi: 10.1109/ACCESS.2023.3337804.
7. R. Pratihar and R. Sankar, "Advancements in Parkinson's Disease Diagnosis: A Comprehensive Survey on Biomarker Integration and Machine Learning," Computers, vol. 13, no. 11, 2024, doi: 10.3390/computers13110293.
8. Z. Ayaz, S. Naz, N. H. Khan, I. Razzak, and M. Imran, Automated methods for diagnosis of Parkinson's disease and predicting severity level, vol. 35, no. 20. Springer London, 2023. doi: 10.1007/s00521-021-06626-y.
9. M. Jyotiyana, N. Kesswani, and M. Kumar, "A deep learning approach for classification and diagnosis of Parkinson's disease," Soft Comput., vol. 26, no. 18, pp. 9155–9165, 2022, doi: 10.1007/s00500-022-07275-6.
10. M. B. T. Noor, N. Z. Zenia, M. S. Kaiser, S. Al Mamun, and M. Mahmud, "Application of deep learning in detecting neurological disorders from magnetic resonance images: a survey on the detection of Alzheimer's disease, Parkinson's disease and schizophrenia," Brain Informatics, vol. 7, no. 1, 2020, doi: 10.1186/s40708-020-00112-2.
11. G. Costantini et al., "Deep-Learning Comparison," Sensors, 2023, [Online]. Available: https://doi.org/%0A10.3390/s23042293
12. K. Deng, Y. Li, H. Zhang, J. Wang, R. L. Albin, and Y. Guan, "Heterogeneous digital biomarker integration out-performs patient self-reports in predicting Parkinson's disease," Commun. Biol., vol. 5, no. 1, 2022, doi: 10.1038/s42003-022-03002-x.

13. M. S. Hema, R. Maheshprabhu, M. Nageswara Guptha, G. Prema Arokia Mary, and A. Sharma, “Prediction of Parkinson Disease using Autoencoder Convolutional Neural Networks,” Int. Interdiscip. Humanit. Conf. Sustain. IIHC 2022 - Proc., pp. 236–239, 2022, doi: 10.1109/IIHC55949.2022.10060292.
14. S. Lin et al., “Wearable sensor-based gait analysis to discriminate early Parkinson’s disease from essential tremor,” J. Neurol., vol. 270, no. 4, pp. 2283–2301, 2023, doi: 10.1007/s00415-023-11577-6.
15. R. S. Vanguri et al., “Multimodal integration of radiology, pathology and genomics for prediction of response to PD-(L)1 blockade in patients with non-small cell lung cancer,” Nat. Cancer, vol. 3, no. 10, pp. 1151–1164, 2022, doi: 10.1038/s43018-022-00416-8.
16. J. Shin, A. S. M. Miah, K. Hirooka, M. A. M. Hasan, and M. Maniruzzaman, “Parkinson Disease Detection Based on In-air Dynamics Feature Extraction and Selection Using Machine Learning,” vol. 4, pp. 1–19, 2024, [Online]. Available: http://arxiv.org/abs/2412.17849
17. H. M. Balaha, A. E. S. Hassan, R. A. Ahmed, and M. H. Balaha, “Comprehensive multimodal approach for Parkinson’s disease classification using artificial intelligence: insights and model explainability,” Soft Comput., vol. 29, no. 3, pp. 1845–1877, 2025, doi: 10.1007/s00500-025-10463-9.
18. Z. Li, J. Yang, Y. Wang, M. Cai, X. Liu, and K. Lu, “Early diagnosis of Parkinson’s disease using Continuous Convolution Network: Handwriting recognition based on off-line hand drawing without template,” J. Biomed. Inform., vol. 130, no. November 2021, p. 104085, 2022, doi: 10.1016/j.jbi.2022.104085.
19. A. Zhao, Y. Liu, X. Yu, and X. Xing, “Artificial intelligence-enabled detection and assessment of Parkinson’s disease using multimodal data: A survey,” no. 62106117, pp. 1–19, 2025, [Online]. Available: http://arxiv.org/abs/2502.10703
20. [20] M. Shaban, “Deep Learning for Parkinson’s Disease Diagnosis: A Short Survey,” Computers, vol. 12, no. 3, 2023, doi: 10.3390/computers12030058.
21. G. Sabherwal and A. Kaur, Machine learning and deep learning approach to Parkinson’s disease detection: present state-of-the-art and a bibliometric review, vol. 83, no. 29. Springer US, 2024. doi: 10.1007/s11042-024-18398-3.
22. S. Chatterjee et al., “TorchEsegeta: Framework for Interpretability and Explainability of Image-Based Deep Learning Models,” Appl. Sci., vol. 12, no. 4, pp. 1–20, 2022, doi: 10.3390/app12041834.
23. K. Rasheed, A. Qayyum, M. Ghaly, A. Al-Fuqaha, A. Razi, and J. Qadir, “Explainable, trustworthy, and ethical machine learning for healthcare: A survey,” Comput. Biol. Med., vol. 149, no. September, p. 106043, 2022, doi: 10.1016/j.compbiomed.2022.106043.
24. M. G. Di Cesare, D. Perpetuini, D. Cardone, and A. Merla, “Machine Learning-Assisted Speech Analysis for Early Detection of Parkinson’s Disease: A Study on Speaker Diarization and Classification Techniques,” Sensors, vol. 24, no. 5, 2024, doi: 10.3390/s24051499.
25. D. Escobar-Grisales, C. D. Ríos-Urrego, and J. R. Orozco-Arroyave, “Deep Learning and Artificial Intelligence Applied to Model Speech and Language in Parkinson’s Disease,” Diagnostics, vol. 13, no. 13, pp. 1–16, 2023, doi: 10.3390/diagnostics13132163.
26. S. Dixit et al., “A Comprehensive Review on AI-Enabled Models for Parkinson’s Disease Diagnosis,” Electron., vol. 12, no. 4, 2023, doi: 10.3390/electronics12040783.
27. A. Sharma and N. Sharma, “A Comprehensive Ensemble Machine Learning Model for Predicting Parkinson’s Disease Progression and Severity,” 2024 IEEE Int. Conf. Interdiscip. Approaches Technol. Manag. Soc. Innov. IATMSI 2024, vol. 2, pp. 1–6, 2024, doi: 10.1109/IATMSI60426.2024.10502487.

28. C. R. Dhivyaa, K. Nithya, and S. Anbukkarasi, "Enhancing Parkinson's Disease Detection and Diagnosis: A Survey of Integrative Approaches Across Diverse Modalities," IEEE Access, vol. 12, no. October, pp. 158999–159024, 2024, doi: 10.1109/ACCESS.2024.3487001.
29. L. Borzì, I. Mazzetta, A. Zampogna, A. Suppa, F. Irrera, and G. Olmo, "Single Inertial Sensor," pp. 1–22, 2022.
30. J. Varghese, A. Brenner, M. Fujarski, C. M. van Alen, L. Plagwitz, and T. Warnecke, "Machine Learning in the Parkinson's disease smartwatch (PADS) dataset," npj Park. Dis., vol. 10, no. 1, pp. 1–11, 2024, doi: 10.1038/s41531-023-00625-7.
31. Y. Wang et al., "An automatic interpretable deep learning pipeline for accurate Parkinson's disease diagnosis using quantitative susceptibility mapping and T1-weighted images," Hum. Brain Mapp., vol. 44, no. 12, pp. 4426–4438, 2023, doi: 10.1002/hbm.26399.
32. M. Martinez-Eguiluz et al., "Machine Learning for Prediction of Cognitive Deterioration in Patients with Early Parkinson's Disease," Appl. Sci., vol. 14, no. 18, 2024, doi: 10.3390/app14188149.
33. S. Srinivasan, P. Ramadass, S. K. Mathivanan, K. Panneer Selvam, B. D. Shivahare, and M. A. Shah, "Detection of Parkinson disease using multiclass machine learning approach," Sci. Rep., vol. 14, no. 1, pp. 1–17, 2024, doi: 10.1038/s41598-024-64004-9.
34. K. S. Choi, J. S. Shin, J. J. Lee, Y. S. Kim, S. B. Kim, and C. W. Kim, "In vitro trans-differentiation of rat mesenchymal cells into insulin-producing cells by rat pancreatic extract," Biochem. Biophys. Res. Commun., vol. 330, no. 4, pp. 1299–1305, 2005, doi: 10.1016/j.bbrc.2005.03.111.
35. C. Gundler et al., "A Unified Data Architecture for Assessing Motor Symptoms in Parkinson's Disease," Stud. Health Technol. Inform., vol. 307, pp. 22–30, 2023, doi: 10.3233/SHTI230689.
36. M. C. Brumm et al., "Parkinson's Progression Markers Initiative: A Milestone-Based Strategy to Monitor Parkinson's Disease Progression," J. Parkinsons. Dis., vol. 13, no. 6, pp. 901–918, 2023, doi: 10.3233/JPD-223433.
37. N. Islam, M. S. A. Turza, S. I. Fahim, and R. M. Rahman, "Advanced Parkinson's Disease Detection: A comprehensive artificial intelligence approach utilizing clinical assessment and neuroimaging samples," Int. J. Cogn. Comput. Eng., vol. 5, no. May, pp. 199–220, 2024, doi: 10.1016/j.ijcce.2024.05.001.
38. J. E. Valerio, G. De Jesús, A. Vera, M. P. F. Gomez, and J. Zumaeta, "Advancing Early Identification of Clinical Trials in Neurosurgical Interventions for Parkinson ' s Disease : The Critical Role of AI-Driven Platforms and Technological Innovation Advancing Early Identification of Clinical Trials in Neurosurgical Intervent," pp. 0–26, 2025, doi: 10.20944/preprints202503.0054.v1.
39. A. Appineni and A. Gupta, "Preemptive Diagnosis of Parkinson's Disease through DaT Scans Using InceptionV3-Based Convolutional Neural Networks," 2023, doi: 10.3390/xx010005.
40. I. Bavli, A. Ho, R. Mahal, and M. J. McKeown, "Ethical concerns around privacy and data security in AI health monitoring for Parkinson's disease: insights from patients, family members, and healthcare professionals," AI Soc., vol. 40, no. 1, pp. 155–165, 2024, doi: 10.1007/s00146-023-01843-6.