

Using ML / DL in Diagnosis of Parkinson's Disease: review

Ezzulddin Sahi Allawi^a, Ahmad Shaker Abdalrada^b, Hasanain Hazim Azeez^c

^a College of Computer Science and Information Technology, Kut, Wasit University, Iraq. Email: stdm.eallawi@uowasit.edu.iq

^b College of Computer Science and Information Technology, Kut, Wasit University, Iraq. Email: aabdalra@uowasit.edu.iq

^c College of Computer Science and Information Technology, Kut, Wasit University, Iraq. Email: hbashagha@uowasit.edu.iq

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ABSTRACT

Significant and ongoing advancements in artificial intelligence (AI) have allowed for employing its techniques in diagnosing many diseases, one of these diseases is Parkinson's disease (PD) which is considered the second most common neurodegenerative disorder. The diagnosis heavily depends on the practitioner's experience because there are no definitive laboratory tests or definitive medical imaging tests. Currently, there is no cure for PD, which makes it a suitable application area for AI techniques. These techniques can address several issues related to PD, such as the lack of experienced medical staff, reducing expenses, and minimizing human error and bias. This study therefore reviewed several published studies that focus on diagnosing PD by employing AI techniques.

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1. Introduction

Parkinson's Disease (PD) is a chronic non-curable progressive neurodegenerative disease. Its effects are clearly shown in the nervous system and its ability to regulate movement [1]. The human brain sends messages to the sensory organs to coordinate movement by using a chemical neurotransmitter called dopamine, which is produced in the substantia nigra, a brain region [2], [3]. PD patients suffer from the progressive death of the dopaminergic neurons that produce dopamine [4]. This leads to a deficiency of dopamine in the brain which is responsible for regulating movement properly resulting in motor symptoms [5]. Usually, symptoms are categorized into motor and non-motor symptoms. As the name suggests, motor symptoms are related to the movement including resting tremor (shaking), rigidity (muscle stiffness), bradykinesia (slowness of movement), postural instability, affecting handwriting, speech, and gait (freezing while moving) [6], [7]. On the other hand, the non-motor symptoms include anxiety, sleep disorder (insomnia or rapid eye movements), depression, olfactory loss (loss of smell), cognitive decline and more [8], [9]. PD is the second most prevalent neurodegenerative disease worldwide affecting approximately 10 million people worldwide [10] most commonly affecting individuals over the age of 55 [11]. To date, the cause of the progressive dying of dopaminergic neurons is still unknown but it can be related to the exposure to environmental factors such as industrial toxins, prolonged exposure to pesticides or herbicides. Approximately 10–15% of cases are related to genetic mutations [12], [13]. Diagnosing PD is difficult because there is no definitive imaging or blood test that can confirm PD [11], [14], [15]. Diagnosis is largely based on physicians

*Corresponding author: *Ezzulddin Sahi Allawi*

Email addresses:

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reviewing the patient's medical history and evaluating clinical symptoms [16]. To assess the severity of the disease, doctors usually use clinical scales like the MDS-UPDRS [17], [18]. Based on the diagnosis and these scales doctors can use various treatments to restore dopamine levels in the brain to alleviate the symptoms [19]. AI techniques such as machine learning (ML) and deep learning (DL) offer a data-driven approach capable of processing massive volumes of data to provide faster, non-invasive, and more accurate diagnosis than traditional diagnostic approaches that rely on physical examination and reviewing patient records which can lead to misdiagnosis rates up to 20% in critical cases [20], [21]. Several studies have successfully employed ML/DL techniques in diagnosing worldwide chronic diseases such as Diabetes mellitus (DM) [22], [23]. Alzheimer's disease, another neurodegenerative disease, has also benefited from ML/ DL techniques with respectable results [24]. Likewise, AI has become an important approach for PD diagnosis; therefore, several studies have been proposed which will be reviewed in this study. Section 2 presents the review methodology. Section 3 reviews the published studies that employed ML and DL techniques for PD diagnosis. Section 4 provides a comparative analysis of the reviewed studies and highlights current research gaps. Finally, Section 5 presents the conclusion.

2. Review Methodology

This review was conducted to examine recent applications of ML and DL techniques for PD diagnosis. Relevant literature was identified through Google Scholar using combinations of keywords including Parkinson's disease, machine learning, deep learning, artificial intelligence, speech analysis, handwriting analysis, EEG, EMG, neuroimaging, gait analysis, and multimodal diagnosis. The review focused on peer-reviewed journal articles and conference papers published between 2021 and 2025. The inclusion criteria required studies to focus on Parkinson's disease diagnosis, employ machine learning or deep learning methods, and provide sufficient methodological information. The included studies utilized different modalities such as speech, handwriting, gait signals, neuroimaging, EEG/EMG recordings, genetic data, and clinical variables. Then studies were classified according to the main modality considered, dataset, reported performance, learning method, and study limitations. This organization enabled the identification of current research trends, commonly used methodologies, and open challenges in AI-assisted PD diagnosis.

3. Related Work

The complexity of diagnosing PD, high misdiagnosis rates in traditional diagnosis and the rapid advancements in AI led to the adoption of AI in PD diagnosis to improve accuracy while reducing cost and make patient follow-up more convenient since this disease mostly affects the elderly. Many researchers published papers on utilizing various ML and DL techniques to diagnose PD by analyzing physiological signals collected from subjects (Speech, EEG and EMG), using Neuroimaging (MRI, fMRI, PET and SPECT) and other tests (Handwriting, Spiral drawing. ... etc.) [17].

3.1. Voice-Based Diagnosis

Shen et al. [25] suggested a PD detection system by extracting voice acoustics features like MFCCs, jitter, and shimmer from voice recording and introduced them into a hybrid model that combines CNN with Recurrent neural networks (RNN), Multiple Kernel Learning (MKL), and MLP with SHARP for explainability to enhance interpretability and trustworthiness. This model achieved accuracy of 91.11%. Similarly, Swain et al. [26] developed a PD detection framework using voice recordings by applying multiple classifiers including Linear Discriminant Analysis (LDA), SVM, KNN, and CNN to analyze acoustic features. The best performance was achieved by KNN with accuracy of 98.0%. Moreover, Di Cesare et al. [27] presented PD detection method using speech signals by combining speaker diarization with MFCC and GTCC feature extraction and classification through Cubic SVM, Fine KNN and a wide neural network technique, they reported best test accuracy of 92.3% for the reading task with combined MFCCs + GTCCs using Fine KNN and the wide neural network, while the spontaneous conversation task achieved accuracy of 90% with Cubic SVM. Similarly, Costantini et al. in [28] focused on the characteristics of the recorded voice of the subjects to determine whether the subject has PD or not, and to track its progression for positively diagnosed PD subjects. The authors used ML techniques and CNN-based models with a range of classifiers to conclude that using correlation-based feature selection (CFS) was the most effective for selecting features and use them as bioacoustics characteristics, later to be used to differentiate between a Healthy Control (HC), a newly diagnosed Parkinson's patient, and a patient on/off medication. The proposed approach resulted in a maximum mean accuracy of 82.25% and a maximum mean AUC of 0.87. As PD affects muscle control, it causes the improper pronunciation of vowels. Nijhawan et al. [29] utilized the extracted dysphonia measures from voice recordings to classify subjects as PD or HC. Their approach was to use a transformer-based method and selecting features based

on gradient-enhanced decision trees. The performance of this approach was compared with commonly used machine learning methods with an increase of 1% in AUC = 0.917 as the primary metric used in the evaluation. Since PD primarily affects the elderly causing difficulties in movement and mobility, Govindu and Palwe [30] saw an opportunity to utilize ML in telemedicine for diagnosing this disease, the authors used audio recordings and trained four classifiers (SVM, KNN, RF and Logistic Regression Models), revealing that RF was most effective in detecting PD with Accuracy of 91.83%. Furthermore, PD symptoms manifest primarily in (motor, non-motor) functions. Escobar-Grisales et al. [31] explored speech pattern modality (motor impairment affecting speech) and language pattern modality (cognitive impairment). Each modality was modeled separately then combined best representation of both models through early, joint and late fusion. They concluded that the speech model discriminated PD or HC more accurately than the language model. The speech model achieved an accuracy up to 11% higher than the multimodal model. Furthermore, Alshammri et al. [32] developed PD detection approach using voice signal features by applying SVM, RF, DT, KNN and Multi-Layer Perceptron (MLP). These models trained with different techniques such as SMOTE, GridSearchCV, and SelectKBest. MLP outperformed the other models with accuracy of 98.31%. Moreover Alalayah et al. [33] focused on using acoustic voice signals by applying Recursive Feature Elimination (RFE) for features selection, followed by dimensionality reduction using t-SNE and PCA, for classification, they used SVM, KNN, DT, RF, and MLP. The RF achieved the highest test accuracy of 97%. Furthermore, Lamba, et al. [34] aimed to design a hybrid PD early diagnosis system that constructed solely on speech signal modality. To overcome the heavily imbalanced dataset, synthetic minority oversampling (SMOTE) was applied prior to model training. They evaluated different combinations of three feature selection strategies (Extra Tree, Mutual Information and Genetic algorithm) with three classification algorithms (Naïve Bayes, KNN and Random Forest). The best reported configuration was (GA + RF) achieving accuracy of 95.58% and an AUC of 0.989. The reviewed voice-based studies demonstrate the growing importance of speech analysis as a non-invasive and cost-effective approach for PD diagnosis. Voice-based diagnosis has been widely explored through the analysis of acoustic biomarkers, particularly jitter, shimmer, MFCCs, and other dysphonia-related measurements. Earlier voice-based studies relied mainly on handcrafted acoustic features, whereas more recent work increasingly used DL and transformer models. Many differences in dataset size, recording procedures, and feature extraction methods complicate direct comparison between studies. Many investigations were also conducted using relatively small cohorts. Several authors reported accuracies exceeding 95%; however, these figures were obtained under different experimental conditions. Regardless of the limitations, the ease of voice acquisition and remote collection capabilities have made it one of the most widely used modalities in the diagnosis of PD. Larger datasets are needed before the reported results can be generalized for clinical use.

3.2. Handwriting-Based Diagnosis

S. K and N. T M [35] proposed RGG-Net, a hybrid deep fusion model for early PD prediction from handwriting spiral and wave images. The model combined ResNet-50 and GoogLeNet for feature extraction followed by Adaptive Feature Fusion (AFF), attention-based feature selection, Hierarchical Ensemble Learning (HEL), fully connected layers, dropout and Grad-CAM for visual explanation. The model achieved an accuracy of 99.12% in the frozen setting and 96.3% in the unfrozen setting. In a different study, Ouabd et al. [36] proposed a handwriting-based PD detection framework that employs multiple ML classifiers, including SVM, RF, Naïve Bayes (NB) with feature selection techniques such as Correlation analysis, LASSO, ANOVA and PCA. The proposed approach achieved an Acc of 83.02%. In addition, Lu et al. [37] inspected dynamic handwriting signals for PD detection by designing a feature extraction approach based on pressure, kinematic, angle, and moment-related measurements. After applying RF, Relief, and LASSO for feature selection, the resulting feature set was evaluated using XGBoost and AdaBoost classifiers. The proposed framework achieved accuracies of 98.67% on the PaHaW dataset and 97.95% on the Cc-PhD dataset. On the other hand, Białek, et al. [38] focused on the handwriting of PD subjects, which is considered one of the distinctive manifestations of PD. Handwriting is affected by motor dysfunction as a consequence of this disease. So, they proposed an analysis based on a sequence of sentences written by PD and HC subjects to assess and evaluate the effect of the disease on handwriting over time. The study employed handcrafted handwriting features aggregated across sequential sentences, exhaustive feature selection and a single SVM classifier. This model achieved accuracy of 91.67%, specificity of 91.67%, sensitivity 91.67% under six-fold cross-validation. With a main focus on handwriting patterns (spiral, wave), Nagamani et al. [39] utilized machine learning classifiers to determine if the subject is PD or HC. Applying Random Forest (RF) on the spiral pattern achieving an accuracy of 86.67% and K-Nearest Neighbors (KNN) achieving an accuracy of 76.67%, both trained independently. Additionally, in this study the features were handcrafted by using Histogram of Oriented Gradients (HOG) which may not capture complex pattern compared to learned representations. Similarly, Wang et al. [40] approached PD diagnosis using dynamic handwriting signals by proposing a hybrid LSTM-CNN model that leverages both temporal and spatial feature extraction to capture distinctive patterns associated with PD. Their method demonstrated a strong performance, achieving an accuracy of 96.2% on DraWritePD dataset. On the other hand, Elbarawy et al. [41] proposed a

handwriting-based diagnostic framework for PD used the same dataset in two parallel settings, first approach: the spiral/meander processed by using CNN-based feature extraction feed to SVM classifier achieving an accuracy of 95% for the spiral data, while the meander data achieved an accuracy of 93.3%. Second approach: nine handcrafted handwriting features derived from the difference between handwritten trace and template, RF results improved after using Best First Strategy feature selection achieved an accuracy of 95.4% and after adding resampling RF achieved an accuracy of 99.04% for spiral data and 98.65% for meander data. The author concluded that BF with resampling with RF yielded the best outcome among the tested configurations. Moreover, Ali et al. [42] proposed PD detection approach using both dynamic and static handwriting signal by combining online features, such as velocity and acceleration with offline handwriting images processed through Gabor and Sobel filtering, and classified using RNN, LSTM, GRU, C-BiRNN, C-Bi-GRU, AlexNet, and VGG19 to capture temporal and spatial features. Achieving accuracy of 82%. Similarly, Ranjan et al. [43] presented a PD detection approach using handwriting images through HOG feature extraction and RF classification, achieving accuracies of 86.67% for spiral drawings and 83.3% for wave drawings. Furthermore, Gerger and Gumuscu [44] investigated the use of spiral drawings for PD classification by formulating the problem as a pattern recognition task. A genetic algorithm was employed to select the most informative features prior to classification from an initial set of 123,066 features extracted from each drawing. The performance of KNN and DT classifiers was subsequently compared, and the results indicated that feature selection contributed positively to classification performance. Two approaches appeared repeatedly in the studies with handwriting-based diagnosis: conventional ML methods built on handcrafted features and deep learning models trained directly on handwriting data. Although the reported results were obtained under different conditions and on different datasets, deep learning studies often reported higher accuracies. Spiral and wave drawing tasks were used in most studies, participant numbers were frequently limited, and acquisition conditions varied across studies. These differences make it difficult to compare results across studies and leave open questions regarding performance on larger and more diverse cohorts.

3.3. Neuroimaging-Based Diagnosis

Majhi et al. in [45] combined VGG16 and InceptionV3 for PD classification using neuroimaging data. Model parameters were optimized using GWO before comparison with other deep learning models. The reported results were exceptionally high, reaching 99.94% accuracy and an AUC of 0.999. While training large imaging datasets and high-dimensional inputs led to near-perfect results, it also increased computational requirements. Unlike speech or handwriting analysis, imaging data provide direct information about brain alterations associated with the disease and contribute to understanding disease mechanisms and supporting diagnostic decision-making. Neuroimaging produced some of the strongest results among the studies included in this review. The need for extensive preprocessing and high computational resources remains a practical challenge when compared with simpler data sources such as speech or handwriting. Besides this modality requires access to specialized imaging facilities and involves a more complex processing pipeline.

3.4. Gait-Based Diagnosis

PD diagnosis and severity assessment are commonly based on clinical manifestations and neurological examination. Wang et al. [46] examined whether gait measurements obtained from foot-mounted wearable sensors could support these tasks using ML techniques. Five classifiers were tested separately for PD detection and severity assessment, with SVM producing the highest performance among the evaluated models. Their findings suggest that gait-related measurements contain information relevant to both disease identification and symptom severity. Measurements collected from wearable sensors provide a quantitative description of motor impairment and can be collected repeatedly over time. The gait study included in this review relied on sensor-derived movement characteristics along with clinical assessment. A major limitation is that recorded gait signals may vary according to walking conditions, sensor placement, and differences in patient mobility. This variation should be thought-out when interpreting reported results and when assessing performance in different populations.

3.5. EEG/EMG-Based Diagnosis

Al-Khasawneh et al. [47] tried different approach by exploiting the human bio-signals for early PD detection. As a neurodegenerative disease, PD affects brain and motor function. The Electroencephalogram (EEG) monitors brain activity and Electromyography (EMG) monitor neuromuscular activity. The authors constructed an Artificial Neural Network (ANN) model as classifier which reported an accuracy of 100% during testing and a maximum recognition rate of 98.9%. The results of this model were evaluated against radiological data (MRI). EEG and EMG provide

measurements that originate directly from neural and muscular activity. Working with physiological recordings provides information relevant to PD classification. At the same time, it introduces practical difficulties. Signal quality can be affected by noise, electrode placement, and recording conditions, making preprocessing an important part of the analysis process. Although these requirements increase the complexity of data preparation, EEG and EMG remain valuable sources of information for studying PD-related physiological changes and developing data-driven diagnostic models.

3.6. Multimodal-Based Diagnosis

Alhawiti [48] proposed an early PD detection framework using two voice-derived modalities, combining structured acoustic biomarkers from the UCI Parkinson's dataset with contrastive speech embeddings generated from DAIC-WOZ audio using Wave2Vec 2.0. The modalities were fused together using an early fusion strategy and DNN with batch normalization, dropout, and residual-attention mechanism. The proposed model achieved an accuracy of 96.2%. Similarly, Meghashree et al. [49] suggested a multimodal framework for early PD detection using voice, gait, and handwriting modalities. The approach employed modality-specific neural networks with self-supervised learning (SSL) based on SimCLR-style contrastive loss for feature extraction, followed by a multimodal transformer with cross-attention for fusion and classification. Moreover, Alrawis et al. [50] introduced a PD diagnosis framework using EEG and MRI modalities. EEG features were extracted using Flexible Analytic Wavelet Transform (FAWT), while MRI features were derived from functional MRI using General Linear Model (GLM). The features were combined and reduced using Principal Component Analysis (PCA), followed by classification with LightGBM. The study reported an accuracy of 97.17%. In addition, Zhu et al. [51] investigated the identification of mild cognitive impairment in PD by combining clinical indicators, plasma biomarkers, T1-weighted MRI, and resting-state fMRI. Differential analysis and RF importance scores were used to identify informative features, which were subsequently evaluated using an SVM classifier. The best-performing model combined clinical indicators, resting-state fMRI, and neurofilament light chain, achieving a mean accuracy of 76.2%. Also Karthigeyan and Rani [52] used multimodal tabular representation derived from resting-state fMRI connectivity features and genetic biomarkers, each modality was processed independently and then fused by using attention-based CNN. They then applied stacked deep learning classifiers (SLDC) combining CNN and LSTM on the fused features. This model reported near-perfect results. However, the combination of high-dimensional feature-level fusion, limited sample size, and a complex ensemble architecture may affect the generalizability of the reported performance. Moreover, Escobar-Grisales et al. [53] utilized the speech and language modalities by extracting Wav2Vec 2.0 embeddings alongside pathology-oriented speech features (prosody, articulation, and phonemic information), while language features were modeled using BETO embeddings with statistical functionals and a 1D-CNN over verbs and nouns. These representations were combined using a multimodal fusion mechanism, including Gated Multimodal Units (GMU), achieving an accuracy of $87.3\% \pm 6.8$. Also, Chatterjee et al. [54] used tabular features by designing an ensemble-based early/premotor-stage PD Detection model named PDD-ET that fuses Clinical, behavioral, demographic and premotor indicators using multiple base learners each of which was trained independently on the same normalized tabular feature-based dataset that constructed from existing datasets. Each model produces its own prediction to be combined by using weight-adjustment mechanism with a different contribution weight assigned for each model based on its performance. Yet, this model has high complexity ensemble architecture and the exact weighting formulation is not mathematically specified in their paper. To improve early PD prediction and provide biological insight, another modality was investigated by Makarious et al. [55] by fusing clinico-demographic, genetic and transcriptomics (RNA) tabular data. They transformed these heterogeneous data types into structured tabular features before being introduced to 12 ML classifiers with AdaBoost emerging as best classifier. With all modalities converted to single tabular representation, limiting the exploitation of modality-specific structure such as gene-gene interaction as networks. This model achieved an AUC of 89.72% with reported balanced accuracy of 82.41%, accuracy of 85.56%, when validated on the external dataset reported an AUC of 85.03%. Multimodal approaches aim to improve PD diagnosis by integrating complementary information obtained from different data sources rather than relying on a single symptom or modality. The multimodal studies reviewed in this work integrated a wide range of data sources, including speech, handwriting, gait measurements, neuroimaging data, EEG signals, clinical variables, and genetic information. The multimodal studies reviewed in this work generally reported strong diagnostic performance, suggesting that different data sources provide complementary information about the disease. However, the effectiveness of these systems was closely linked to the chosen fusion strategy. The reviewed multimodal studies did not follow a single strategy for data integration. Most models are designed with all modalities available for each patient, which is often not the case in clinical settings. This makes it difficult for the model to maintain stable performance if any modality is missing. A recurring issue across several investigations was the reliance on complete data availability. In some studies, information from different modalities was converted into a unified feature table before classification. Other studies retained modality-specific representations and combined

them through feature-level fusion or attention-based mechanisms. Table 1. provides a summary of the reviewed studies including data modalities, datasets, methods, performance measures and reported limitations.

Table 1. Summary of the studies

Study	Method(s)	Data type(s)	Dataset(s)	metric(s)	Limitations
Shen et al. (2025) [25]	CNN, RNN, MKL, MLP, SHAP	Speech (acoustic signal features)	Figshare Voice dataset (81 recordings)	Acc of 91.11%	Single modality, small dataset
Swain et al. (2024) [26]	LDA, SVM, KNN, CNN	Voice Recordings	195 voice sample (23 features)	Acc of 98%	Small dataset, Single modality
Di Cesare et al. (2024) [27]	speaker diarization, Cubic SVM, Fine KNN, wide neural network	Speech (Reading + spontaneous conversations)	MDVR-KCL	Test Acc 92.3%	limit number of subjects,
Costantini et al. in (2023) [28]	ML vs. CNN comparison	Voice recordings	Custom Italian voice dataset (426 subjects)	Acc=82.25% AUC =0.87 (mean)	No Multimodal inputs
Nijhawan et al. (2023) [29]	Transformer-based neural network + feature selection	Voice recordings (tabular features)	UCI PD speech dataset	AUC=0.917	No Multimodal inputs
Govindu and Palwe (2023) [30]	SVM, KNN, RF and Logistic Regression	Audio Recordings	collects audio data from PPMI and UCI	Acc of 91.83%	unbalanced small size dataset, relaying on single modal

Models		(PD=23, HC=8).			
Escobar-Grisales et al. (2023) [31]	Wav2Vec 2.0, BERT, 1,2D CNN,	Audio Recordings	PD =80, HC=85.	Speech model Acc of 88.5±8.3, language model Acc of 77.9±8.4, Multi-modal Acc of 73.9± 12.8	small dataset size
Alshammri et al. (2023) [32]	SVM, RF, DT, KNN, MLP +SMOTE+ GridSearchCV +SelectKBest	Speech (voice signal features)	UCI Parkinson's dataset (recording s =195 from 31 subjects)	Acc of 98.31%, Recall= 98%, Precision =100%, F1 Score=99%	Single modality, small dataset, class imbalanced
Alalayah et al. (2023) [33]	SVM, KNN, DT, RF, and MLP	Speech (acoustic signal features)	UCI voice dataset (PD=147, HC=48)	RF Acc of 97%	Single modality, small dataset
Lamba et al. (2021) [34]	Hybrid ML framework combining feature selection and classifiers	Clinical and voice signal-based (tabular features)	Public PD datasets (UCI-based)	Acc=95.58% AUC=0.989	No Multimodal inputs; Handcrafted features
S. K and N. T M (2025) [35]	RGG-Net	Handwriting images (Spiral, wave Drawing).	original 204 images Augmented into (PD=1632, HC=1632)	in frozen setting Acc =99.12%, in unfrozen setting Acc =96.5%.	small dataset size heavily depends on Augmentation

Ouabd et al. (2025) [36]	SVM, RF, NB with (Correlation analysis, LASSO Regression, ANOVA and Linear PCA) as feature selection	tabular data extracted from Handwritin g Images	NewHand PD (PD=31, HC=35)	Acc of 83.02%	Small dataset may limit the generalization, Single modality
Lu et al. (2025) [37]	RF, Relief, Lasso Xgboost, AdaBoost	Handwritin g images	PaHaWa and privately collected Cc-PhD 24 PD + 24 HC handwriti ng samples Dataset from	Acc of 98.67% on PaHaW dataset, and Acc of 97.95% on Cc- PhD dataset.	Small dataset, Single modality
Białek et al. (2024) [38]	Feature extraction + SVM	Handwritin g images	Dataset from Kaggle (102 spiral images, 102 wave images)	Acc=91.67%	Very small sample size; No Multimodal inputs
Nagamani et al. (2024) [39]	ML (RF, KNN)	Handwritin g images	DraWriteP D (PD=20, HC=29)	for spiral Acc of 86.67%, for wave Acc of 76.67%.	small size dataset, relay on handcrafted Features
Wang et al. (2024) [40]	LSTM-CNN	Handwritin g images	And PaHaWa (PD=37, HC=38)	Acc of 96.2% on DraWritePD dataset	Small dataset, Single modality

				best configuration	
Elbarawy et al. (2023) [41]	CNN, SVM, RF	Handwriting images (Spiral, Meander Drawing)	HandPD PD =592, HC=144	Acc of 99.04% for spiral data and 98.65 for meander	no external validation
Ali et al. (2023) [42]	C-Bi-GUR + VGG19	Handwriting images	PaHaWa	Acc of 82%	Small dataset, Single modality
Ranjan et al. (2023) [43]	HOG + RF	Handwriting images	108 images dataset	Acc of 86.67% for spiral drawing and Acc of 83.3% for wave drawing	Small dataset, Single modality
Gerger and Gumuscu (2022) [44]	KNN, DT	Handwriting images (Spiral Drawing)	UCI Machine learning Repository (PD =62, HC =15)	GA-KNN Acc of 88.73%, GA-DT Acc of 100%	high computational requirements, limited generalization
Majhi et al. (2024) [45]	CNNs + Grey Wolf Optimization	MRI (T1/T2) and SPECT DaTscan images	PPMI MRI & DaTscan datasets	Acc=99.94% AUC =0.999	No Multimodal inputs; High computational requirements
Wang et al. (2024) [46]	Signal decomposition + ML (SVM, RF, KNN)	Gait signals (VGRF time-series)	PhysioNet gait database	98.20% accuracy (binary)	Sensor-based setup; lab-controlled conditions; No Multimodal inputs
Al-Khasawneh et al. (2023) [47]	Deep learning with signal processing	EEG time-series signals	EEG dataset from PD and HC subjects	Acc≈100%	Small dataset; controlled acquisition environment; No Multimodal inputs

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Alhawiti (2025) [48]	Wav2Vec 2.0, DNN	Voice biomarkers, speech embeddings	Parkinson' s dataset, DAIC- WOZ corpus	Acc of 96.2%	Same-source modalities
Meghashre e <i>et al.</i> (2025) [49]	SimCLR, cross- attention	voice, gait, handwriting	1000 subjects	Acc of 96.5%	No missing- modality support
Alrawis <i>et al.</i> (2024) [50]	FAWT, Fmri/GLM, PCA, LightGBM	EEG, MRI	PD-DS-I, PD-DS-II	Acc of 97.17%	No missing- modality support
Zhu <i>et al.</i> (2024) [51]	Differential analysis, RF, feature selection, liner SVM	clinical. (NfL), MRI, fMRI	a local/clinical cohort of 173 individuals	Acc of 76.2%	No missing- modality support
Karthigeyan and Rani (2024) [52]	Stacked deep learning classifiers (SDLC)	rfMRI images + gene expression data	PPMI + ADNI	Acc= 99.4%, F1 = 0.99	High computational complexity; limited deployability
Escobar- Grisales <i>et al.</i> (2023) [53]	Wav2Vec 2.0, BETO, 1D-CNN, GMU	Speech, Language	Extended PC-GITA corpus, participan t = 165 (PD=80, HC=85)	Acc of 87.3%± 6.8	The modalities are not fully independent since both are derived from the same source
Chatterjee et al. (2023) [54]	ML Ensemble (multiple classifiers)	Clinical, behavioral, demographi c, premotor	Customize d large dataset + Kaggle PD	97.52% accuracy	No Multimodal inputs; High complexity Architecture

	indicators	data			
		MRI, PET/SPECT images, genetics, clinical/de mographic data (converted to tabular features before training)	PPMI and related public datasets	Balanced Acc=82.41% and AUC=89.72	Heterogeneous modalities; complex pipeline; limited discussion on missing-modality handling
Makarious et al. (2022) [55]	Multiple ML models with AdaBoost as best classifier				

4. Comparative Analysis and Research Gaps

Speech recordings and handwriting samples can be obtained with limited equipment and relatively low cost. This positively affects the number of studies that uses speech and handwriting data type more than neuroimaging, gait, EEG/EMG, and multimodal data. This pattern is likely related to the practical aspects of data collection. In contrast, imaging and physiological data require specialized acquisition procedures. The choice of datasets also exhibited similar differences. The UCI Parkinson's Disease Dataset appeared repeatedly in voice-based studies, while PPMI was used mainly in neuroimaging and multimodal research. The most commonly used datasets in handwriting studies are PaHaW, HandPD and DraWritePD. Table 2 lists the datasets that appeared most frequently in the reviewed literature.

Table 2. Most Frequently Used Datasets in PD Diagnosis Studies

Dataset	Primary Modality	Representative Studies
UCI Parkinson's Disease Dataset	Voice	[29], [32], [33], [34], [49]
PPMI	Neuroimaging / Multimodal	[30], [45], [52], [55]
PaHaW	Handwriting	[37], [40], [42]
HandPD	Handwriting	[41]
DraWritePD	Handwriting	[40]
PhysioNet Gait Database	Gait	[46]

The reviewed studies employed a wide range of learning algorithms. CNNs, RNNs, transformer models, and hybrid deep learning architectures were frequently adopted. Reported results were generally high across different modalities, with many studies exceeding 95% accuracy. These algorithms were frequently utilized when working with speech signals, handwriting images, neuroimaging data, or multimodal inputs. The selection of a particular algorithm was often determined by the characteristics of the data rather than by a consistently superior method. In contrast, traditional approaches such as SVM, RF, KNN, DT, and AdaBoost were commonly used when diagnosis relied on handcrafted features. However, the reported performance was obtained under different conditions, involving different datasets, cohort sizes, preprocessing procedures, and evaluation protocols. These differences make direct comparison difficult. Another observation concerns model validation. Most studies evaluated their

methods on a single dataset, whereas independent external validation was reported less frequently. The multimodal studies also differed substantially in the way information from multiple sources was combined, making it difficult to identify a fusion strategy that consistently performed better than the others. In addition, several high-performing models relied on complex architectures and considerable computational resources, which may affect their practicality outside research settings.

Table 3. Average Performance by Diagnostic Modality

Modality	Number of studies	Average Accuracy (%)
Voice-Based Diagnosis	9	92.76
Handwriting-Based Diagnosis	10	91.18
Neuroimaging-Based Diagnosis	1	99.94
Gait-Based Diagnosis	1	98.20
EEG/EMG-Based Diagnosis	1	99.45
Multimodal-Based Diagnosis	7	91.19

Note that in Table 3. Average accuracies were calculated using the studies included in this review. Studies reporting only AUC values were excluded from the calculation. Modalities represented by a single study should be interpreted cautiously, as the reported value corresponds to a single publication rather than an aggregate estimate. Table 3 indicates that the highest average accuracies were reported by neuroimaging, gait, and EEG/EMG studies. These averages, however, were calculated from a much smaller number of studies than those available for speech and handwriting. Speech-based and handwriting-based diagnosis accounted for most of the reviewed literature and consistently achieved strong performance while relying on data that are easier to acquire and less expensive to collect. Multimodal studies also reported competitive results in several cases. Because the reviewed studies differed in datasets, participant characteristics, experimental design, and evaluation procedures, the values reported in Table 3 should be viewed as a general indication rather than a definitive ranking of diagnostic modalities.

5. Conclusion

This review examined recent studies that applied ML and DL techniques to PD diagnosis using various modalities such as speech, handwriting, neuroimaging, gait signals, EEG/EMG recordings, and multimodal data. Both conventional ML methods and deep learning architectures were widely used, with the choice of model often influenced by the nature of the available data. The reviewed literature shows that speech and handwriting continue to dominate this research area, while neuroimaging, physiological signals, and multimodal systems have received increasing attention in recent years. Many studies reported high diagnostic performance. However, the reported results were obtained using different datasets, sample sizes, and evaluation procedures. As a result, performance values reported in different publications are not always directly comparable. Another recurring observation was the limited use of external validation, as many studies assessed their models on a single dataset. The reviewed literature still demonstrates that AI-based approaches can assist PD diagnosis across multiple data modalities. Further progress will require broader validation on independent cohorts, more consistent evaluation practices, and diagnostic frameworks that can maintain strong performance while remaining practical for real clinical use.

References

- [1] A. Rana, A. Dumka, R. Singh, M. K. Panda, N. Priyadarshi, and B. Twala, "Imperative Role of Machine Learning Algorithm for Detection of Parkinson's Disease: Review, Challenges and Recommendations," *Diagnostics*, vol. 12, no. 8, p. 2003, Aug. 2022, doi: 10.3390/diagnostics12082003.
- [2] S. Paul *et al.*, "Bias Investigation in Artificial Intelligence Systems for Early Detection of Parkinson's Disease: A Narrative Review," *Diagnostics*, vol. 12, no. 1, p. 166, Jan. 2022, doi: 10.3390/diagnostics12010166.
- [3] A. Razaq, S. Ramzan, S. Jabbar, M. M. Iqbal, M. A. Habib, and U. Raza, "A Deep Learning Framework for Early Parkinson's Disease Detection: Leveraging Spiral and Wave Handwriting Tasks with EfficientNetV2-S," *Diagnostics*, vol. 15, no. 21, p. 2795, Nov. 2025, doi: 10.3390/diagnostics15212795.
- [4] Y. Huang, K. Chaturvedi, A.-A. Nayan, M. H. Hesamian, A. Braytee, and M. Prasad, "Early Parkinson's Disease Diagnosis through Hand-Drawn Spiral and Wave Analysis Using Deep Learning Techniques," *Information*, vol. 15, no. 4, p. 220, Apr. 2024, doi: 10.3390/info15040220.
- [5] S. Shokrpour, A. MoghadamFarid, S. Bazzaz Abkenar, M. Haghi Kashani, M. Akbari, and M. Sarvizadeh, "Machine learning for Parkinson's disease: a comprehensive review of datasets, algorithms, and challenges," *npj Parkinsons Dis.*, vol. 11, no. 1, p. 187, Jul. 2025, doi: 10.1038/s41531-025-01025-9.

- [6] S. B. Arnab, M. I. A. Palash, R. Islam, H. H. Ovi, M. A. Yousuf, and M. Z. Uddin, "Analysis of Different Modality of Data to Diagnose Parkinson's Disease Using Machine Learning and Deep Learning Approaches: A Review," *Expert Syst.*, vol. 42, no. 2, p. e13790, Feb. 2025, doi: 10.1111/exsy.13790.
- [7] J. D. Gallo-Aristizabal, D. Escobar-Grisales, C. D. Ríos-Urrego, J. F. Vargas-Bonilla, A. M. García, and J. R. Orozco-Arroyave, "Towards Parkinson's Disease Detection Through Analysis of Everyday Handwriting," *Diagnostics*, vol. 15, no. 3, p. 381, Feb. 2025, doi: 10.3390/diagnostics15030381.
- [8] S. C. Chou, C. Cong, R. Brownson-Smith, M. Milne-Ives, and E. Meinert, "Assessment of mental and behavioural non-motor symptoms of Parkinson's Disease using Artificial Intelligence (AI): a systematic review," *Commun. Med.*, vol. 6, no. 1, p. 101, Feb. 2026, doi: 10.1038/s43856-025-01304-9.
- [9] A. Ravichandran, T. Kathirvel Murugan, L. Govindaraj, and V. M., "Explainable multimodal feature fusion networks for Parkinson's disease prediction," *Front. Digit. Health*, vol. 8, p. 1771281, Feb. 2026, doi: 10.3389/fdgth.2026.1771281.
- [10] K. Bounsall, M. Milne-Ives, A. Hall, C. Carroll, and E. Meinert, "Artificial Intelligence Applications for Assessment, Monitoring, and Management of Parkinson Disease Symptoms: Protocol for a Systematic Review," *JMIR Res. Protoc.*, vol. 12, p. e46581, Jun. 2023, doi: 10.2196/46581.
- [11] Aiesha Mahmoud Ibrahim and Mazin Abed Mohammed, "A comprehensive review on advancements in artificial intelligence approaches and future perspectives for early diagnosis of Parkinson's disease," *Int. J. Math. Stat. Comput. Sci.*, vol. 1, pp. 173–182, Jan. 2024, doi: 10.59543/ijmscs.v2i.8915.
- [12] S. Zadoo, Y. Singh, and P. K. Singh, "Automated Parkinson's Disease Detection: A Review of Techniques, Datasets, Modalities, and Open Challenges," *Int. J. Smart Sens. Intell. Syst.*, vol. 17, no. 1, p. 20240008, Jan. 2024, doi: 10.2478/ijssis-2024-0008.
- [13] R. S. Ashok and K. D. Anil, "Machine learning-based early detection of Parkinson's disease using handwriting and vocal features," *Res. Eng. Struct. Mater.*, 2025, doi: 10.17515/resm2025-835ml0422rs.
- [14] G. Verma, "Interpretable hybrid deep learning model for Parkinson's disease screening from hand-sketch spiral and waveform images," *Pol. J. Radiol.*, vol. 91, no. 1, pp. 75–94, Feb. 2026, doi: 10.5114/pjr/213689.
- [15] W. Abbas Hadi, "Classification Of Parkinson's Disease Using Machine Learning Technique," *J. Al-Qadisiyah Comput. Sci. Math.*, vol. 17, no. 2, Jun. 2025, doi: 10.29304/jqscm.2025.17.22189.
- [16] N. Salari, M. Kazemini, H. Sagha, A. Daneshkhah, A. Ahmadi, and M. Mohammadi, "The performance of various machine learning methods for Parkinson's disease recognition: a systematic review," *Curr. Psychol.*, vol. 42, no. 20, pp. 16637–16660, Jul. 2023, doi: 10.1007/s12144-022-02949-8.
- [17] S. Saravanan et al., "A Systematic Review of Artificial Intelligence (AI) Based Approaches for the Diagnosis of Parkinson's Disease," *Arch. Comput. Methods Eng.*, vol. 29, no. 6, pp. 3639–3653, Oct. 2022, doi: 10.1007/s11831-022-09710-1.
- [18] M. Ianculescu, C. Petean, V. Sandulescu, A. Alexandru, and A.-M. Vasilevski, "Early detection of Parkinson's disease using AI techniques and image analysis," *Diagnostics*, vol. 14, no. 23, p. 2615, Nov. 2024, doi: 10.3390/diagnostics14232615.
- [19] H. Rabie and M. A. Akhloufi, "A review of machine learning and deep learning for Parkinson's disease detection," *Discov. Artif. Intell.*, vol. 5, no. 1, p. 24, Mar. 2025, doi: 10.1007/s44163-025-00241-9.
- [20] N. Farhah, "Utilizing deep learning models in an intelligent spiral drawing classification system for Parkinson's disease classification," *Front. Med.*, vol. 11, p. 1453743, Sep. 2024, doi: 10.3389/fmed.2024.1453743.
- [21] K. Samer Ali and A. S. Abdalrada, "Deep Learning for Chest X-Ray Classification: A Comprehensive Review of Methods, Advances, and Clinical Integration," *J. Al-Qadisiyah Comput. Sci. Math.*, vol. 17, no. 4, Dec. 2025, doi: 10.29304/jqscm.2025.17.42537.
- [22] A. Abdalrada, Ali Fahem Neamah, and Hayder Murad, "Predicting Diabetes Disease Occurrence Using Logistic Regression: An Early Detection Approach," *Iraqi J. Comput. Sci. Math.*, vol. 5, no. 1, pp. 160–167, Jan. 2024, doi: 10.52866/jqscm.2024.05.01.011.
- [23] M. M. Abd Zaid and A. Abed Mohammed, "Hybrid Models in Diabetes Prediction: A Review of Techniques, Performance, and Potential," *J. Al-Qadisiyah Comput. Sci. Math.*, vol. 16, no. 4, Dec. 2024, doi: 10.29304/jqscm.2024.16.41805.
- [24] Z. Abdalhussain Kareem and A. Shaker Abdalrada, "Deep Learning for Alzheimer's Disease Diagnosis from Brain MRI: Review," *J. Al-Qadisiyah Comput. Sci. Math.*, vol. 17, no. 3, Sep. 2025, doi: 10.29304/jqscm.2025.17.32429.
- [25] M. Shen, P. Mortezaagha, and A. Rahgozar, "Explainable artificial intelligence to diagnose early Parkinson's disease via voice analysis," *Sci. Rep.*, vol. 15, no. 1, p. 11687, Apr. 2025, doi: 10.1038/s41598-025-96575-6.
- [26] K. P. Swain, S. R. Samal, and V. Ravi, "Towards Early Intervention: Detecting Parkinson's Disease through Voice Analysis with Machine Learning," *Open Biomed. Eng. J.*, vol. 18, no. 1, p. e18741207294056, Apr. 2024, doi: 10.2174/0118741207294056240322075602.
- [27] M. G. Di Cesare, D. Perpetuini, D. Cardone, and A. Merla, "Machine Learning-Assisted Speech Analysis for Early Detection of Parkinson's Disease: A Study on Speaker Diarization and Classification Techniques," *Sensors*, vol. 24, no. 5, p. 1499, Feb. 2024, doi: 10.3390/s24051499.
- [28] G. Costantini et al., "Artificial Intelligence-Based Voice Assessment of Patients with Parkinson's Disease Off and On Treatment: Machine vs. Deep-Learning Comparison," *Sensors*, vol. 23, no. 4, p. 2293, Feb. 2023, doi: 10.3390/s23042293.
- [29] R. Nijhawan et al., "A Novel Artificial-Intelligence-Based Approach for Classification of Parkinson's Disease Using Complex and Large Vocal Features," *Biomimetics*, vol. 8, no. 4, p. 351, Aug. 2023, doi: 10.3390/biomimetics8040351.
- [30] A. Govindu and S. Palwe, "Early detection of Parkinson's disease using machine learning," *Procedia Comput. Sci.*, vol. 218, pp. 249–261, 2023, doi: 10.1016/j.procs.2023.01.007.
- [31] D. Escobar-Grisales, C. D. Ríos-Urrego, and J. R. Orozco-Arroyave, "Deep Learning and Artificial Intelligence Applied to Model Speech and Language in Parkinson's Disease," *Diagnostics*, vol. 13, no. 13, p. 2163, Jun. 2023, doi: 10.3390/diagnostics13132163.
- [32] R. Alshammri, G. Alharbi, E. Alharbi, and I. Almubark, "Machine learning approaches to identify Parkinson's disease using voice signal features," *Front. Artif. Intell.*, vol. 6, p. 1084001, Mar. 2023, doi: 10.3389/frai.2023.1084001.
- [33] K. M. Alalayyah, E. M. Senan, H. F. Atlam, I. A. Ahmed, and H. S. A. Shatnawi, "Automatic and Early Detection of Parkinson's Disease by Analyzing Acoustic Signals Using Classification Algorithms Based on Recursive Feature Elimination Method," *Diagnostics*, vol. 13, no. 11, p. 1924, May 2024, doi: 10.3390/diagnostics13111924.
- [34] R. Lamba, T. Gulati, H. F. Alharbi, and A. Jain, "A hybrid system for Parkinson's disease diagnosis using machine learning techniques," *Int. J. Speech Technol.*, vol. 25, no. 3, pp. 583–593, Sep. 2022, doi: 10.1007/s10772-021-09837-9.
- [35] S. K. and N. T. M., "Design of a deep fusion model for early Parkinson's disease prediction using handwritten image analysis," *Sci. Rep.*, vol. 15, no. 1, p. 20437, Jul. 2025, doi: 10.1038/s41598-025-04807-6.
- [36] A. Ouabd, A. Jilbab, A. Benba, and A. Hammouch, "Enhancing early Parkinson's disease diagnosis through handwriting analysis," *Inform. Autom. Pomori W Gospod. Ochr. Šr.*, vol. 15, no. 3, pp. 45–49, Sep. 2025, doi: 10.35784/iapgos.7002.
- [37] H. Lu et al., "A novel feature extraction method based on dynamic handwriting for Parkinson's disease detection," *PLOS ONE*, vol. 20, no. 1, p. e0318021, Jan. 2025, doi: 10.1371/journal.pone.0318021.
- [38] K. Białek, A. Potulska-Chromik, J. Jakubowski, M. Nojszewska, and A. Kostera-Pruszczyk, "Analysis of Handwriting for Recognition of Parkinson's Disease: Current State and New Study," *Electronics*, vol. 13, no. 19, p. 3962, Oct. 2024, doi: 10.3390/electronics13193962.

- [39] T. Nagamani, "Automatic Diagnosis of Parkinson's Disease using Handwriting Patterns," *J. Electr. Syst.*, vol. 20, no. 7s, pp. 1395–1405, May 2024, doi: 10.52783/jes.3712.
- [40] X. Wang *et al.*, "LSTM-CNN: An efficient diagnostic network for Parkinson's disease utilizing dynamic handwriting analysis," Nov. 20, 2023, *arXiv: arXiv:2311.11756*. doi: 10.48550/arXiv.2311.11756.
- [41] Y. M. Elbarawy, W. A. Ghonaim, and A. S. Desuky, "Diagnostic Study for Parkinson's Disease Based on Handwriting Analysis Using Computational Intelligence Techniques," vol. 50, no. 1, 2023.
- [42] S. Ali, A. Hashmi, A. Hamza, U. Hayat, and H. Younis, "Dynamic and Static Handwriting Assessment in Parkinson's Disease: A Synergistic Approach with C-Bi-GRU and VGG19," *J. Comput. Theor. Appl.*, vol. 1, no. 2, pp. 151–162, Dec. 2023, doi: 10.33633/jcta.v1i2.9469.
- [43] N. M. Ranjan, G. Mate, and M. Bembde, "Detection of Parkinson's Disease using Machine Learning Algorithms and Handwriting Analysis," *J. Data Min. Manag.*, vol. 8, no. 1, pp. 21–29, Mar. 2023, doi: 10.46610/JoDMM.2023.v08i01.004.
- [44] M. Gerger and A. Gumuscu, "Diagnosis of Parkinson's Disease Using Spiral Test Based on Pattern Recognition".
- [45] B. Majhi *et al.*, "An improved method for diagnosis of Parkinson's disease using deep learning models enhanced with metaheuristic algorithm," *BMC Med. Imaging*, vol. 24, no. 1, p. 156, Jun. 2024, doi: 10.1186/s12880-024-01335-z.
- [46] Q. Wang, W. Zeng, and X. Dai, "Gait classification for early detection and severity rating of Parkinson's disease based on hybrid signal processing and machine learning methods," *Cogn. Neurodyn.*, vol. 18, no. 1, pp. 109–132, Feb. 2024, doi: 10.1007/s11571-022-09925-9.
- [47] M. A. Al-Khasawneh, A. Alzahrani, and A. Alarood, "An Artificial Intelligence Based Effective Diagnosis of Parkinson Disease Using EEG Signal," in *Data Analysis for Neurodegenerative Disorders*, D. Koundal, D. K. Jain, Y. Guo, A. S. Ashour, and A. Zaguia, Eds., in Cognitive Technologies., Singapore: Springer Nature Singapore, 2023, pp. 239–251. doi: 10.1007/978-981-99-2154-6_14.
- [48] K. M. Alhawiti, "Multi-Modal Decentralized Hybrid Learning for Early Parkinson's Detection Using Voice Biomarkers and Contrastive Speech Embeddings," *Sensors*, vol. 25, no. 22, p. 6959, Nov. 2025, doi: 10.3390/s25226959.
- [49] M. B. Meghashree, K. D. Kumar, N. Vinutha, and D. Akash, "The Multimodal Fusion of Voice, Gait, and Handwriting Detection of Parkinson's Disease Using Machine Learning," *Int. Res. J. Multidiscip. Scope*, vol. 06, no. 04, pp. 1062–1074, 2025, doi: 10.47857/irjms.2025.v06i04.06552.
- [50] M. Alrawis, S. Al-Ahmadi, and F. Mohammad, "Bridging Modalities: A Multimodal Machine Learning Approach for Parkinson's Disease Diagnosis Using EEG and MRI Data," *Appl. Sci.*, vol. 14, no. 9, p. 3883, May 2024, doi: 10.3390/app14093883.
- [51] Y. Zhu, F. Wang, and P. Ning, "Multimodal neuroimaging-based prediction of Parkinson's disease with mild cognitive impairment using machine learning technique," *Npj Park. Dis.*, vol. 10, no. 1, p. 218, Nov. 2024, doi: 10.1038/s41531-024-00828-6.
- [52] C. M. T. Karthigeyan and C. Rani, "Optimizing Parkinson's Disease Diagnosis with Multimodal Data Fusion Techniques," *Inf. Technol. Control*, vol. 53, no. 1, pp. 262–279, Mar. 2024, doi: 10.5755/j01.itc.53.1.34718.
- [53] D. Escobar-Grisales, T. Arias-Vergara, C. D. Ríos-Urrego, E. Nöth, A. M. García, and J. R. Orozco-Arroyave, "An Automatic Multimodal Approach to Analyze Linguistic and Acoustic Cues on Parkinson's Disease Patients," in *INTERSPEECH 2023*, ISCA, Aug. 2023, pp. 1703–1707. doi: 10.21437/Interspeech.2023-2287.
- [54] K. Chatterjee *et al.*, "PDD-ET: Parkinson's Disease Detection Using ML Ensemble Techniques and Customized Big Dataset," *Information*, vol. 14, no. 9, p. 502, Sep. 2023, doi: 10.3390/info14090502.
- [55] M. B. Makarious *et al.*, "Multi-modality machine learning predicting Parkinson's disease," *Npj Park. Dis.*, vol. 8, no. 1, p. 35, Apr. 2022, doi: 10.1038/s41531-022-00288-w.