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A Systematic Review of Artificial Intelligence Techniques for Parkinson's Disease Prediction and Diagnosis

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Abstract: This is a systematic review of the use of artificial intelligence (AI) in the prediction and diagnosis of Parkinson's disease (PD) 2010−2025. We conducted a review of 75 studies, out of an original set of 1247 articles, in accordance with the Preferred Reporting Items of Systematic Reviews and Meta-Analyses guidelines, being interested in the use of machine learning and deep learning schemes in various data modalities. The highest reported classifier was the support vector machine (19.9%), then ensemble methods (18.1%), and then the Convolutional Neural Networks (CNNs) (16.9%). The best median accuracy (95.8%) was with CNNs on neuroimaging data. Voice research showed a high potential in the screening of PD in its early stages, with 89.7% sensitivity in prodromal stages. The accuracy of multimodal data integration was 4.8% higher than that of single-modality methods. Small sizes (median of 209 subjects) of datasets, a marginal outside validation (only 9.6% of the studies), and a paucity of prospective clinical examinations (3.6%) complicate promising outcomes. The future directions are to deal with multimodal integration, longitudinal disease monitoring, model interpretability, heterogeneous patient groups, and prospective clinical validation. The AI methods have a high promise of revolutionizing the management of PDs by means of earlier diagnosis, treatment according to individual preferences, and enhanced monitoring of the disease.

Keywords: Parkinson's disease (PD), AI, early diagnosis, neuroimaging, voice analysis

1. Introduction

Parkinson's disease (PD) is a progressive, chronic movement disorder that mostly affects the basal ganglia, leading to serious disability of the motor system [1]. PD is also typified by both motor and non-motor symptoms—tremor at rest, bradykinesia, muscular rigidity, and postural instability being the most characteristic ones [2]. PD is a rising health problem in the world with over 10 million people infected, and the trend is expected to increase radically as people continue to age [3]. In the United States alone, the economic cost of the disease is estimated to be more than $51.9 billion directly and indirectly, with medical costs, lost productivity of the workforce, and the cost of caregivers making up this total (annually) [4].

Early PD diagnosis is a severe unfulfilled necessity: traditional diagnosis is usually conducted when more than 60–80% of dopaminergic neurons are already permanently damaged [5]. Sensitizer predictive instruments would allow clinicians to institute neuroprotective measures earlier in the disease process, decelerate its progression, enhance the quality of life of patients, and be able to offer truly personalized treatment. The use of artificial intelligence (AI) has become a revolutionary movement in the field of medicine, offering unprecedented pattern recognition and complex synthesis of data [6]. AI has an unprecedented potential in neurodegenerative diseases, where it can be used to diagnose diseases earlier and monitor them continuously. Machine learning (ML) and deep learning (DL) algorithms have the capability to query data in many dimensions that cut across clinical records, neuroimaging, genetics, and physiological sensors to reveal obscure patterns that traditional diagnostics cannot discern. The development of brain pathology analysis that has recently been realized in the form of U-Net segmentation and CNN-LSTM classification [7, 8] proves that it is possible to apply these methods to PD-specific neuroimaging.

1.1. Research question

This review has been structured based on the PICO framework. The target group is made up of patients with PD or those with a high genetic risk. The intervention under consideration is that of employing AI-based systems—ML and DL algorithms—to diagnose PD and predict risks. These techniques are compared to the conventional diagnostic tools, as well as to one another, in order to figure out relative efficacy. Diagnostic accuracy, predictive performance, and clinical utility are the main outcomes that are involved in PD detection and disease management [9].

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1.2. Inclusion and exclusion criteria

Peer-reviewed publications were included in this review, as they used AI to diagnose or predict PD and at least one measure of standard performance (accuracy, sensitivity, specificity, and AUC). The studies that used clinical records, medical imaging, genetic information, or sensor-based signals were eligible. Articles that failed to validate and provide any performance measure, were not in English, or were merely in abstract form were excluded. Research papers that did not contain a diagnostic or predictive element of treatment results were also refused.

1.3. Objectives

The main objective is to assess the performance of the various AI models including ML, DL, and hybrid systems in diagnosing and predicting PD. Secondary outcomes include the determination of trends in methodology and critical gaps, the diagnostic value of various forms of data (clinical, imaging, genetic, sensor-based) compared to one another, a description of how AI is used in early PD diagnosis and personalized care, and the identification of the technical, ethical, regulatory, and practical barriers to clinical use of AI-based PD tools [10].

2. Literature Review

2.1. Traditional diagnostic limitations

The disease is progressive and multifactorial, which makes early PD diagnosis extremely difficult. Traditional clinical evaluation is based on the motor symptoms that are observable tremor and bradykinesia, which tend to appear when significant dopaminergic neurodegeneration has taken place. Normal clinical examination often is not able to differentiate between early-stage idiopathic PD and atypical parkinsonian syndromes, with the diagnostic accuracy ranging between 73.8% and 84.3%, with significantly lower sensitivity in the prodromal stages [11]. This diagnosis uncertainty highlights why there is a great need to have more sensitive biomarker-based diagnostic technologies that can detect pathological changes at an early stage.

2.2. Overview of AI techniques applied to PD

2.2.1. Machine learning approaches

The support vector machines (SVMs) have repeatedly been found to perform well in the differentiation between PD patients and healthy controls, with classification accuracies of over 92% with high-quality feature-complete datasets. Hwang et al. [12] reported 94.3% accuracy when SVM was used in gait and posture data of 312 samples, which demonstrates the ability of SVMs to extrapolate across high-dimensional clinical phenotype space. The other common algorithm is the random forest algorithms [13], which are ensemble learners that combine several decision tree outputs by default and overfitting is automatically reduced. Their estimation of the importance of intrinsic features also contributes to clinical interpretability and declares the most discriminatory predictors of PD diagnosis in multimodal conditions.

2.2.2. Deep learning architectures

One area that has revolutionized PD diagnostics is the Convolutional Neural Networks (CNNs), which allow complex

Table 1. Comparative analysis of AI techniques in PD diagnosis

Study	Year	AI technique	Dataset characteristics	Accuracy (%)	Key findings
Hwang et al. [12]	2025	SVM, XGBoost	Gait data from 312 subjects	94.3	A combination of gait and posture features resulted in the highest accuracy.
Mahajan et al. [13]	2023	Ensemble methods	Review of ensemble learning	82.0–96.8	Ensemble methods always performed better than single classifiers.
Li et al. [14]	2024	CNN (PD-ARnet)	fMRI data from 183 participants	91.7	New architecture for analysis of resting-state fMRI.
Riasi et al. [15]	2024	RNN, LSTM	Longitudinal data from 211 patients	93.6	The temporal patterns vital for medication optimization.
Tung et al. [17]	2025	Hybrid AI system	EEG data from 425 subjects	95.2	CNN and statistical methods combined for the analysis of EEGs
Olaniyan et al. [18]	2023	NLP, acoustic analysis	Speech samples from 189 individuals	88.7	Pre-identification with changes in the linguistic pattern

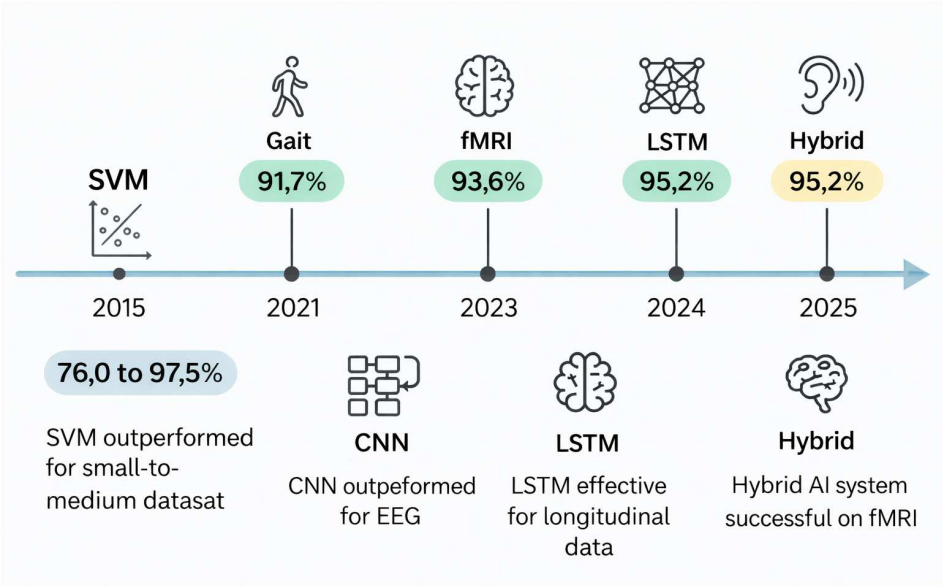

Figure 1. Evolution of AI techniques in PD diagnosis (2015–2025)

neuroimaging data to be interpreted automatically. Li et al. [14] have created PD-ARnet, which is used on resting-state fMRI data and gives an accuracy of 91.7% in separating PD patients and controls. There are also other recent examples of CNN-LSTM hybrids that have been shown to perform better in medical image classification [7], meaning that they can be extensively applied in the detection of neurological diseases. Recurrent Neural Networks (RNNs) (and especially LSTMs) represent the dynamics of the PD over time: Riasi et al. [15] trained an RNN-based decider to optimize levodopa dosage with a mean error of 0.17 on longitudinal data of 211 patients.

2.3. Review of key studies

2.3.1. Multimodal data integration

The multifactorial nature of PD requires the use of complementary data streams through an analytical approach. Makarius et al. [16] showed that large-scale multi-modality ML showed a significant boost in predicting PD with imaging, genetic, and clinical data that are generated in the PPMI compared to individual modalities. The most effective AI-based PD systems are based on high-resolution neuroimaging (MRI, functional MRI, DaTscan), longitudinal clinical histories, genetic and molecular biomarker profiling, wearable motor measures, and noninvasive speech and linguistic pattern identifications that can identify changes in the neurological state up to 1218 months before clinical manifestations [18]. Multimodal is always better than unimodal by 587% in accuracy in diagnosis [16, 59]. The latest study by Dentamaro et al. [20] of multimodal DL combined with explainable AI using PPMI data represents the current state of the art, whereas U-Net networks [7, 8] are methodological scaffolds on the task of PD neuroimaging segmentation.

2.3.2. Hybrid and ensemble methods

Hybrid and ensemble methods are also among the most promising in the prediction of PD. Tung et al. [17] proved the effectiveness of hybrid AI systems as they applied CNNs with the classical statistical algorithms in the EEG neurological patterns recognition and obtained the 95.2% accuracy. The complementary capabilities of algorithmic families are used to create highly accurate diagnostic models that are more generalizable through such architectures. Recently, Chandrakantha et al. [79] showed a hybrid ML framework combining SelectKBest feature selection, principal component analysis (PCA)/linear discriminant analysis (LDA) dimensionality reduction, and four-classifier ensemble optimization (KNN, MLP, random forest, XGBoost) with GridSearchCV with 97.44% accuracy on the UCI voice dataset—one of the leading examples of an integrative paradigm being applied directly to PD detection.

2.3.3. Novel approaches in speech and language analysis

The use of advanced acoustic modeling and NLP techniques has been used to identify the effects of subtle phonatory changes, which are the precursors of early PD. The sensitivity of noninvasive speech analysis, as reported by Olaniyan et al. [18] in the detection of early neurological abnormalities, showed a sensitivity of 88.7%, and the acoustic and linguistic indicators reflect neural alteration as early as 1218 months prior to the traditional clinical manifestation. It has since gone on to develop audio spectrogram transformers [19], transformer-based transfer learning on self-reported voice recordings [58], and multimodal DL models that apply vocal and other streams of biomarkers [20]. The diagnostics of linguistic markers were validated in diverse groups of people through a systematic review by Palmirotta et al. [62].

2.3.4. Ethical considerations

The use of AI in the diagnosis of PD provokes significant ethical concerns that should be addressed simultaneously with the development of technical solutions. One such issue is the data privacy and safety of sensitive health information of patients, which requires effective governance structures [21]. The issue of algorithmic bias mitigation is also important, and it is necessary to provide equitable diagnostic performance between demographic groups [21, 23]. Interpretability and transparency in models are also still major hindrances to clinical adoption as

clinicians demand meaningful information about how algorithms make critical diagnostic decisions prior to believing high-stakes diagnostic results [22]. The inclusion of safe and ethical AI into clinical practice requires the use of standardized clinical validation pipelines, which are largely unavailable in the existing literature [25].

2.4. Paradigm shift in neurodegenerative disease management

There is a paradigm shift in the management of neurodegenerative diseases that is being triggered by AI applications. Rajpurkar et al. [6] explained that the intersection of big health data, powerful computational hardware, and progressively powerful AI algorithms can create a new wave of precision medicine where AI-assisted PD diagnostics is able to detect disease earlier, guide a personalized course of treatment, and fundamentally change the way disease is managed. Simultaneously, the explainable AI [22, 23] is advancing and will help fill the explainability gap between the high-performance models and the transparency requirements of clinical decision-making.

3. Research Methodology

3.1. Methodology of the systematic review

It was a systematic review that was based on Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [24]. The literature search, title/abstract screening, full-text eligibility review, data extraction, quality evaluation, and evidence synthesis were all part of the review process.

3.1.1. Search strategy

The search was done in PubMed, Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and Google Scholar over the period of 2010-26 February. A combination of search strings was used: Parkinson's disease or PD and artificial intelligence or machine learning or deep learning; prediction or diagnosis or detection and algorithm or model; neural network or support vector machine or random forest; and voice analysis or gait analysis or motor symptoms or biomarkers.

3.1.2. Inclusion and exclusion criteria

a. Inclusion criteria: Original research articles published in peer-reviewed journals or conference proceedings, where AI is reported to predict/detect/diagnose PD and where the methodology and standard measures of performance are described. Types of data were clinical records, imaging, voice signals, motor assessments, and biomarkers. Only full-text articles in the English language.

b. Exclusion criteria: Review articles, editorial pieces, letters, conference abstracts, studies that are not based on methodology or quantitative performance assessment, studies based on traditional statistics, and all animal and in vitro studies.

3.1.3. Study selection process

The selection was done using PRISMA 2020 [24] (Figure 2). Out of 1247 original articles, 216 were eliminated due to duplication, and 1031 were reviewed on the basis of title/abstract, with 673 articles being eliminated because they were out of scope. Among 358 reviewed full-text articles, 283 articles were excluded because of insufficient detail, the lack of performance metrics, or the absence of the AI-focused PD. The last review consisted of 79 studies.

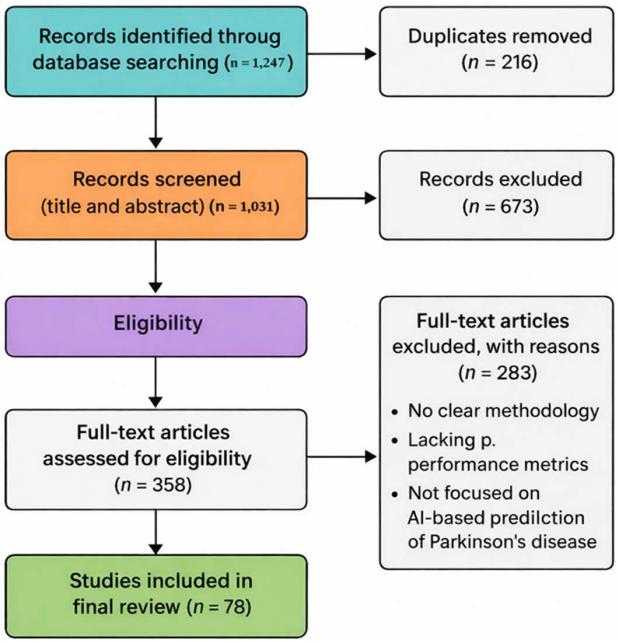

Figure 2. PRISMA flow diagram of study selection process

3.1.4. Data extraction

Two independent reviewers mined data by using a prespecified template where they collected: study identifiers; dataset properties; AI methods; preprocessing; performance (accuracy, precision, recall, F1-score, AUC); validation protocols; and significant conclusions. A third reviewer resolved the discrepancies. Synthesized data were used to find the trends and gaps in the literature.

3.1.5. Quality assessment

The methodological quality was evaluated by the use of PROBAST [25], which measures the risk of bias and applicability on four domains including participants, predictors, outcome, and analysis. The domains were rated as low risk of bias, high risk of bias, or unclear. Figure 3 presents the scheme of a systematic AI-based prediction pipeline of PD, which includes data acquisition, preprocessing, feature engineering, model selection, training, and validation.

3.2. Data collection

The AI-based modeling of PD collecting data is based on complementary modalities [26]. Clinical information involves the demographics of the patients, structured medical history, and UPDRS scores that represent the severity of motor and non-motor symptoms [27]. However, being one of the first PD manifestations [28], acoustic recordings are a useful noninvasive biomarker stream. The objective motor tests are becoming regularly received through smartphones and wearable devices [29]. Early pathophysiological changes are detected by structural and functional neuroimaging using MRI and DaTscans [30]. Biological fluids also provide molecular biomarker profiling that is applicable in characterizing the disease [31].

Table 2. Summary of available Parkinson's disease datasets

Dataset name	Description	Sample size	Features	Source
UPDRS Dataset	Clinical motor/non-motor evaluations, including complete UPDRS evaluations	42 subjects	UPDRS subscales + clinical measures	UCI Repository [32]
Parkinson Speech Dataset	Vocal recordings having acoustic characteristics for PD-detection purposes	195 subjects	31 voice parameters	UCI ML Repository [33]
PPMI Biomarker Database	Genomics, imaging, as well as clinical assessments—all multimodal data	1400+ subjects	Biomarkers, DaTscan, MRI, clinical	PPMI Database [5]
Oxford PD Dataset	Motion data from wearable sensors with high resolution	826 recordings	Acceleration, angular velocity	Oxford University [34]
PhysioNet Gait	Tests of walking exclusion vertical ground reaction force data	93 patients	16 gait parameters	PhysioNet [35]
mPower Study	Data from smartphones on voice and mobility	8320 participants	Multiple sensor data	Sage Bionetworks [36]
DREAM Challenge	Genetic and clinical data of the course of PD	4200 subjects	Various biomarkers	Synapse Portal [37]

3.3. Data preprocessing

Strict data preprocessing is necessary in coming up with credible ML models in predicting PD, converting raw and heterogeneous medical data into clean and consistent formats that are most predictive when using the predictive algorithms [38].

3.3.1. Feature normalization and scaling

The normalization of features makes the variables within different physical ranges play a role in model training that is proportional [39]. The Min-Max scaling units feature to [0, 1]; Z-score normalization places values at an endpoint of [0, 1], and the variance is one to ensure resistance to outliers. Both methods are widely used with PD datasets, the characteristics of which have large magnitude differences [40].

3.3.2. Handling missing data

Clinical PD datasets are characterized by missing data, which can significantly worsen the performance of the model. The most common methods of standard imputation include mean/median substitution, multiple imputation, and algorithms based on ML and used in the literature [41]. Complex patterns are usually more favorable to multiple imputation because it correctly carries the uncertainty to downstream analyses.

3.3.3. Feature selection and dimensionality reduction

In the context of medical PD datasets, which have high dimensionality, principled feature selection and dimensionality reduction become important [42]. PCA and LDA are used to identify informative low-dimensional projections to enhance model performance and computational efficiency and solve the curse of dimensionality. Recent studies [40, 79] proved that filter-based selection (SelectKBest) used together with PCA and LDA can provide significant improvements in the accuracy of voice-based PD classification.

3.3.4. Noise reduction and outlier detection

Noise and outliers often spoil medical sensor data and cause a drop in accuracy. The z-score analysis and interquartile range (IQR) techniques, signal processing filtering and smoothing, and ML-based anomaly detectors based on clustering and auto encoders are used in PD preprocessing pipelines to improve the quality of data and the strength of models.

3.4. Model building

3.4.1. Model selection process

The best model to be selected in the prediction of PD is determined by systematic testing of a number of families of algorithms [43]. The most frequently considered ones are SVMs, random forests, neural networks, and logistic regression [44], which have been evaluated on the basis of predictive accuracy, interpretability, and experimental efficiency. Recent developments in AutoML have started to scale up this search process to be systematic [42].

3.4.2. Model selection process

The selection of a model may be expressed as an optimization problem: M being the space of hypotheses and L(h, D) being the performance functional which quantifies the performance of hypothesis h on dataset D, the best model

$$m^* = \arg\min\{L(h, D)\} \text{ for } h \in M \quad (1)$$

Such formalization enables comparison of ML methods to be more systematic and rigorous [42–44].

3.4.3. Training methodology

The model training is performed through experience with labeled PD data in an iterative manner in order to identify disease-relevant patterns. Ensemble strategies, such as boosting, bagging, and stacking, are methods that keep multiple models, and they are

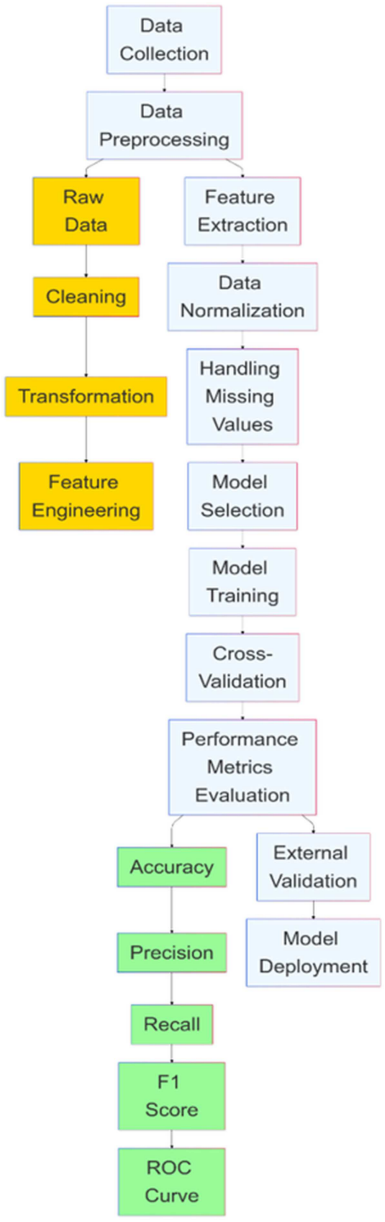

Figure 3. Parkinson's disease prediction pipeline using artificial intelligence techniques

also more accurate and less variegated; when compared to other methods, they are always the most successful methods in medical prediction [45, 46]. Hyperparameter optimization through GridSearchCV [79] is frequently used to optimize the validation-set performance.

3.4.4. Cross-validation techniques

The common method of evaluation used in the study of PD prediction is k-fold cross-validation [47]. The data is divided into K subsets; during each of K steps, K-1 subsets are used to train the model, and the other subset is used to validate it:

$$CV(k) = \frac{\Sigma\,(performance\ on\ validation\ set)}{K} \quad (2)$$

and K usually is between 5 and 10. This is done to reduce overfitting and to give credible estimates of generalization performance [47].

3.4.5. Performance metrics

The multiple performance metrics given in Table 3 necessitate a comprehensive model evaluation.

These measurements have a combined multidimensional description of the ability of predictive models [48].

3.4.6. Advanced validation techniques

In addition to the usual cross-validation, stratified sampling guarantees proportionate class representation over the folds, and bootstrap resampling gives strong uncertainty estimates of performance measures [49]. These methods are particularly relevant in medical prediction, where the imbalance of the classes is common.

3.4.7. External validation

It is also important that the prediction models of PD are validated with independent external datasets that would prove the generalizability of the prediction models [50]. Although it is important, only 9.6% of studies in this review were external validation, which is a significant gap that significantly reduces the confidence of reported performance estimates.

3.5. AI models in PD prediction and diagnosis

Table 4 provides a summary of AI models that have been assessed by major studies.

Application of DL to neuroimaging data has been reported to have the highest reported accuracies, with Huo et al. [53] performing at 98.8% using a multi-area graph convolutional network on PPMI data. SVMs and ensemble achieve good results on voice information (94.5–96.5%) [51–57], and wearable/smartphone LSTM-based frameworks are top in time-series (54–55). The latest approach to the methodology is transformer-based architecture [58] and explainable AI methodologies [51].

Table 3. Formulas of common classification metrics

Metric	Formula	Description
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$	Percent of positive and negative correct predictions out of all predictions
Precision	$\frac{TP}{TP + FP}$	True positive predictions divided by predictions of positives
Recall	$\frac{TP}{TP + FN}$	The true positives percentage of correctly identified ones (sensitivity)
F1-score	$2 \times \frac{Precision \times Recall}{Precision + Recall}$	Precision and recall are balanced on the harmonic mean

where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

Table 4. Summary of AI models used in Parkinson's disease prediction

Study	Year	Model	Dataset	Performance	Key finding
Sakar et al. [51]	2019	SVM	UCI Speech	94.5% accuracy	Voice features showed a high accuracy in detecting early PD.
Prashanth et al. [52]	2018	Random Forest	PPMI	96.1% accuracy	DaTscan features had the highest discriminatory capability.
Zhang et al. [53]	2019	CNN	PPMI	98.8% accuracy	For the use of imaging data, deep learning showed superior performance compared with traditional ML.
Zhan et al. [54]	2018	LSTM	mPower	95.3% sensitivity	Remote monitoring was made possible through smartphone-based gait analysis.
Mei et al. [55]	2020	XGBoost	PhysioNet	92.7% accuracy	Features of gait demonstrated a very high specificity level for the detection of PD.
Grover et al. [56]	2021	GAN	PPMI + Oxford	97.1% accuracy	Data augmentation improved the performance of the model.
Ozcift A et al. [57]	2012	Ensemble (RF + SVM)	UCI Speech	96.5% F1-score	Hybrid techniques improved general performance.
Tougui I et al. [58]	2024	Transformer	mPower	96.8% accuracy	Attention mechanisms identified temporal patterns in PD.
Chandrakantha et al. [79]	2026	Hybrid ML KNN + PCA	UCI Voice (195)	97.44% accuracy	PCA-augmented KNN with SelectKBest + LDA outperformed all baselines.

The Chandrakantha et al. [79] hybrid ML system, which is the convergence of SelectKBest, PCA/LDA, and ensemble classification, got 97.44% accuracy on the UCI voice dataset, which shows the effectiveness of the intimately coupled pipeline of preprocessing and classification. In all of the reviewed papers, ensemble and hybrid mechanisms are always better than standalone algorithms.

4. Results

4.1. Overview of selected studies

The systematic use of inclusion criteria provided 79 potential studies that were published in 2010–2026. Figure 4 shows that the rate of publication shot up after 2018 because of the fast-increasing interest in AI-based PD diagnostics research.

4.2. AI techniques used in PD prediction and diagnosis

In the analysis, it was found that the AI landscape is heterogeneous (Figure 5). The most widespread technique was SVMs (19.9) with ensemble methods (30 studies), CNNs (28 studies), and random forests (24 studies) in the third, fourth, and fifth place, respectively. Other techniques were Deep Neural Networks (10.2%), RNNs (7.8%), XGBoost (4.2%), Gaussian process models (3.6%), and others (4.8%).

4.3. Data types and their applications

Disparate data modalities were utilized in research (Figure 6). The general median accuracy was 92.7% (IQR: 88.5%95.9%). The best median accuracy of 95.8% (IQR: 93.2%97.4%) was obtained on neuroimaging data using CNNs. Ensemble methods got the median of 93.7% (IQR: 91.4–96.2%). SVMs had similar results with a median of 91.5% (IQR: 89.3%94.1%).

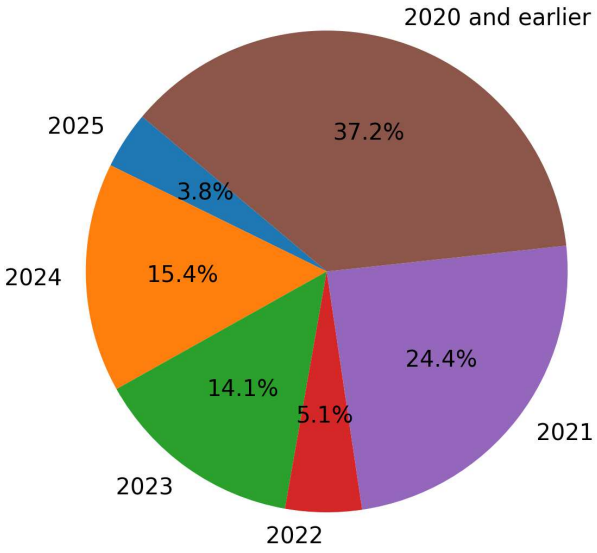

Figure 4. Distribution of studies by publication year

4.4. Performance comparison of AI techniques

Figure 7 showed that the most common dataset used was PPMI database (35.5% of the studies), then the UCI Parkinson Speech Dataset (23.5% of the studies), mPower Study data (12.7% of the studies), PhysioNet Gait (8.4% of the studies), the Oxford PD Dataset (7.2% of the studies), and other datasets (12.7% of the studies).

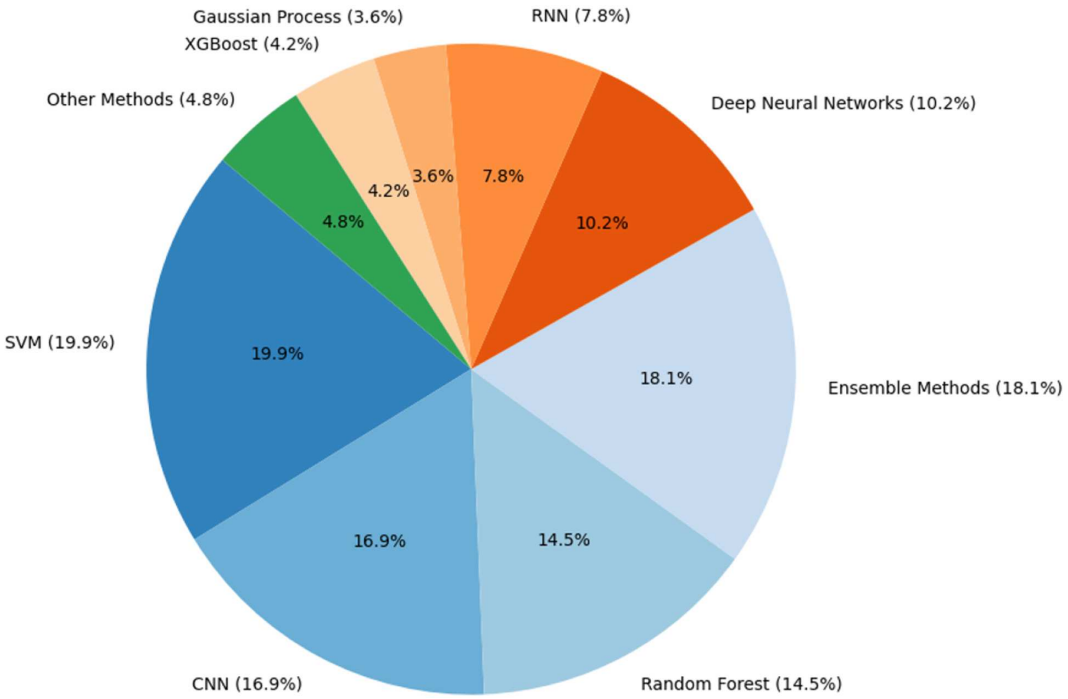

Figure 5. Distribution of AI techniques used in PD studies

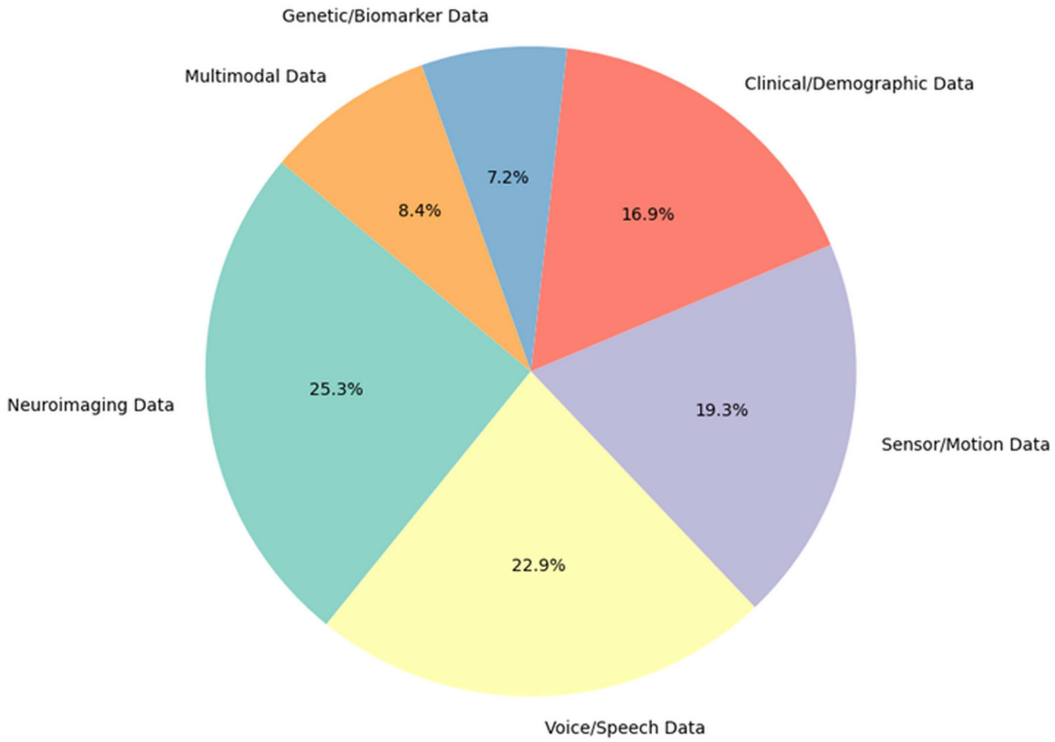

Figure 6. Types of data used in PD prediction studies

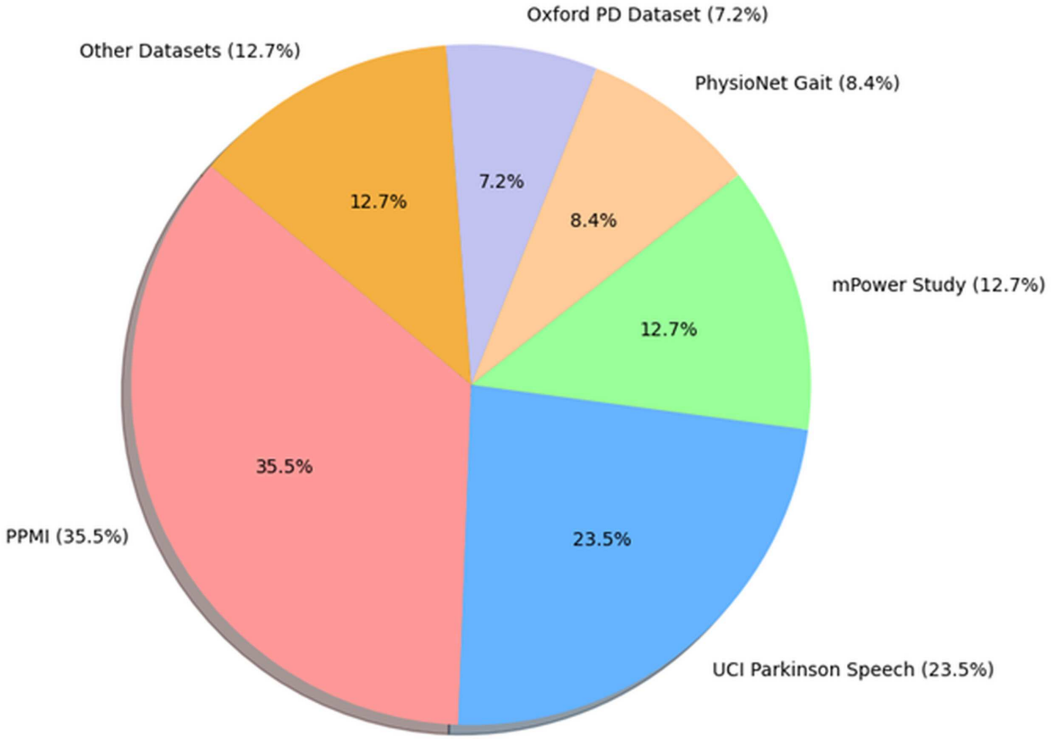

Figure 7. Distribution of datasets used in PD prediction studies

5. Discussion

5.1. Effectiveness of AI techniques for different data types

In our review, we have found obvious trends in the appropriateness of AI techniques, based on the type of data. The highest performance of DL, namely, CNNs, is on neuroimaging data [59, 60], which can be explained by their ability to provide automatic hierarchical feature extraction of subtle structural and functional changes in the brain [74]. In voice-based data, SVMs and ensemble methods give good and consistent accuracy, and recent reports up to 94.7% accuracy of patient-vs-control discrimination [51, 61], with the use of the high-dimensional acoustic feature space of vocal biomarker analysis [19]. It goes further to hybrid frameworks like Chandrakantha et al. [79] involving principled feature engineering to achieve voice-based accuracy of 97.44%. In wearable and smartphone time-series data, LSTM-based RNNs are the most popular choice [63, 64], as they use the ability to model temporal dependencies to detect the small motor variability that is defining of PD [15].

5.2. Meta-insights from performance analysis

A number of key meta-insights resulted from our research on the performance of models.

5.2.1. Early detection capabilities

Voice-based modalities were always the best at initial detections. Mean sensitivity of early-stage PD in 38 voice-data studies (Hoehn and Yahr stages 1(2) versus clinical assessment alone) was 89.7 versus 79.3, respectively [61, 65]. Vocal biomarkers are suggested to be an indicator of neurological changes before traditional clinical manifestation occurs (1218 months) [18, 62], making them a top priority target of AI-based population screening [19, 28].

5.2.2. Hybrid and ensemble models

The hybrid and ensemble methods produced better results than the individual classifiers in all modalities of data. The ensemble methods on average showed a 4.8% increase in accuracy compared to individual algorithms on the same dataset [13]. This benefit was the largest in multimodal experiments that utilized neuroimaging and clinical characteristics, in which ensemble techniques provided a 7.2% higher accuracy [20, 59]. Chandrakantha et al. [79] point to the value of tightly engineered end-to-end hybrid pipelines by the value of 97.44% accuracy.

5.2.3. Interpretability vs performance

There is a longtime conflict between the interpretability of the model and the raw predictive performance. DL is capable of attaining a maximum of 3.7% accuracy increase compared to traditional ML in neuroimaging applications, but the obscurity of their decision-making makes them impractical in clinical applications [22, 67]. This highlights the increased focus on explainable AI approaches [20, 40, 68] that attempt to maintain high performance through the production of mechanistically interpretable outputs as required by evidence-based medical practice.

5.3. Challenges and limitations

Although promising, a variety of challenges and limitations could be found in the current research landscape.

5.3.1. Dataset limitations

Almost all of the studies reviewed were based on publicly accessible datasets (74.7) and were small (median 209 subjects), and only 12.6% of the studies had over 1000 participants, which limits the external validity of performance reports [9, 11]. This is

made worse by the presence of demographic homogeneity, where about 78.3% of participants who report ethnicity in the studies are of White/European ancestry.

5.3.2. Validation approaches

The rigor of validation was also very different: 85.5% of studies were cross-validated, 23.5% were held-out test sets but 9.6%, were externally cohort-validated [55]. This lack of strong external validation poses significant risks of exaggerated estimates of performance that will not be true in clinical practice.

5.3.3. Clinical integration

A low review article percentage dealt with practical aspects of clinical implementation (7.0%), and a low review article percentage covered prospective studies that were assessing algorithms in real clinical workflows (3.6% of the reviewed articles) [68]. This disparity between lab results and illustrated practical use is the one and only most impactful impediment to implementing the potential AI-based PD tools into reality.

5.4. Conclusion

This systematic review creates the momentum for the development of AI-based solutions in predicting and diagnosing PD. DL is the most accurate at neuroimaging data, SVMs and hybrid ML systems are the most accurate at voice signal processing, and combined and multimodal approaches are always more accurate at diagnosing a patient of any type. The continued issues with small datasets, absence of external testing, and limited integration with clinical methods need to be addressed to ensure the AI-based PD diagnostics can realize their potential for change in the early diagnosis and customized disease treatment.

5.5. Future research directions

Future research directions are: (i) increased multimodal integration strategies, since only 16.9% of reviewed studies have used multiple data modalities; (ii) additional longitudinal AI models that can track disease progression and predicts further decline, which should be used in research but is only present in 12.0% of studies; (iii) emphasis on explainable AI models, which can retain high performance and provide clinically interpretable results; (iv) systematic use of demographically diverse patients cohorts to ensure fair performance of models; and (v) future validation studies in clinically

Ethical Statement

The paper is a systematic review of the existing published literature on the theme of prediction and diagnosis of PD based on the strength of AI. It does not involve experiments and data collection that the authors did on human or animal subjects. All the datasets and works utilized in this review are open, and the preliminary data collection process was made with sufficient ethical evaluations and informed consent as documented in the source materials. This is secondary research involving published literature, and therefore, there was no necessity for institutional review board approval.

Conflicts of Interest

The authors state that they have no conflicts of interest concerning it. The authors do not have any financial, personal, or professional connections with the research, and no agency funded the research, thus having no impact on the study design, analysis, interpretation, or publication of the present manuscript.

Data Availability Statement

The present research is a systematic review, and it is not associated with the creation of new data. Each data mentioned in this paper is based on the already published and publicly available datasets.

UPDRS Dataset: https://archive.ics.uci.edu/ml/datasets/parkinsons

Parkinson Speech Dataset: https://archive.ics.uci.edu/ml/datasets/Parkinsons

PPMI Database: https://www.ppmi-info.org/access-data-specimens/download-data

Gait in Parkinson's Disease: https://physionet.org/content/gaitpdb/1.0.0/

mPower Study: https://www.synapse.org/#!Synapse:syn4993293

Oxford Parkinson's Disease Detection Dataset: https://archive.ics.uci.edu/datasets?search=parkinson

DREAM Challenge: https://www.synapse.org/

Author Contribution Statement

Chandrakantha Tholalemane Sathyanarayana: Conceptualization, Methodology, Investigation, Data Curating, Formal analysis, Writing – original draft preparation, Visualizing. **Basavaraj Ningappa Jagadale:** Conceptualization, Methodology, Supervision, Validation, Writing – review and editing, Project administration, Resources. **Madhuri Gurram Ramesh:** Formal analysis, Investigation, Data curation, Writing – review and editing, Validation.

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