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Advances in Parkinson's disease diagnosis and treatment using artificial intelligence: a review

Mehr Ali Qasimi[1], Züleyha Yılmaz Acar[2]
[1]Department of Computer Engineering, Institute of Science and Technology, Selçuk University, Konya, Türkiye
[2]Department of Computer Engineering, Faculty of Technology, Selçuk University, Konya, Türkiye

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ABSTRACT

Parkinson's disease (PD) diagnosis and monitoring have significantly improved because to current advancements in artificial intelligence (AI), particularly in the areas of deep learning (DL) and machine learning (ML). Early-stage insensitivity of traditional diagnostic techniques necessitates the use of clever, data-driven alternatives. AI-powered noninvasive diagnostic methods like speech recognition, handwriting analysis, and neuroimaging categorization are the main topic of this technical review. We provide a summary of comparative performance measures from recent models, highlighting their practical usefulness, data modality, and accuracy. Also covered are important issues like data variability, real-world implementation, and model interpretability. Unlike prior surveys that primarily report accuracy metrics, this review explicitly focuses on identifying the gap between experimental AI performance and real-world clinical deployment, emphasizing interpretability, validation, and scalability challenges in PD diagnosis. The purpose of this letter is to provide guidance for researchers creating deployable and clinically valid AI systems for PD detection.

Corresponding Author:

Mehr Ali Qasimi
Department of Computer Engineering, Institute of Science and Technology, Selçuk University
Konya, Türkiye
Email: q1.mehrali@gmail.com

1. INTRODUCTION

Parkinson's disease (PD) is a degenerative neurological disorder marked by movement difficulties, rigidity, and tremors, resulting from the loss of dopaminergic neurons. The disease manifests through a broad spectrum of motor and non-motor symptoms, including tremor, bradykinesia, muscular rigidity, postural instability, speech impairment, anxiety, cognitive decline, and loss of smell. These motor and non-motor manifestations of PD are illustrated in Figure 1, highlighting the broad symptom spectrum that motivates the development of multimodal artificial intelligence (AI)-based diagnostic approaches. The development of AI systems utilizing multimodal biomedical data has been prompted by the need for early diagnosis [1]. AI techniques can identify small biomarkers in speech, gait, electroencephalography (EEG), and imaging data, in contrast to traditional diagnoses that depend on clinical evaluations. The focus of this review is on deep learning (DL) and machine learning (ML) models that have the potential to be implemented in the real world and have excellent diagnostic accuracy [2]. PD has a substantial negative impact on a patient's quality of life, social interactions, family dynamics, and finances for both people and society. PD symptoms include tremor, slowness of movement, tight muscles, irregular gait, and problems with balance and coordination [3].

Curing PD is not yet possible, and effective medication is still very difficult to come by. A mix of hereditary and environmental variables are thought to contribute to PD, while the precise reasons are yet

unknown. A person's quality of life may also be impacted by non-motor illnesses including depression and dementia. Because there is no one blood test or laboratory test that can accurately diagnose PD and track its progression, timely diagnosis is critical to preserving a high quality of life [4]. Since these neurotransmitters are essential for regulating movement, motor function is the PD primary feature. The illness develops in five phases, with the first stage exhibiting minor tremors and mobility problems and the last stage exhibiting severe and incapacitating symptoms, loss of movement, and an elevated chance of developing other chronic conditions [5]. Based on our research and reviews, a large number of articles have discussed various methods for detecting or diagnosing PD and its unique variety.

In this paper, we present a systematic review of recent studies on PD that apply AI, ML, and DL techniques for diagnosis and treatment. Following the PRISMA framework, 31 studies published between 2016 and 2024 are analyzed and categorized according to diagnostic modalities, treatment approaches, AI techniques, and PD subtypes. This structured synthesis provides an organized overview of recent advances and lays the foundation for identifying current limitations and open research challenges.

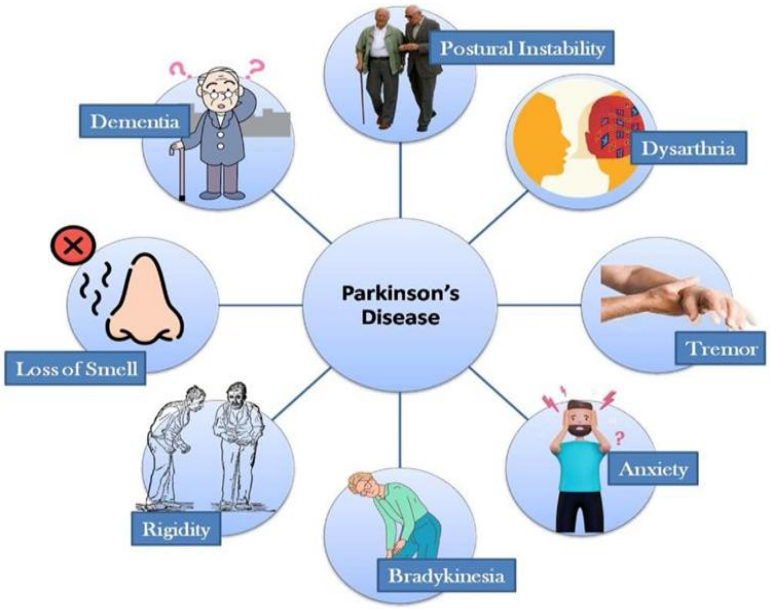

Figure 1. Parkinson's disease can show up in significant motor and non-motor ways [6]

2. METHOD

We used keywords like "Parkinson's Disease", "Machine Learning", "Deep Learning" and "Diagnosis" to search and select papers from PubMed, Google Scholar, Science Direct, and Nature that were published between 2016 and 2024. We only considered research that reported AI-based diagnostic models with performance measures. Excluded were studies that only examined clinical outcomes without including AI innovation. After thoroughly reviewing the full texts of relevant studies and removing duplicates, we followed the PRISMA statement framework for preparation and reporting, as shown in Figure 2.

The steps in the framework are listed below:

i) Step 1: there were 114 articles produced after the search strategy was applied using keywords from the four databases (Science Direct, Nature, PubMed, and Google Scholar). Of these, 82 were retrieved from Google Scholar, 15 from Science Direct, 12 from PubMed, and 5 from the Nature database. In this step 24 duplicated papers were found and removed.
ii) Step 2: following an analysis of the abstracts and titles, the authors eliminated 30 publications that did not use AI, ML, or DL techniques, were irrelevant, or were paid for.
iii) Step 3: 29 articles failed to match the inclusion requirements at the final stage, following full-text evaluation, for example, not being relevant articles or using AI, ML, or DL approaches.
iv) Step 4: finally, we achieved 31 main or relevant ones and included them in our study.

Among the 31 studies reviewed, 9 concentrate on PD, 8 articles address its diagnosis and treatment, and 11 papers explore the use of AI and various ML or DL methods for PD prediction. Additionally, 3 papers focus on different types of PD. The percentage analysis of these values is illustrated in Figure 3.

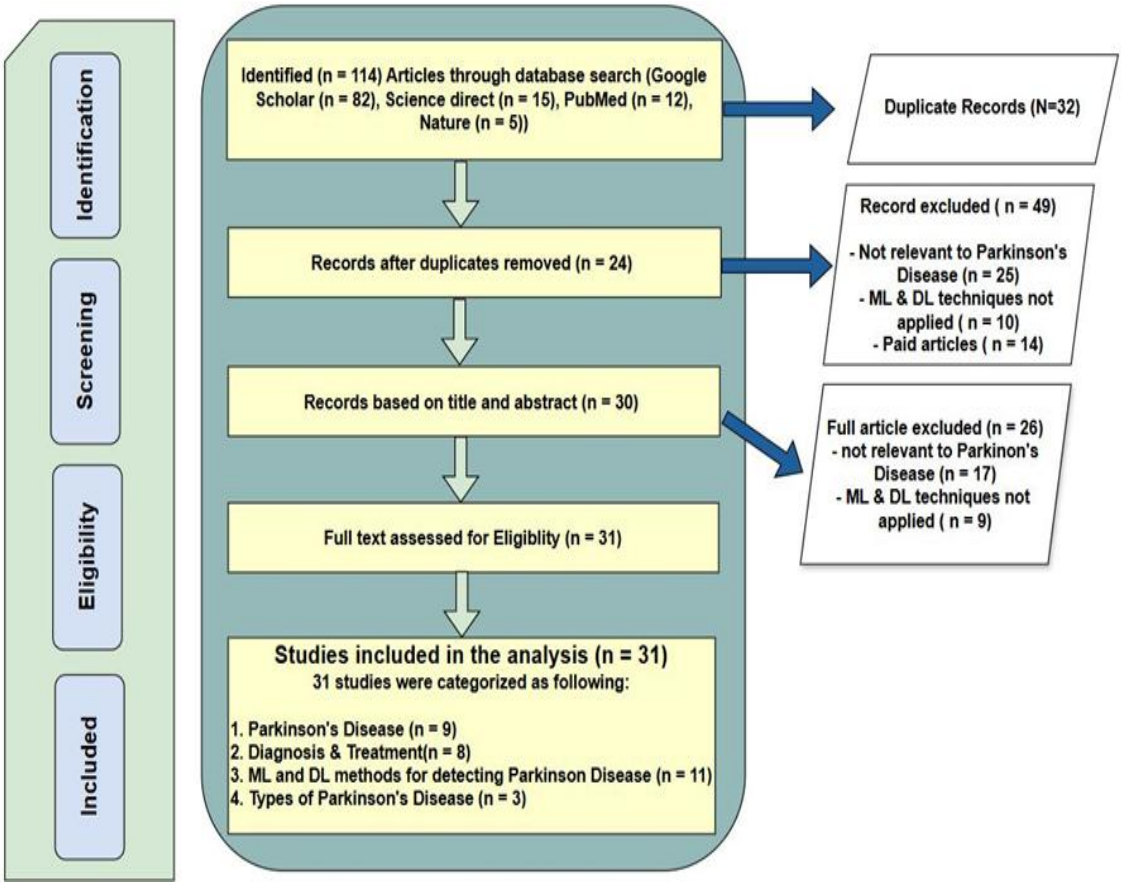

Figure 2. PRISMA diagram of Parkison's disease from different papers and databases

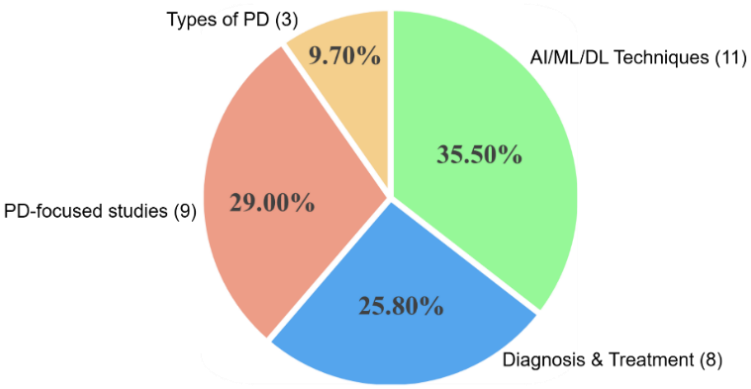

Figure 3. Distribution of reviewed studies on Parkinson's disease

3. OVERVIEW OF PARKINSON'S DISEASE

According to our systematic review, which covers all 31 of the chosen publications, we identified three distinct subsections. These include types of PD, AI, ML, and DL models for quick and precise PD diagnosis. The final subsection focuses on PD treatment.

3.1. Types of Parkinson's disease

PD is classified into two basic categories:

– Akinetic-rigid type is primarily defined by stiffness and slowness of movement.
– Tremor-dominant form is distinguished by significant tremors, especially at rest.

These kinds might be useful in comprehending and treating the many symptoms that people with PD might encounter [7].

3.2. Parkinson's disease diagnosis

A subset of AI called ML uses data analysis and rapid, non-programming decisions. It uses training data to automatically generate analytical models [8]. PD has been identified using a number of techniques based on data from speech, gait patterns, force monitoring, smell identification, and spontaneous cardiovascular oscillations. Many strategies have showed potential, including establishing an early detection system based on reduced vocal features and evaluating speech disorders using SWIPE scheme [9]. The effectiveness of these approaches varies across studies due to differences in data modality, feature structure, and dataset size, indicating that performance is highly context-dependent rather than universally optimal. Furthermore, a gait signal-based 1D convolutional neural network PD detection system has been shown. Gait tracking and inspection still face a number of difficulties, including the requirement for specialist equipment, plenty of room, and sensitivity to background noise in speech recordings. Although DL models can capture complex temporal patterns in gait signals, their performance may be constrained in small datasets where simpler models generalize more effectively. The ability to slow down the progression of PD makes early and precise PD identification crucial [10]. To enhance the identification of PD, numerous data-driven techniques have been created over time. A historical data set is all that is needed for data-driven detection approaches, as opposed to model-based detection techniques, which require the previous availability of an analytical model [11]. However, reliance on limited historical datasets may lead to optimistic accuracy estimates and reduced robustness when models are applied to unseen populations. Through magnetic resonance imaging (MRI), the structural changes in the brain caused by dopamine depletion in PD patients can be shown.

In the work, a DL neural network has been utilized to try and categorize MR images of PD patients and healthy controls. For the early diagnosis of PD, neuroimaging methods including MRI, PET, and SPECT are often utilized. Because of these techniques, pathophysiological alterations in the brain can be seen, facilitating early intervention and improved therapeutic approaches. The early characterisation and monitoring of PD utilizing MRI techniques has shown encouraging outcomes in recent research [12]. Despite high reported accuracy, neuroimaging-based methods face practical limitations related to cost, accessibility, and scalability in routine clinical settings. A key non-invasive technique for diagnosing PD is speech signal analysis. Clinical professionals and neuroscientists are attracted to non-invasive PD prediction and detection technologies. The diagnosis of speech problems in PD patients may enable identification and treatment prior to the onset of physically incapacitating complaints. Both the healthcare system and the patients' quality of life may be seriously affected by this. Research spanning multiple disciplines, particularly AI and multimodal signal processing, is essential to the advancement of modern speech processing technology [13]. Several observations from the analysis of PD speech suggest that individuals with PD exhibit increased maximum phonation time, jitter and shimmer, pitch range, and phonation threshold pressure [14]. In such structured feature spaces, traditional ML classifiers may outperform DL models because handcrafted features already capture disease-relevant patterns effectively. Detecting PD from speech involves a two-step process. Initially, the input speech signal must be converted into speech feature vectors or tensors suitable for analysis by DL models.

The speech characteristics of PD patients encompass multiple dimensions., such as articulation, phonation, and prosody. Phonation features are characterized by bowing and inadequate closure of vocal folds and are related to perturbation measures such as jitter, shimmer, amplitude perturbation quotient (APQ), and pitch perturbation quotient (PPQ) [15]. The EEG makes it simple to determine the roles of the cortical and subcortical regions of the brain. Using the EEG signals, neurological conditions such as epilepsy, schizophrenia, and Alzheimer's can also be identified. We use EEG for PD diagnosis. Since EEG signals are inherently complex and nonlinear, numerous linear feature extraction methods can't adequately describe them. PD is seen to worsen when there is complexity in the EEG signal. This is caused by the nonlinear elements in the EEG signals. Thus, it can be concluded that the separation of normal and PD EEG signals might benefit from application of nonlinear features extraction techniques [16]. Nevertheless, EEG-based approaches are sensitive to noise and inter-subject variability, which can affect consistency across studies. Molecular imaging methods like PET and SPECT are employed to investigate a range of medical conditions. A cyclotron is needed for PET, which has particular tracers and great resolution, although SPECT is more widely available. Dopamine production and neuron density are measured in order to aid in the diagnosis of neurodegenerative diseases, including PD. Radiotracers specific to dopamine transporters and D1/D2 receptors are among the several that are available for PET/SPECT imaging. However, lesser resolution still makes it difficult to distinguish PD from other Parkinsonian disorders or healthy people. It is believed that the most sensitive method of diagnosis combines pre- and post-synaptic imaging with clinical observations [17].

3.3. Parkinson's disease treatment

Detecting PD at an early stage is crucial to slowing its progression and ensuring patients can access treatments that modify the disease. The premotor stage of PD should be closely watched in order to achieve this. To determine early on whether a person has PD or not, a novel deep-learning technique based on premotor traits is introduced [18]. PD frequently leads to death in its later stages. It is critical to create a low-cost, effective, and precise approach for early-stage PD diagnosis because the current diagnostic tests are costly and not very accurate. Researchers are looking at biomarkers to identify PD early, but there is still no clear-cut method for diagnosing the condition. Current treatments help alleviate symptoms, but they don't halt or delay the disease's course. To possibly stop the advancement of the disease, it's critical to recognize non-motor symptoms as soon as they appear. Yet, it might be difficult to diagnose PD only on the basis of symptoms, as other conditions can have similar symptoms [19].

3.4. Predicting Parkinson's disease using AI and ML/DL techniques

ML and DL techniques have emerged as powerful tools in the realm of medical diagnostics, particularly for predicting and diagnosing PD. These data-driven algorithms analyze extensive patient data, including motor symptoms and medical history, enabling accurate predictions and classifications of the disease. ML techniques fall into four categories: supervised, semi-supervised, unsupervised, and reinforcement learning. Each has special benefits for handling and analyzing intricate clinical data. Recent advancements highlight various ML techniques that assess PD severity through physiological signals. For instance, certain studies have reported achieving up to 97.5% accuracy by implementing neural networks on speech data, which is a promising indicator of the potential for accurate early diagnosis. Such high accuracy values may be influenced by optimized feature selection or limited datasets and should therefore be interpreted with caution regarding generalizability. Additionally, techniques such as principal component analysis (PCA) have refined feature sets for better efficiency, while SVM have successfully differentiated PD patients from healthy individuals. Ensemble learning methods, including stacking classifiers, further enhance predictive accuracy, underscoring the effectiveness of AI-driven approaches in diagnosing PD [20].

AI methodologies are not limited to just one type of data; they span diverse sources including speech recordings, handwriting samples, gait patterns, and MRI scans. Non-invasive speech processing has gained traction due to its ability to detect early vocal biomarkers of PD. Accuracy rates in these applications are remarkable, with certain models achieving as high as 99.49% using a set of key speech attributes, while others have reached 98% accuracy by leveraging multivariate vocal data. Near-perfect performance may reflect subject-dependent evaluations or extensive tuning rather than true clinical robustness, emphasizing the need for critical comparison across studies. Handwriting analysis, employing DL architectures like CNN and CNN-BLSTM, has also shown significant promise. In addition, sEMG signals processed through lightweight convolutional networks, such as S-Net, have been utilized to evaluate tremor severity effectively [21]. Gait dynamics serve as another critical modality, with models that analyze spatial- temporal features categorizing PD patients and assessing their condition severity. Techniques like ResNet, VGG19, and InceptionV3, when utilized through transfer learning, have reduced training times while maintaining high classification accuracy [22]. Furthermore, ML methods like SVM and multilayer perceptron (MLP) have proven particularly effective in classifying PD based on non-motor symptoms, showcasing the vast potential of advanced AI and ML techniques in transforming the diagnostic landscape for PD [23].

Despite the promising accuracy reported across numerous studies, most existing AI-based approaches for PD diagnosis are evaluated in controlled experimental environments. Clinical validation involving neurologists, multi-center cohorts, and real-world deployment scenarios remains limited. Furthermore, many high-performing DL models operate as black-box systems, offering limited interpretability, which poses challenges for clinical trust and adoption. These factors highlight a gap between experimental performance and practical clinical applicability. Overall, the synthesis of the reviewed literature demonstrates that speech analysis, gait assessment, and neuroimaging—particularly MRI—emerge as the most promising modalities for PD diagnosis. This systematic consolidation of results enables a clearer comparison of AI techniques and performance trends, providing a structured reference for researchers while emphasizing the incremental yet valuable contribution of comprehensive synthesis over isolated study reporting.

3.5. Challenges and open research issues

Although significant progress has been achieved, several challenges remain unresolved in current PD research. Many studies rely on small and imbalanced datasets, which can bias model performance and limit generalizability. In addition, reproducibility is often hindered by inconsistent evaluation protocols and the absence of standardized benchmarks. Longitudinal studies that track disease progression over time are also scarce, restricting the ability of existing models to support long-term monitoring and prognosis. Addressing these challenges is essential for advancing clinically reliable and deployable AI-based solutions.

4. RESULTS AND DISCUSSION

The research obtained from the article search results is as follows: the study suggests a hybrid DL strategy that combines artificial neural networks (ANN) with regression analysis (RA). While ANN is used to identify PD patients by comparing outcomes with a threshold value, RA is utilized for data preparation and probability calculation. The model performed better than conventional classifiers like support vector machine (SVM) and k-nearest neighbor (k-NN), with 93.46% accuracy when evaluated on a dataset including speech recognition, iron content, and pulse rate. The study found that characteristics such as iron accumulation in the spinal cord and reduced pitch period entropy (PPE) illustrate the hybrid method's effectiveness for early PD detection [24]. The improved performance of this approach appears to arise from the complementary strengths of ANN in capturing nonlinear patterns and RA in structuring probabilistic relationships, although such hybrid frameworks may remain sensitive to feature selection and dataset consistency.

The study uses voice features to evaluate DL and ML models for the early identification of PD. It employs a dataset from the UCI repository containing 5876×22 entries, comprising recordings from Healthy people and those with PD. The work compares six supervised ML algorithms, two DL architectures (CNN, RNN), and an ensemble method (XGBoost). Among all the methods tested, the KNN algorithm with k =5 achieved the highest accuracy of 97.43%, outperforming both ensemble (XGBoost at 94.87%) and DL approaches (RNN at 96.65%, CNN at 84.61%). Every model was assessed utilizing metrics such precision, recall, F1-score, specificity, and sensitivity through three-fold cross-validation. The findings show that simple yet effective ML models like KNN, when properly tuned, can outperform complex DL models for structured tabular datasets in the context of PD diagnosis [25]. This result indicates that DL architectures may be disadvantaged when dataset size and feature structure are insufficient to fully exploit their representational capacity, whereas simpler models benefit from well-defined feature spaces.

The work offers a thorough analysis of AI methods that have been proposed between 2016 and 2022 for the screening, staging, and biomarker identification of PD using data from speech tests, handwriting examinations, EEG, MRI, and sensory data [26]. Despite promising results across modalities, differences in data acquisition protocols, cohort size, and population characteristics contribute to variability in reported performance and limit cross-study comparability. The research aims to enhance the early detection of PD by employing DL models refined through Grey Wolf Optimization (GWO). It presents four DL frameworks optimized with GWO—GWO-VGG16, GWO-DenseNet, GWO-DenseNet + LSTM, GWO-InceptionV3—and a combined model, GWO-VGG16 + InceptionV3. These models are utilized on T1, T2-weighted MRI, and SPECT DaTscan datasets.

Comprehensive preprocessing steps, such as skull stripping, normalization, and the elimination of empty tuples, are implemented to ensure superior data quality. The hybrid model GWO-VGG16+ InceptionV3 demonstrated the highest performance, achieving 99.94% accuracy and 99.99% AUC on the T1, T2-weighted dataset, and 100% accuracy with 99.92% AUC on the SPECT DaTscan dataset. All models significantly surpass previous methods, including traditional CNNs and ensemble models, confirming the promise of metaheuristically tuned hybrid DL architectures for reliable PD diagnosis [27]. While these results highlight strong potential, the exceptionally high accuracy is likely influenced by controlled experimental conditions and curated datasets, which may not fully reflect real-world clinical variability. The work explores system-based voice features for detecting PD using ML algorithms. It analyzes voice recordings containing 23 acoustic features from individuals with PD and healthy controls. Five supervised ML models—logistic regression (LR), k-NN, SVM, random forest (RF), and AdaBoost—are evaluated for their diagnostic performance. The results demonstrate that SVM and RF achieved the highest classification accuracy of 95%, followed by AdaBoost (93%), k-NN (92%), and LR (86%). The study emphasizes these models' efficacy, particularly SVM and RF, in distinguishing PD from healthy controls based on vocal biomarkers, emphasizing their potential for early and non-invasive diagnosis of PD. The assessment was carried out using standard performance metrics (accuracy, precision, recall, F1-score) and confusion matrices [28]. The strong performance of SVM and RF can be attributed to their robustness against noise and feature redundancy commonly present in speech-derived datasets.

The work focuses on improving PD diagnosis using multipool chemical exchange saturation transfer (CEST) MRI combined with DL techniques. A modified 1D U-Net model, called Z-spectral compressed sensing (CS), was proposed to reconstruct dense Z-spectra from sparsely sampled data, significantly reducing MRI scan time. The DL model demonstrated superior reconstruction fidelity compared to traditional interpolation methods. In classification tasks, the combined CEST contrast achieved the best diagnostic performance (AUC =0.84), outperforming individual contrasts such as APT (AUC =0.73). The study concludes that DL–based Z-spectral CS can accelerate CEST MRI by up to 67% without significantly compromising accuracy, showing strong potential for efficient, non-invasive PD diagnosis [29]. However, the cost of advanced imaging equipment and the computational requirements of DL-based reconstruction may limit widespread clinical adoption.

The paper offers predicting PD through speech disorders using ML and ensemble techniques. It evaluates 20 classifiers, including KNN, XGBoost (XGBC), and MLP, across two different acoustic datasets. The study emphasizes the impact of hyperparameter tuning and robust evaluation strategies such as stratified k-fold and leave-one-out cross-validation (LOOCV), especially given the small and unbalanced nature of the datasets. To enhance classification performance, ensemble voting classifiers were proposed. The first ensemble combines KNN and MLP on dataset I (195 samples) and achieved an accuracy of 96.41%. The second combines KNN and XGBC on dataset II (756 samples), achieving an accuracy of 97.35%. The results demonstrate that ensemble models significantly outperform individual classifiers, highlighting the potential of AI-based voting strategies for accurate and early detection of PD using vocal biomarkers [30]. Nevertheless, ensemble approaches often reduce model interpretability, which remains a critical consideration for clinical decision-making.

The work presents a comprehensive study employing ML and DL techniques to detect PD using voice signal features. It utilizes data preprocessing methods including SMOTE to address class imbalance, SelectKBest for feature selection, and RandomizedSearchCV for hyperparameter tuning. Various classifiers such as Kernel SVM (KSVM), RF, decision tree (DT), k-NN, and feed-forward neural network (FNN) were evaluated. Among them, the FNN model achieved the highest classification accuracy of 99.11%, followed by KSVM with 95.89%. The study emphasizes the effectiveness of DL models, particularly FNN, in capturing subtle vocal impairments associated with PD. It further highlights the viability of voice-based, non-invasive diagnostic systems as a promising alternative to conventional clinical methods, offering faster and more accessible early detection of PD [31]. Despite their high accuracy, DL models often lack transparency, posing challenges for regulatory approval and clinical trust.

This thorough systematic review's objective is to compile the body of research on the use of AI, ML, and DL in the diagnosis and treatment of PD. We describe the issues, identify possible research directions for these technologies, the results of AI models, and the challenges faced during their deployment. Overall, while many models achieve high diagnostic performance under experimental conditions, issues related to dataset heterogeneity, interpretability, cost, and regulatory validation remain key barriers to real-world clinical implementation.

A comparative summary of AI and ML/DL-based PD prediction studies is provided in Table 1. Studies focusing on different types and subtypes of PD are summarized in Table 2. Research addressing diagnosis- and treatment-oriented AI approaches for PD is presented in Table 3. General PD research employing AI techniques is summarized in Table 4.

Table 1. AI and ML/DL techniques for Parkinson's disease prediction papers

Author	Categories	Methods	Dataset	Acc (%)	Reference	Year
Babita Majhi *et al.*	Supervised learning	VGG16, DenseNet, InceptionV3	MRI_SPECT, PD_MRI_SPECT	99 to 100	[27]	2024
Sourabarna Roy *et al.*	Supervised learning	SVM, MLP, CNN, LSTM, ResNet, VGG19, InceptionV3, ANN	PPMI, HandPD, GYENNO, UCI, AIBL	93.46	[21]	2024
Keserwani *et al.*	Supervised learning	CNN	PD_Review, PD_Combined	75.56 to 99.49	[20]	2024
Mohamed Shaban *et al.*	Unsupervised and supervised	ANN, KNN, LSTM	EEG, MRI (DTI, SWI), Speech (Oxford, Istanbul)	99.99	[26]	2023
Aditi Govindu *et al.*	Supervised learning	SVM, KNN, LR	MDVP audio dataset (from PPMI and UCI)	91.83	[2]	2023
Lipsita Sahu *et al.*	Supervised learning	ANN, SVM, KNN, CNN	Custom_Speech, Speech741_Custom	97.43	[24]	2022
Changqin Quan *et al.*	Supervised learning	LSTM, CNN, SVM, KNN, MLP	GYENNO_PD_Speech	84.29	[15]	2021
Mounika *et al.*	Supervised learning	CNN, KNN, RNN	UCI_PD	-	[25]	2021
Sivaranjini *et al.*	Supervised learning	CNN	PPMI_T2	89.3	[12]	2020
Shu Lih Oh *et al.*	Supervised learning	SVM, KNN, CNN, ANN, RNN, PSO	UKM_PDvsHC_EEG	75.4 to 100	[16]	2020
Gupta *et al.*	Supervised learning	SVM	PaHaW_PD	79.55	[11]	2020

Table 2. Studies addressing types and subtypes of Parkinson's disease

Author	Categories	Methods	Dataset	Acc (%)	Reference	Year
Reddy *et al.*	Supervised and unsupervised learning	ANN, CNN, RNN, SVM KNN	Multi-modal data (PET, EEG, MRI, biomarkers)	91.83	[23]	2024
Khachnaoui *et al.*	Supervised learning	CNN, ANN, KNN, SVM, ResNet, VGG.	Multiple datasets (e.g., PPMI, PC-GITA, HandPD, SNUH)	75 to 99.42	[17]	2021
El Maachi *et al.*	Supervised learning	CNN, MLP	PhysioNet gait in PD dataset	98.7	[10]	2020

Table 3. Studies on diagnosis and treatment of Parkinson's disease

Author	Categories	Methods	Dataset	Acc (%)	Reference	Year
Nusrat Islam *et al.*	Supervised learning	SVM, KNN, CNN, MLP	PPMI dataset.	98.44	[22]	2024
Sorathiya *et al.*	Supervised learning	SVM, KNN, ResNet, DenseNet	UCI PD, spiral/wave handwriting datasets.	96.67	[1]	2024
Al-Nefaie *et al.*	Supervised learning	KNN, SVM, AdaBoost, RF	UCI Parkinson's dataset.	95	[28]	2024
Rahman *et al.*	Supervised learning	XGBoost, DNN, SVM, KNN	UCI Parkinson's dataset.	95	[19]	2023
Mridha *et al.*	Supervised learning	CNN, RNN, GAN, SVM	LIDC-IDRI, LUNA16, NSLT, TCIA, JSRT.	96 to 100	[3]	2022
Wu Wang *et al.*	Supervised learning	FNN, SVM, KNN, BOOST_TREE	PPMI dataset.	96.68	[7]	2020
Salim Lahmiri *et al.*	Supervised learning	SVM.	UCI Parkinson's Telemonitoring dataset.	97.03	[14]	2017
Prashanth *et al.*	Supervised learning	SVM, naïve Bayes, LR	PPMI dataset.	96.40	[18]	2016

Table 4. General Parkinson's disease research

Author	Categories	Methods	Dataset	Acc (%)	Reference	Year
Md. Ariful Islam *et al.*	Supervised and unsupervised learning	SVM, KNN, RNN, CNN, LSTM	UCI, PPMI, HandPD, PDMultiMC.	100	[6]	2024
Srinivasan *et al.*	Supervised learning	FNN, SVM, KNN, DT	UCI Parkinson's dataset.	99.11	[31]	2024
Shawki Saleh *et al.*	Supervised learning	KNN, MLP, SVM, XGBOOST, AdaBoost	CEST MRI dataset (simulated + rat brain).	97.35	[30]	2024
Lin Chen *et al.*	Supervised learning	U-NET	PPMI, handPD, GYENNO, UCI, AIBL.	84	[29]	2024
Mohtashim Mian *et al.*	Supervised learning	CNN, RNN, ANN, LSTM	N/A	N/A	[8]	2024
Gunjan Pahuja *et al.*	Supervised learning	SVM, ANN, KNN	Parkinson's voice dataset.	95.89	[4]	2021
Vojtech Illner *et al.*	Supervised learning	Signal processing/feature extraction	Czech smartphone PD speech dataset.	95	[9]	2020
Solana-Lavalle *et al.*	Supervised and unsupervised learning	KNN, MLP, SVM, RF	Istanbul PD speech dataset.	94.7	[5]	2020
Delic *et al.*	N/A	RNN, CNN, DNN, LSTM, GANs	N/A	N/A	[13]	2019

5. LIMITATIONS AND FUTURE DIRECTIONS

Despite encouraging outcomes, there are a number of obstacles to clinical adoption. Physician trust is hampered by the restricted interpretability of the model. Repeatability is hampered by dataset bias and a lack of uniformity. Furthermore, real-time connection with mobile or wearable platforms is essential for ongoing monitoring but has not received enough attention. Future research should prioritize the development of deployable and clinically validated AI systems through the use of standardized and publicly available datasets to improve reproducibility and cross-study comparability. In addition, incorporating explainability frameworks such as SHAP and LIME could enhance model transparency and physician trust. The integration of multimodal data fusion techniques, combining speech, imaging, sensor, and clinical data, may further improve diagnostic robustness. Longitudinal monitoring using wearable and

mobile health technologies should also be explored to capture disease progression over time. Finally, seamless integration of AI systems into existing healthcare workflows is essential to support real-world clinical decision-making and adoption.

6. CONCLUSION

AI, including ML and DL, is rapidly transforming the diagnosis, monitoring, and management of PD. AI-driven diagnostic tools have demonstrated impressive accuracy across diverse modalities such as speech, handwriting, gait analysis, neuroimaging, and EEG, with some models exceeding 95% accuracy. These advancements enable earlier detection and more personalized treatment strategies, paving the way for improved patient outcomes. Although this review does not introduce new experimental results or a quantitative meta-analysis, it provides a structured and critical synthesis of AI-based PD research. Future research should prioritize clinically validated, interpretable, and reproducible AI models, supported by longitudinal and multi-center datasets, to bridge the gap between experimental success and real-world deployment.

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BIOGRAPHIES OF AUTHORS

Mehr Ali Qasimi is a Master degree student in Computer Engineering at Selcuk University, where he currently serves as an assistant professor in the Department of Information System at Badakhshan University Afghanistan. His master degree focused on developing artificial intelligence techniques for identifying disease. He has published different papers in AI and disease detection. He can be contacted at email: q1.mehrali@gmail.com or q.mehrali@yahoo.com.

Züleyha Yılmaz Acar is a Ph.D. holder in Computer Engineering from Selçuk University, where she currently serves as an assistant professor in the Department of Computer Engineering within the Faculty of Technology. She has authored studies, in the fields of artificial intelligence, biomedical image processing, and machine learning/deep learning algorithms. She continues to work on AI-based medical diagnostic approaches. She can be contacted at email: zuleyhayilmaz@selcuk.edu.tr.