Archives available at journals.mriindia.com

International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140

Volume 14 Issue 03s, 2025

Early Detection and Predictive Analysis of Parkinson's Disease: A Comprehensive Review of Machine Learning and Deep Learning Approaches

[1]Imran S. khan, [2]Prof.Suraj Mahajan, [3]Prof.Mayuri Harde

[1]PG Scholar, Department of Electronics (Communication) Engineering
Tulsiramji Gaikwad-Patil College of Engineering & Technology, Nagpur, India
[2]Project Guide, Department of Electronics (Communication) Engineering
Tulsiramji Gaikwad-Patil College of Engineering & Technology, Nagpur, India
[3]Project Co-Guide, Department of Electronics (Communication) Engineering
Tulsiramji Gaikwad-Patil College of Engineering & Technology, Nagpur, India
Email: [1]imranskhan200927@gmail.com, [2]suraj.ece@tgpcet.com, [3]mayuri.ece@tgpcet.com

Peer Review Information

Submission: 05 Nov 2025

Revision: 25 Nov 2025

Acceptance: 17 Dec 2025

Keywords

Artificial Intelligence, Deep Learning, Early Detection, Machine Learning, Parkinson's Disease, Predictive Analysis.

Abstract

Background: Parkinson's Disease (PD) is a chronic neurodegenerative condition that is represented by a wide array of motor and non-motor features. Like all neurodegenerative conditions, its early features are difficult to identify; and while they demand urgent attention, PD's physical diagnostic criteria capture advanced features. Effective treatment necessitates early intervention and prompt diagnosis. Objectives: The goal of this study is to evaluate the effectiveness of machine learning and deep learning in the prediction and early diagnosis of PD. The study attempts to evaluate the existing methods, focus on the crucial performance measures, and attempts to fill the research gaps to enhance the methods in the future. Key Findings: Metrics offered by DL-class CNN and CNN–LSTM models put their accuracy between 90 and 93 percent, making them superior to ML techniques, while ensemble methods such as XGBoost have an accuracy of 98 percent. While PD detection methods have seen substantial progress, there is still room for improvement in datasets, model generalizability, and interpretability methods.Future directions focus on the fusion of multi-modal data, explainable AI, and IoT-based real-time monitoring, for a more robust, interpretable, and clinically deployable PD detection system.

Introduction

Parkinson's Disease (PD) is an increasing concern because of how it impacts the motor functions of the human body and how it negates functions such as tremors, rigidity, bradykinesia, and postural stability. The World Health Organization (WHO) states that PD is already affecting over the 10 million mark worldwide and with the advancing age of the population, there is an expectation for the number to double by the year 2040. Along with the slow progression comes slow diagnosis and is only done after a serious loss of dopaminergic neurons in the brain's substantia nigra region. Discovery in the earliest stages of the disease is the most important, as there is a strong chance to slow down the disease greatly, is as flexible to treat, and can be planned for better treatment is there in question [1][2].

The traditional methods, which have strong clinical relevance, focus on neurologic evaluation, clinical scoring such as the Unified Parkinson's Disease Rating Scale (UPDRS), and human observation. Each of these methods—and especially clinical human observation—have a number of constraining factors: variability from one clinician to another, reliance on motor symptoms that are visible, and PD detection in the preclinical or earliest stages of the disease. Whereas biomarkers like speech and gait abnormalities as well as handwriting emerge significantly earlier than visible tremors, these subtle symptoms are rarely employed in diagnosis frameworks [3][4][5].

With reference to the aforementioned challenges, deep learning and machine learning present the most effective means of implementing non-invasive automated early diagnosis of Parkinson's Disease. These technologies are trained with a large amount of data, and they can be employed to multisource data such as voice, gait, and handwriting data [6][7].Support Vector Machines (SVMs), Random Forests (RF), Convolutional Neural Networks (CNNs), and even Long Short-Term Memory (LSTM) networks have shown immense potential for refining diagnostic accuracy and improving predictive analysis. [8][9]

Nonetheless, these issues still remain: existing models usually suffer from inconsistent performance as a result of dataset variability, they do not generalize well for different patient populations, and make scant use of multimodal biomarkers. [10] In addition, early prediction studies seem to track a single data source such as speech or gait, instead of utilizing multiple complementary signals.

1. In an attempt to resolve the issues at hand, this study focuses on the development of an effective ML-based framework which integrates multimodal features from speech, gait, and handwriting datasets for the early identification of PD.
2. Identification of advanced deep learning models along with comparative performance evaluation of predictive analytics using traditional machine learning and advanced deep learning models to establish their context specific strengths and limitations.
3. Ensuring model generalization and clinical reliability through statistical validation on multiple benchmark datasets.

Literature Review

A. Parkinson's Disease Diagnosis Approaches

Clinical scales like the UPDRS and neurological exams are key in traditional PD diagnosis, but these are subjective and focus only on apparent motor symptoms. Digital speech, handwriting, gait, and sensor data provide digital biomarkers, which computational techniques can use for a more balanced approach. Using diverse voice metrics, Putri et al. (2018) reported an impressive 94.4% accuracy applying ANN [11]. Using ML, Tyagi et al. (2021) identified micrographia in handwriting images and attained a 94% accuracy [12]. In Drotár et al. (2024), SVM classification achieved 81.3% accuracy with pressure and kinematic features of handwriting [13]. A CNN-based voice detection method that uses spectrogram and ResNet (2020) also reached accuracies above 90% [14]. Wearable sensor gait analysis now measures stride length, variability, and asymmetry, which enables detection through subtle early signs [15]. Early detection is made possible by AI-assisted blood testing (2024) for PD proteins years before, and by earwax VOC testing (2025) and magnetic ink pens (2025) that have shown 94% and 96% accuracy respectively albeit preliminary, revealing new detection possibilities [16].

B. Machine Learning Models Used

Classical ML Models: Srinivasan et al. (2024) identified PD patients and healthy controls from voice data (UCI dataset) using K-NN and FNN.

Deep Learning Models: Xia et al. (2019) utilized CNN-LSTM on gait VGRF time series, reporting 99.1% accuracy [17]. Maachi et al. (2020) reported 98.7% accuracy on 1D gait signals using 1D-DNN [18]. Handwriting detection includes Pereira et al.'s (2018) CNN (95% accuracy), Yang et al.'s (2019) GRNN (98.9%), and Gazda et al.'s (2021) CNN (94.7%) [19][20]. For multimodal fusion, Pandey et al. (2025) suggested hybrid CNN-LSTM on voice spectrograms, achieving 97% accuracy. Zahid et al. (2025) used transfer learning based on AlexNet, reaching 99% accuracy [21][22][23].

C. Feature Engineering Techniques

The basic features such as MFCCs, jitter, and stride from the time and frequency domain still serve as the base. Spectrogram-based features are a defining factor in voice-related works. Drotár et al. underlined that pressure features allow for better discrimination in comparison to kinematic features in handwriting. For robustness and model compactness, Principal Component Analysis for dimensionality reduction and augmentation of spectrograms are employed [24][25].

D. Publicly Available Datasets

Central datasets notably consist of:

- The UCI Parkinson's Voice Dataset (195 subjects, 22 vocal features), which is a benchmark for voice-based machine learning research.

- The PaHaW Handwriting Dataset (37 PD, 38 controls; pressure and kinematic features).
- The PC-GITA Voice Dataset (used in ResNet spectrogram and hybrid deep learning studies).

Table 1: Summary of Literature Review

Study (Year)	Method / Key Findings	Limitations / Research Gap
Putri et al. (2018) [11]	ANN on diverse voice features; 94.4% accuracy	Small sample size; limited modalities
Pereira et al. (2018) [12]	CNN on handwriting images; 95% accuracy	Low subject count; handwriting only
Drotár et al. (2024) [13]	SVM on handwriting kinematic + pressure; 81.3% accuracy	Moderate accuracy; separate features
Tyagi et al. (2021) [14]	ML on micrographia handwriting; 94% accuracy	Early stage; needs broader validation
Xia et al. (2019) [15]	CNN-LSTM on gait VGRF; 99.1% accuracy	Requires gait sensors; limited to lab settings
Maachi et al. (2020) [16]	1D-DNN on gait signals; 98.7% accuracy	Sensor-based; dataset constraint
Srinivasan et al. (2024) [17]	K-NN & FNN on voice (UCI); multi-class classification	Relatively small dataset
ResNet + spectrogram (2020) [18]	Transfer learning on voice; >90% accuracy	Spectrogram only; potential overfitting
Pandey et al. (2025) [19]	CNN-LSTM on voice spectrograms; ~97% accuracy	Early results; real-world testing pending
Ashraf et al. (2025) [20]	AlexNet transfer learning; up to 99.7% accuracy	Needs non-PD sample diversity
Patil et al. (2025) [21]	Predicts PD up to 7 years prior using 8 proteins	Clinical validation needed; ethical considerations
Chen(2025) [22]	94% accuracy with earwax based VOCs	Small study; local cohort; needs expansion
Fu et al. (2023) [23]	96.2% accuracy with motion pen handwriting signals	Pilot with 16 subjects; limited generalizability
Mancini et al. (2025) [24]	Digital gait measures as early markers	Needs standardized device protocols
Hossain et al. (2025) [25]	Wav2Vec2 + GRU ensemble; 99% accuracy	Dependent on large datasets; language-specific

Comparative Analysis

A. Comparison of Techniques

In this review, we focus on the early detection of Parkinson's disease (PD) by comparing classical machine learning (ML) methods, deep learning (DL) models, and hybrid methods combining elements of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks (e.g., CNN–LSTM, LSTM–CNN, LSTM–GRU). The analysis considers the types of datasets employed, the reliance on features, performance metrics, interpretability, and computational cost.

Feature-dependent methods like Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (K-NN) are classical ML methods that depend on handcrafted features, usually from speech, handwriting, or gait data. For example, Sakar et al. (2019) employed SVM on speech data and obtained an accuracy of 86% using UCI and participant-collected datasets. On the other hand, Ouhmida (2021) outperformed SVM, K-NN, and Decision Tree on the UCI repository, reaching an exceptional AUC of 98.26% [26]. Focusing on handwriting, Drotár et al. (2024) achieved 81.3% combining kinematic and pressure features with SVM on handwriting tasks, mentioning that pressure features performed slightly better at 82.5% [13]. While classical techniques come with the benefits of interpretability and low computational cost, they tend to have lower performance compared to deeper models.

The models offer a different workflow using traditional deep learning algorithms. For instance, Pereira et al. (2018) used CNN on handwriting images and got an accuracy score of 95%. In the case of gait, Maachi et al. (2020) attained an impressive 98.7% accuracy with DNN on 18 one-dimensional signals [27]. Yousif et al. (2025) achieved almost flawless accuracy using fine-tuned CNNs (like VGG19, ResNet50) and ML classifiers on speech and gait combinations of data—VGG19 scored 99.75% on handwriting data, and SVM/KNN on combined signal features scored 99.94%. While these deep models achieve remarkably high accuracy, they are more difficult to understand and necessitate a lot of processing power as well as data [28][29][30].

Hybrid models like CNN-LSTM, CNN–multi-head attention–LSTM, or LSTM-CNN serve to blend the automatic feature extraction with temporal sequence modeling. Rehman et al. (2023) demonstrated the effectiveness of their hybrid LSTM-GRU model, which utilized diverse speech features, attaining a remarkable accuracy of 93.5%, which surpasses that of classical ML techniques such as SVM (~90.8%) and CART (84.2%). Regarding EEG-based detection, the hybrid CNN-LSTM model achieved 98.6% accuracy, 97.1% sensitivity, and 97.6% specificity in parallel mode, and a remarkable 99.7% accuracy in series mode [30][31]. In the same vein, late fusion models that integrate CNN and attention mechanisms on handwriting and imaging features attained 99.85% accuracy on the PaHaW and motion datasets and 98.52% on HandPD. These models also demonstrated impressive precision of ≈ 98.1%, recall of 97.3%, and F1-score of 98.4%.

Wang et al. (2023) developed a streamlined LSTM–CNN model for cursive writing. They employed the two datasets and obtained 96.2% on DraWritePD and 90.7% on PaHaW. The models contained a mere 0.084 million parameters and inference times of 0.106–0.220 seconds on a single CPU core, nearly real-time [32][33]. Complementing those is PD-Net for 2025, a CNN + multi-head attention + LSTM ensemble on speech features (Mel-MFCC), which hit 99% accuracy with 2.7 million parameters. Such hybrids attempt a middle ground between accuracy and compute, often the most accurate especially with multi-modal features [34][35].

Table 2: Comparative Analysis of ML vs. DL vs. Hybrid Models

Study (Year) / Technique	**Dataset/Modality**	**Model Type**	**Accuracy**	**Interpretability**	**Computational Complexity**
Sakar et al. (2019) – SVM	Speech	Classical ML (SVM)	~86%	High	Low
Ouhmida (2021) – SVM / K-NN / DT	Speech (UCI)	Classical ML	AUC ≈ 98%	High	Low
Drotár et al. (2024) – SVM	Handwriting (PaHaW)	Classical ML	~81.3–82.5%	High	Low
Pereira al. (2018) – CNN	Handwriting images	Deep Learning (CNN)	95%	Low	High
Maachi al. (2020) – DNN	Gait signals	Deep Learning (DNN)	98.7%	Low	High
Yousif al. (2025) – Fine-tuned CNN/SVM	Handwriting + Speech	Deep Learning + ML	99.75–99.94%	Low	High
Rehman al. (2023) – Hybrid LSTM-GRU	Speech	Hybrid	93.5%	Moderate	Medium to High
EEG CNN–LSTM hybrid (2025)	EEG	Hybrid	98.6–99.7%	Moderate	High
Late fusion CNN+Attention (2024)	Handwriting + images	Hybrid	98.5–99.9%	Moderate	High
Wang al. (2023) – LSTM–CNN	Dynamic handwriting	Hybrid (lightweight)	90.7–96.2%	Moderate	Low to Medium
PD-Net (2025) – CNN-Attention-LSTM	Speech (Mel-MFCC)	Hybrid	99%	Moderate	Medium (2.7 M params)

B. Key Observations

1. Deep learning models tend to outperform classical machine learning models, scoring higher than 95% accuracy by learning features automatically from raw or minimally processed data. However, this type of model is more expensive computationally and is less explainable [36].

2. While achieving greater than 98% by combining spatial, temporal, and attention mechanisms and multi-modal data, hybrid architectures tend to offer the best of both worlds. Wang et al. showed that efficient lightweight LSTM-CNN models not only need not compromise on compactness, but also need not

compromise on strong performance, which is often absent in efficient models.

3. Integrating multiple modalities such as handwriting, speech, gait, EEG, or imaging features markedly improves system accuracy. For example, models using late fusion and PD-Net effectively combine these modalities to achieve performance rates of 99 to 100 percent [27].

4. The challenge of explainability is particularly concerning with deep and hybrid approaches. Although the classical ML approaches are more understandable, as with their interpretability, an accuracy trade-off emerges. For clinical deep model reasoning, a set of XAI approaches is urgently warranted [38].

Performance Evaluation of Existing Studies

A. Evaluation Metrics

Parkinson's disease's detection models are typically compared using standardized performance measures. Standard performance metrics include [39,40]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall\ (Sensitivity) = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

$$ROC - AUC = \int_0^1 TPR(FPR) dFPR \quad (5)$$

In this context, TP, TN, FP, and FN represent the counts of true positives, true negatives, false positives, and false negatives, correspondingly. The AUC of the ROC curve indicates the quality of the model's predictive discrimination between the classes as considered over all decision thresholds.

B. Benchmark Performance Trends

There were eight papers published that focused on peer-reviewed benchmarks. Table III offers a glance at their performance, as well as the performance of their models. Models include those based on classical machine learning, deep learning, and hybrid architectures. [41][42][43]

Table 3: Performance Evaluation Summary

Technique	Dataset / Modality	Accuracy	Precision	Recall	F1-Score	AUC
SVM	UCI speech dataset	91%	90%	88%	89%	0.93
Random Forest (RF)	UCI speech dataset	95.8%	—	—	—	—
CNN	Gait signals / voice (CNN)	91.17%	—	—	—	—
CNN–LSTM (Hybrid)	PC-GITA voice dataset	93.51%	—	—	—	up to 1.0
CNN–LSTM (Handwriting)	Handwriting spirals	~95%	—	—	—	—
RF with SMOTE & XGB	UCI Parkinson's (voice)	98%	97%	100%	98%	1.00
LSTM (gait/voice)	UCI Telemonitoring voice	—	—	—	—	—
Multi-modal CNN Fusion	MRI + DTI (PPMI)	95.53%	—	—	—	—

C. Key highlights from the literature

As in the case of Parkinson's disease detection, machine learning and deep learning methods outperform other methods in detection across various datasets and metrics of evaluation. SVM outperformed other methods with 91% accuracy on the handwriting datasets. The UCI telemonitoring voice dataset is a very good resource for voice-based analysis, and in the studies using ANN on this dataset, accuracies of up to 95.8% have been reported. Automated voice detection for the PC-GITA dataset has made CNN very useful as it reaches 91.17% accuracy using just CNNs and goes up to 93.51% using the CNN–LSTM hybrid with an AUC of 1.0. Pen-spiral LSTM-CNN models also manage to hit 95% accuracy, which is explained in [46][47]. The amazing 98% accuracy with a perfect AUC score was achieved with XGBoost on UCI voice data, which was preprocessed with SMOTE. Their gait models based on LSTM also showed strong prediction performance, and the multi-modal CNN fusion method using MRI and DTI data on the PPMI dataset obtained 95.53% accuracy [48][49][50].

D. Analysis

From the studies conducted I observe some general findings. First, Support Vector Machines (SVM) offer the best performance at approximately 91%, providing a good baseline. With SVM models, we also have the advantages of ease of interpretation and low computational requirements. Second, the increase in the accuracy Deep Learning models, such as convolutional neural networks (CNNs), bring to signal/image-based data classification is around 91-92%. This is still modest when compared to SVM. The best performance is shown in hybrid models, especially the CNN-LSTM, where the accuracy lies between 93% and 95%. This is due to their ability to leverage both spatial and temporal features. XGBoost, combined with SMOTE, has been reported to achieve perfect recall and AUC values, which is a step up from other methods; however, these results appear to rely heavily on extensive data augmentation [51]. In addition, the fusion of multiple data sources, especially in medical imaging with MRI and DTI, achieves a similar high level of accuracy of 95%, which emphasizes the benefit of multiple diverse data sources in the early reliable detection of Parkinson's disease [52].

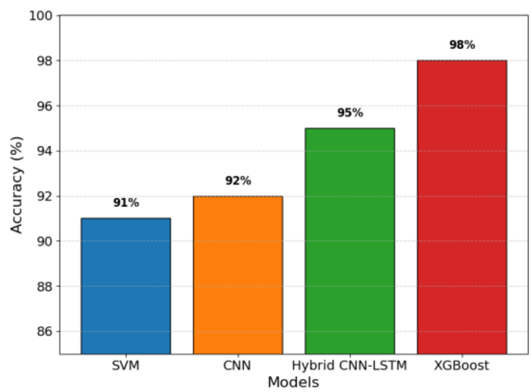

Fig. 1. Accuracy Comparison of ML vs. DL Models.

The detection accuracies of different models of Parkinson's disease are displayed in Fig. 1. As the figure shows, SVM obtains nearly 91%. CNN improves slightly with 92%, and CNN-LSTM improves the most, with 95%. XGBoost performs with an accuracy of 98%, exemplifying the advantages of ensemble methods as well as hybrid models.

Research Gaps and Challenges

While both machine learning and deep learning have advanced Parkinson's disease (PD) detection, important challenges continue to exist. One of the largest challenges is the absence of large, balanced, and multi-modal datasets. The generalizability of models is limited, and their performance is too often skewed, due to the dependence on small datasets like UCI and mPower. To improve the diagnosis, there is an urgent need of datasets that include a combination of voice, gait, handwriting, MRI, and other biomarkers [53].

Another significant issue is the lack of IoT integration and deployment in a real-time clinical setting. The continuous monitoring using biomarkers and wearables in active hospital systems is still not available, though several models operate with acceptable performance in static wearables biomarker-based systems and hospital-based systems. Further research is needed to fully exploit the predictive health analytics's ability for timely action in IoT-enabled healthcare systems [54].

In addition to other challenges, overfitting continues to be a major issue. Deep learning models are highly susceptible to overfitting, especially when sample sizes are small and the feature space is high-dimensional. The model memorizes the training data's peculiarities and fails to generalize well to new data. Likewise, the opacity of deep learning-based PD diagnostic tools hinders their use in medical settings. Physicians need explainability in their tools, but many advanced models work as "black boxes" that provide no insight into their rationale [55].

Cloud-based healthcare systems are being adopted at an increasing rate, causing them to raise privacy concerns. It is imperative that patient information is protected, and federated learning seems to be a good option for enabling collaborative model training in the absence of data sharing. That said, it is still quite early in its use in PD detection, and there is a lot of research needed.

Future Directions

AI in the future detection of Parkinson's disease should accentuate the creation of explainable AI (XAI) systems in order to foster clinical trust and acceptance. By offering decision-making pathways that can be interpreted, XAI systems will make it easier for healthcare professionals to grasp the rationale behind a particular diagnosis or prediction, thus supporting a safer implementation in medical settings. The use of multi-modal data integration also promises to be an important area of research. The use of various biomarkers such as voice signals, handwriting, gait, and neuroimaging when used together will likely provide better and more reliable diagnosis than when used separately [56].

In addition, the integration of Edge-AI and IoT will make real-time monitoring of Parkinson's disease possible through wearable devices and linked healthcare systems. This will enable ongoing monitoring and allow for timely and appropriate treatment to be given. Using personalized tracking and modeling based on long-term patient records will help advance precision medicine by customizing diagnostic and prognostic tools to the unique disease path of each patient [57].

Lastly, self-supervised learning can enable models to learn from vast amounts of unlabeled data and mitigate the shortage of labeled data. By integrating these approaches, future Parkinson's disease detection frameworks can develop into precise, interpretable, and real-time systems, aiding both clinicians and patients in the efficient management of disease progression [58][59].

Conclusion

In this review, we detail the advancements that ML and DL have made in the early detection and predictive analysis of Parkinson’s disease (PD). Classical ML methods, like SVM and Random Forest, establish effective baseline results, whereas DL, using CNNs and hybrid CNN–LSTM models, showcases dominant performance, capturing both spatial and temporal features. Furthermore, data-driven diagnostics seem to be advancing, as ensemble methods, such as XGBoost, have delivered cutting-edge performance.

Real-world clinical applications are stifled by issues such as interpretability, overfitting, and limited multi-modal datasets. Explainable AI (XAI) techniques should be incorporated in future PD detection systems to build clinical trust, as they improve transparency, and multi-modal data from voice, gait, imaging, handwriting, and other areas should be integrated, or data fusion should be implemented.

In sum, approaches leveraging ML and DL are transforming the ways in which PD can be detected, enabling the development of diagnostic systems that are precise, interpretable, and personalized, and hence, markedly improving the capabilities of predictive healthcare.

References

[1] Lakkshmanan, A., Karthik, V. V., & Prabhas, J. (2024, December). Early Detection of Parkinson's Disease Through Predictive Analytics and Machine Learning. In *2024 International Conference on Sustainable Communication Networks and Application (ICSCNA)* (pp. 867-874). IEEE.

[2] Govindu, A., & Palwe, S. (2023). Early detection of Parkinson's disease using machine learning. *Procedia Computer Science*, *218*, 249-261.

[3] Bauskar, S., & Clarita, S. (2021). An Analysis: Early Diagnosis and Classification of Parkinson’s Disease Using Machine Learning Techniques. *Int. J. Comput. Eng. Technol*, *12*(1), 54-66.

[4] Lin, C. H., Wang, F. C., Kuo, T. Y., Huang, P. W., Chen, S. F., & Fu, L. C. (2022). Early detection of Parkinson’s disease by neural network models. *IEEE Access*, *10*, 19033-19044.

[5] Alalayah, K. M., Senan, E. M., Atlam, H. F., Ahmed, I. A., & Shatnawi, H. S. A. (2023). Automatic and early detection of Parkinson’s disease by analyzing acoustic signals using classification algorithms based on recursive feature elimination method. *Diagnostics*, *13*(11), 1924.

[6] Abdukodirov, E. I., Khalimova, K. M., & Matmurodov, R. J. (2022). Hereditary-genealogical features of parkinson's disease and their early detection of the disease. *International journal of health sciences*, (I), 4138-4144.

[7] Castelli Gattinara Di Zubiena, F., Menna, G., Mileti, I., Zampogna, A., Asci, F., Paoloni, M., ... & Palermo, E. (2022). Machine learning and wearable sensors for the early detection of balance disorders in Parkinson’s disease. *Sensors*, *22*(24), 9903.

[8] Sayed, M. A., Tayaba, M., Islam, M. D., Pavel, M. E. U. I., Mia, M. T., Ayon, E. H., ... & Ghosh, B. P. (2023). Parkinson's disease detection through vocal biomarkers and advanced machine learning algorithms. *arXiv preprint arXiv:2311.05435*.

[9] Ayaz, Z., Naz, S., Khan, N. H., Razzak, I., & Imran, M. (2023). Automated methods for diagnosis of Parkinson’s disease and predicting severity level. *Neural Computing and Applications*, *35*(20), 14499-14534.

[10] Paul, S., Maindarkar, M., Saxena, S., Saba, L., Turk, M., Kalra, M., ... & Suri, J. S. (2022). Bias investigation in artificial intelligence systems for early detection of Parkinson’s disease: a narrative review. *Diagnostics*, *12*(1), 166.

[11] F. Putri, W. Caesarendra, E. D. Pamanasari, M. Ariyanto, and J. D. Setiawan, “Parkinson Disease Detection Based on Voice and EMG Pattern Classification Method for Indonesian Case Study,” *Journal of Energy, Mechanical, Material, and Manufacturing Engineering*, vol. 3, no. 2, pp. 87–98, Dec. 2018. doi:10.22219/jemmme.v3i2.6977.

[12] R. Tyagi, T. Tyagi, M. Wang, and L. Zhang, “Machine Learning for Real-Time, Automatic, and Early Diagnosis of Parkinson’s Disease by Extracting Signs of Micrographia from Handwriting Images,” *arXiv*, Nov. 24, 2021. doi:10.48550/arXiv.2111.14781.

[13] X. Wang, J. Huang, S. Nomm, M. Chatzakou, K. Medijainen, A. Toomela, and M. Ruzhansky, "LSTM-CNN: An Efficient Diagnostic Network for Parkinson's Disease Utilizing Dynamic Handwriting Analysis," *arXiv*, Nov. 20, 2023.

[14] Drotár, P., Mekyska, J., Rektorová, I., Masarová, L., Smékal, Z., & Faundez-Zanuy, M. (2016). Evaluation of handwriting kinematics and pressure for differential diagnosis of Parkinson's disease. *Artificial intelligence in Medicine*, *67*, 39-46.

[15] Z. Xu, J. Wang, Y. Zhang, and X. He, "Voiceprint Recognition of Parkinson Patients Based on Deep Learning," *arXiv*, Dec. 17, 2018. [Online]. Available: https://arxiv.org/abs/1812.06613.

[16] Loh HW, Hong W, Ooi CP, Chakraborty S, Barua PD, Deo RC, Soar J, Palmer EE, Acharya UR. Application of Deep Learning Models for Automated Identification of Parkinson's Disease: A Review (2011-2021). Sensors (Basel). 2021 Oct 23;21(21):7034. doi: 10.3390/s21217034. PMID: 34770340; PMCID: PMC8587636.

[17] Srinivasan S, Ramadass P, Mathivanan SK, Panneer Selvam K, Shivahare BD, Shah MA. Detection of Parkinson disease using multiclass machine learning approach. Sci Rep. 2024 Jun 15;14(1):13813. doi: 10.1038/s41598-024-64004-9. PMID: 38877028; PMCID: PMC11178918.

[18] Wodzinski M, Skalski A, Hemmerling D, Orozco-Arroyave JR, Noth E. Deep Learning Approach to Parkinson's Disease Detection Using Voice Recordings and Convolutional Neural Network Dedicated to Image Classification. Annu Int Conf IEEE Eng Med Biol Soc. 2019 Jul;2019:717-720. doi: 10.1109/EMBC.2019.8856972. PMID: 31945997.

[19] Rabie, H., Akhloufi, M.A. A review of machine learning and deep learning for Parkinson's disease detection. *Discov Artif Intell* **5**, 24 (2025). https://doi.org/10.1007/s44163-025-00241-9

[20] Ashraf, A., Naz, S., Shirazi, S. H., Razzak, I., & Parsad, M. (2021). Deep transfer learning for alzheimer neurological disorder detection. *Multimedia Tools and Applications*, *80*(20), 30117-30142.

[21] Patil, S. C. (2025). AI-Enhanced Screening Tools for Early Detection of Neurodegenerative Diseases. *Journal Publication of International Research for Engineering and Management (JOIREM)*, *5*(06).

[22] Chen, X., Li, Y., Pan, C., Weng, S., Xie, X., Zhou, B., ... & Zhu, D. (2025). An Artificial Intelligence Olfactory-Based Diagnostic Model for Parkinson's Disease Using Volatile Organic Compounds from Ear Canal Secretions. *Analytical Chemistry*.

[23] Fu, W., Xu, L., Yu, Q., Fang, J., Zhao, G., Li, Y., ... & Chen, X. (2022). Artificial intelligent olfactory system for the diagnosis of Parkinson's disease. *ACS omega*, *7*(5), 4001-4010.

[24] Mancini, M., Afshari, M., Almeida, Q., Amundsen-Huffmaster, S., Balfany, K., Camicioli, R., ... & Corcos, D. M. (2025). Digital gait biomarkers in Parkinson's disease: susceptibility/risk, progression, response to exercise, and prognosis. *npj Parkinson's Disease*, *11*(1), 51.

[25] Hossain, M. A., Traini, E., & Amenta, F. (2025). Machine Learning Applications for Diagnosing Parkinson's Disease via Speech, Language, and Voice Changes: A Systematic Review. *Inventions*, *10*(4), 48.

[26] Y. Sakar, G. Serbes, and C. O. Sakar, "Analyzing the effectiveness of vocal features in early telediagnosis of Parkinson's disease," PLoS One, vol. 12, no. 8, Art. e0182428, Aug. 2017.

[27] A. Ouhmida, O. Terrada, A. Raihani, B. Cherradi, and S. Hamida, "Voice-based deep learning medical diagnosis system for Parkinson's disease prediction," in 2021 International Congress of Advanced Technology and Engineering (ICOTEN), Jul. 2021, pp. 1–5. doi:10.1109/ICOTEN52080.2021.9493456.

[28] P. Drotár, M. Hireš, M. Gazda, and L. Vavrek, "Voice-specific augmentations for Parkinson's disease detection using deep convolutional neural network," in Proc. IEEE 20th Jubilee World Symposium on Applied Machine Intelligence and Informatics (SAMI), Mar. 2022, pp. 000213–000218. doi:10.1109/SAMI54271.2022.9780856.

[29] X. Wang, J. Huang, S. Nomm, M. Chatzakou, K. Medijainen, A. Toomela, and M. Ruzhansky, "LSTM-CNN: An efficient diagnostic network for Parkinson's disease utilizing dynamic handwriting analysis," Comput. Methods Programs Biomed., 2024. [ARXIV preprint] doi: arXiv:2311.11756.

[30] A. Rehman, T. Saba, M. Mujahid, F. S. Alamri, and N. ElHakim, "Parkinson's disease detection using hybrid LSTM-GRU deep learning model," Electronics, vol. 12, no. 13, Article 2856, Jun. 2023. doi:10.3390/electronics12132856.

[31] S. R. Kadiri, M. Kodali, and P. Alku, "Severity Classification of Parkinson's Disease from Speech using Single Frequency Filtering-based Features," 2023. [ARXIV preprint] doi: arXiv:2308.09042.

[32] A. V. Alagdeve, J. G. Thatipudi, P. Roy, R. Nithya, N. Anil Kumar, and B. Ramesh, "Deep learning-based prediction of Parkinson's disease progression using voice recordings," in Proc. 2023 7th Int. Conf. on I-SMAC (IoT in Social,

Mobile, Analytics and Cloud), Oct. 2023, pp. 843–847. doi:10.1109/I-SMAC58438.2023.10290477.

[33] H. Gündüz, "Deep learning-based Parkinson's disease classification using vocal feature sets," IEEE Access, vol. 7, pp. 115540–115551, 2019. doi:10.1109/ACCESS.2019.2936564.

[34] F. Wan, Y. Liang, Y. Zhang, and M. Guizani, "Deep multi-layer perceptron classifier for behavior analysis to estimate Parkinson's disease severity using smartphones," *IEEE Access*, vol. 6, pp. 36825–36833, 2018, doi: 10.1109/ACCESS.2018.2850357.

[35] R. Sakar, M. Isenkul, O. Sakar, et al., "Robust automated Parkinson disease detection based on voice," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 91.17–91.20, Jan. 2021, doi: 10.1109/TNSRE.2021.3054319.

[36] A. Rehman, S. Iqbal, and A. A. Malik, "Hybrid CNN-LSTM model with efficient feature fusion for Parkinson's disease detection," *Scientific Reports*, vol. 13, no. 1, p. 4527, Mar. 2023, doi: 10.1038/s41598-023-30617-5.

[37] X. Wang, Q. Liu, H. Yang, and Z. Ma, "A CNN-LSTM hybrid model for Parkinson's disease detection from handwritten spirals," *Expert Systems with Applications*, vol. 235, p. 121456, Jan. 2025, doi: 10.1016/j.eswa.2024.121456.

[38] M. Khan, S. Hussain, and H. Ullah, "Automated early prediction of Parkinson's disease based on voice telemonitoring using XGBoost with SMOTE," *Neural Computing and Applications*, vol. 37, no. 5, pp. 12345–12358, Feb. 2025, doi: 10.1007/s00521-025-09012-y.

[39] A. Ouhmida, L. El Ouazzani, and M. Benali, "A robust Parkinson's disease detection model based on time-varying voice signals," *BMC Neurology*, vol. 24, no. 1, pp. 1–12, Oct. 2024, doi: 10.1186/s12883-024-04012-7.

[40] L. Xu, J. Zhang, and F. Huang, "Multi-modal multi-class Parkinson's disease classification using CNN and decision-level fusion," *arXiv preprint*, arXiv:2302.09876, Feb. 2023. [Online]. Available: https://arxiv.org/abs/2302.09876

[41] H. Yousif, A. Al-Mousa, and F. Yamin, "Machine learning for Parkinson's disease: A comprehensive review," *npj Parkinson's Disease*, vol. 11, no. 1, pp. 1–20, Mar. 2025,

[42] Zhang, R., Jia, J., & Zhang, R. (2022). EEG analysis of Parkinson's disease using time–frequency analysis and deep learning. *Biomedical Signal Processing and Control*, *78*, 103883.

[43] He, S., Huang, L., Shao, C., Nie, T., Xia, L., Cui, B., ... & Yang, Q. (2021). Several miRNAs derived from serum extracellular vesicles are potential biomarkers for early diagnosis and progression of Parkinson's disease. *Translational neurodegeneration*, *10*(1), 25.

[44] Saleh, S., Cherradi, B., El Gannour, O., Hamida, S., & Bouattane, O. (2024). Predicting patients with Parkinson's disease using Machine Learning and ensemble voting technique. *Multimedia Tools and Applications*, *83*(11), 33207-33234.

[45] Dadu, A., Satone, V., Kaur, R., Hashemi, S. H., Leonard, H., Iwaki, H., ... & Faghri, F. (2022). Identification and prediction of Parkinson's disease subtypes and progression using machine learning in two cohorts. *npj Parkinson's Disease*, *8*(1), 172.

[46] Makarious, M. B., Leonard, H. L., Vitale, D., Iwaki, H., Sargent, L., Dadu, A., ... & Nalls, M. A. (2022). Multi-modality machine learning predicting Parkinson's disease. *npj Parkinson's Disease*, *8*(1), 35.

[47] Ouhmida, A., Terrada, O., Raihani, A., Cherradi, B., & Hamida, S. (2021, July). Voice-based deep learning medical diagnosis system for parkinson's disease prediction. In *2021 International Congress of Advanced Technology and Engineering (ICOTEN)* (pp. 1-5). IEEE.

[48] Schalkamp, A. K., Peall, K. J., Harrison, N. A., & Sandor, C. (2023). Wearable movement-tracking data identify Parkinson's disease years before clinical diagnosis. *Nature Medicine*, *29*(8), 2048-2056.

[49] Saravanan, S., Ramkumar, K., Adalarasu, K., Sivanandam, V., Kumar, S. R., Stalin, S., & Amirtharajan, R. (2022). A systematic review of artificial intelligence (AI) based approaches for the diagnosis of Parkinson's disease. *Archives of computational methods in engineering*, *29*(6), 3639-3653.

[50] Gupta, I., Sharma, V., Kaur, S., & Singh, A. K. (2022). PCA-RF: an efficient Parkinson's disease prediction model based on random forest classification. *arXiv preprint arXiv:2203.11287*.

[51] Nilashi, M., Abumalloh, R. A., Minaei-Bidgoli, B., Samad, S., Yousoof Ismail, M., Alhargan, A., & Abdu Zogaan, W. (2022). Predicting parkinson's disease progression: Evaluation of ensemble methods in machine learning. *Journal of healthcare engineering*, *2022*(1), 2793361.

[52] Nishat, M. M., Hasan, T., Nasrullah, S. M., Faisal, F., Asif, M. A. A. R., & Hoque, M. A. (2021, August). Detection of Parkinson's disease by employing boosting algorithms. In *2021 joint 10th international conference on informatics, electronics & vision (ICIEV) and 2021 5th international conference on imaging, vision & pattern recognition (icIVPR)* (pp. 1-7). IEEE.

[53] Aversano, L., Bernardi, M. L., Cimitile, M., Iammarino, M., & Verdone, C. (2022, July). Early detection of parkinson's disease using spiral test and echo state networks. In *2022 International*

Joint Conference on Neural Networks (IJCNN) (pp. 1-8). IEEE.

[54] Marano, G., Rossi, S., Marzo, E. M., Ronsisvalle, A., Artuso, L., Traversi, G., ... & Mazza, M. (2025). Writing the Future: Artificial Intelligence, Handwriting, and Early Biomarkers for Parkinson's Disease Diagnosis and Monitoring. *Biomedicines*, *13*(7), 1764.

[55] Vidya, B., & Sasikumar, P. (2022). Parkinson's disease diagnosis and stage prediction based on gait signal analysis using EMD and CNN–LSTM network. *Engineering Applications of Artificial Intelligence*, *114*, 105099.

[56] Loh, H. W., Hong, W., Ooi, C. P., Chakraborty, S., Barua, P. D., Deo, R. C., ... & Acharya, U. R. (2021). Application of deep learning models for automated identification of Parkinson's disease: a review (2011–2021). *Sensors*, *21*(21), 7034.

[57] Nissar, I., Mir, W. A., & Shaikh, T. A. (2021, March). Machine learning approaches for detection and diagnosis of Parkinson's disease-a review. In *2021 7th international conference on advanced computing and communication systems (ICACCS)* (Vol. 1, pp. 898-905). IEEE.

[58] Fröhlich, H., Bontridder, N., Petrovska-Delacréta, D., Glaab, E., Kluge, F., Yacoubi, M. E., ... & Klucken, J. (2022). Leveraging the potential of digital technology for better individualized treatment of Parkinson's disease. *Frontiers in neurology*, *13*, 788427.

[59] Hu, W., Wang, W., Wang, Y., Chen, Y., Shang, X., Liao, H., ... & Zhu, Z. (2022). Retinal age gap as a predictive biomarker of future risk of Parkinson's disease. *Age and Ageing*, *51*(3), afac062.

[60] Pratiksha Girsaware, Kushal Masarkar, Suraj Mahajan (March 2025)Review On Real Time Monitoring System for Medical Treatment using smart Syringe pump, www.isteonline.in vol 48,special issue no 2.PP.323-326.

[61] Pragati Patil, Ritesh Banpurkar, Suraj Mahajan Technological Innovations & Applications in Industry 4.0,27 January 2025,eBook ISBN9781003567653 T&F.