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Review Article

Parkinson's Prism: Diagnostic Algorithm Insights across Signals, Images, and Motion Modalities

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Abstract - *Parkinson's Disease (PD) is a neurodegenerative disorder that displays intricate motor symptoms and non-motor symptoms, making diagnosis difficult both in terms of timeliness and precision. Modern advancements in biomedical engineering, together with computational analysis, support the use of various diagnostic signals for early detection of PD. This study examines five commonly evaluated PD indicators, which include voice patterns, alongside Magnetic Resonance Imaging (MRI) results, Electroencephalogram (EEG) output, and spiral drawing tests, together with walking assessments. The evaluation analyzes each diagnostic method through its relation to physiological factors and provides details on acquisition methods and features that lead to Machine Learning and Artificial intelligence-based diagnostic results. This review describes essential progress together with advantages and disadvantages of each method, as it shows how these methods function in real-world clinical practices. This paper identifies major obstacles within these systems, including variations in data quality and difficulties with standardization, together with interpretation, limitations of models that hinder their widespread implementation. This research establishes a practical guide for scientists and medical professionals who pursue the development of non-invasive, cost-efficient, and modality-oriented detection approaches for Parkinson's disease.*

Keywords - *Electroencephalograms, Gait analysis, Magnetic Resonance Imaging, Parkinson's disease detection, Spiral drawings, Voice analysis.*

1. Introduction

Chronic progressive Parkinson's Disease (PD) impacts the central nervous system by destroying targeted dopaminergic neurons in the substantia nigra portion of the midbrain [1]. The dopamine deficiency that develops after the substantia nigra damage prevents the basal ganglia from performing their normal movement coordination tasks. Among all neurodegenerative diseases, PD ranks as the second most widespread condition worldwide, with its main impact directed at senior citizens, but researchers have observed early-onset instances too. Parkinson's disease symptoms include both motor symptoms and non-motor manifestations.

The Parkinson's Disease progression manifests through bradykinesia, which is movement slowness, together with resting tremors, rigidity, and postural instability, which develop asymmetrically and become progressively worse. Motor symptoms of PD develop after non-motor symptoms. Some of the non-motor symptoms include sleep issues along with constipation, depression, cognitive decline, and speech alterations that affect patients' quality of life [2]. Different people show different symptom patterns in PD, which enhances the challenges of diagnosis and treatment.

The consequences of Parkinson's disease affect physical health and reach all aspects of a person's well-being. Patients alongside their caregivers experience multiple psychological, emotional, and social challenges as a result of the disease [3].

The decline in total wellness emerges from the continuous deterioration of independence, alongside communication issues and movement limitations. Efficient diagnostic and monitoring strategies become essential because the economic burden stemming from long-term care expenses, medication costs, and productivity loss requires immediate attention.

Current diagnosis methods are mainly clinical and depend on observing motor symptoms, but patients usually have substantial neurodegeneration before this stage is reached [4]. The length of time before diagnosis reduces prospects for early treatment interventions and delays in the treatments that modify disease progression. Research efforts now focus on discovering independent diagnostic tools to identify PD in an early phase and with enhanced precision.

Early detection of PD appears viable through various diagnostic tools that examine unique sections of Parkinson's

pathology. Accurate diagnosis of PD becomes possible through voice recording analysis that reveals speech deficiencies, MRI imaging that tracks brain structures and functions, and EEG scans that measure brain signals and spiral drawing tests for movement assessment, combined with gait analysis of posture and walking patterns.

The evaluation examines each diagnostic indicator in depth by analyzing its biological root causes alongside data acquisition approaches, as well as analytical strategies, along with their performance metrics for clinical applications.

The outline of the paper comprised the discussions on Parkinson's disease detection using various factors such as voice analysis models, MRI image models, spiral drawing models, EEG signals models, and Gait models in Section 2 and concluding remarks in Section 3.

2. Parkinson's Disease Detection

2.1. Voice Analysis

Parkinson's Disease can be detected by utilizing the voice recordings of the people, which was considered as research work by many authors, as illustrated in Table 1. The research in [5] established a deep learning (DL) system that applies voice biomarkers for Parkinson's disease identification. The mPower Voice dataset contains voice recordings that underwent frequency-time transformation for Convolutional Neural Network (CNN) fine-tuning of SqueezeNet1_1, ResNet101, and DenseNet161. The DenseNet161 architecture provided optimal results. Transfer learning methods made the model operate with limited labeled datasets while speeding up model development time. Integrated smart electronic devices enabled with the model offer remote, real-time PD early detection opportunities for both medical facilities and non-medical establishments.

Table 1. PD detection using voice analysis models

S.No.	Paper Title and Author	Algorithm applied	Dataset used	Performance	Limitations
1	Karaman et al. used voice signal analysis and transfer learning for PD detection [5].	DenseNet with Transfer Learning	mPower Voice Dataset	Accuracy: 89.75%, Recall: 91.50%, Precision: 88.40%	Model success depends on the quality and consistency of voice data input. The study does not explore cross-subject validation or external testing on different cohorts.
2	Xie et al. explored a framework for PD that utilizes diverse voice signal features [6].	1D-CNN with Particle Swarm Optimization (PSO)	The dataset included voice and speech samples from Italian-speaking individuals, and voice data were collected via mobile devices at King's College London.	Accuracy: 100%	Unverified performance in real-world, noisy environments. PSO-based network design can be computationally expensive.
3	Ghaheri et al. developed a PD detection approach featuring SHAP-based feature interpretation with an ensemble classifier using voice signal data [7].	Hard Voting Ensemble with Shapley Additive exPlanations (SHAP)	The dataset provided replicated acoustic features.	Accuracy: 85.42%, F1-score: 84.94%, Precision: 86.77%, Recall: 83.20%, Specificity: 87.62%	Limited to PCC for feature selection; advanced methods like ANOVA could improve performance

4	Zdancewicz et al. used speech signals with PD, focusing on phonation, articulation, and prosodic features [8].	SVM and 1-NN	Speech samples capturing clinically relevant vocal features from Parkinson's patients for diagnostic studies.	Recognition rate: 92.2%, Sensitivity: 91.1%, Specificity: 93.3%	Lacks DL or ensemble approaches that might capture more complex, non-linear patterns in speech features
5	Veetil et al. developed a voice-based framework for the detection of PD [9].	1D-CNN with VMD	The dataset contained sustained phonation recordings in both Spanish and Italian, facilitating cross-linguistic studies of vocal biomarkers in Parkinson's disease.	Accuracy: 95%, Generalizability: 63%	The method showed reduced performance under realistic recording conditions, indicating that the system may not be robust enough for use in uncontrolled or noisy environments.

Xie et. al. presented a PD diagnostic system that adapts to voice signals in developing more reliable and adaptable voice-based diagnosis methods [6]. The system operates through two essential components, which include hybrid voice data extraction features and Particle Swarm Optimization (PSO)-based dynamic network configuration. The application of PSO enabled a 1D-CNN architecture configuration for automatically identifying optimal feature classification networks. The system successfully operated on both English and Italian datasets and achieved better accuracy results while showing broader language compatibility. The combination of compound voice features with automated network design enabled the system to adapt to different input characteristics without human intervention. The study conducted by Ghaheri et. al. presented a PD diagnosis technique on voice signals to overcome diagnostic challenges presented by both motor symptoms assessment and neuroimaging scans, as these techniques provide poor accessibility, substantial monetary requirements, and lengthy examination time [7]. Here, initial feature selection was done by Pearson Correlation Coefficients (PCCs) to identify high correlation among four machine learning models. The predictions from these models underwent an Ensemble Method to produce the final output by counting majority votes.

The evaluation using SHapley Additive exPlanations (SHAP) revealed the most important characteristics for diagnosis decision-making. The proposed diagnostic approach resulted in an accuracy measurement of 85.42% as well as 84.94% F1-score performance and 86.77 % precision rates, while showing 87.62% specificity and 83.20% sensitivity, rather than existing approaches. Future improvements to model performance will include the implementation of ANOVA feature selection methods, together with other selection methods.

Zdancewicz et. al. proposed the abnormality in patients' voices-based phonations, articulations, and prosodies in detecting Parkinson's Disease (PD) with a variety of speech signals [8]. The study had three different PD diagnostic systems modeled after specific features in speech signals. Initially, a classification was done using the Support Vector Machine (SVM) and k-Nearest Neighbor (kNN) methods, followed by feature selection and feature fusion methods in subsequent stages. Classification performance thus improved through feature-fused data, with k-NN achieving 92.2% recognition, sensitivity at 91.1% and specificity at 93.3%. The outcomes indicated clinical relevance in phonation and articulation, along with prosody, as features for detecting PD.

Veetil et al. developed a language-independent model of PD classification based on Variational Mode Decomposition. The developed approach was intended to develop a DL framework by establishing cross-lingual validity as in [9]. This study performed a comparison and assessed the generalizability of the classification model. Additionally, the analysis was evaluated with the gender bias effects on the realistic data. The method achieved cross-lingual accuracy in the range of 65% to 80%, within the same dataset between 90% and 95%, and generalizability of 63% on an independent dataset. The developed technique produced reliable results irrespective of the speaker's gender, thus making it possible to create a sound, language-independent model for PD voice-based detection. However, it suffered from the limitations of only being tested on two languages, such as Spanish and Italian, and therefore, it might not generalize well to other languages or cultural contexts without further adaptation.

2.2. MRI Image

Further, PD can also be detected by utilizing the MRI image data, which was treated as research work, as illustrated in Table 2. The study [10] proposed a deep CNN method for classifying MRI of healthy individuals and patients with PD. To account for limited training data, transfer learning and GAN-based data augmentation were employed. The original dataset contained 504 MRI images, which were augmented by another 360 images. The refinement of the model was achieved using a pre-trained AlexNet architecture, which achieved an accuracy of 89.23%. This method shows an improved level of diagnostic performance compared to other research works. However, the constraints of this work include limitations in GAN-based augmentation and a small dataset, which may result in possible overfitting of the model.

Milton et. al. focused on a DL model involving T1-weighted MRI data for PD classification [11]. Here, 2041 MRI datasets were collected from 13 different studies, comprising 1024-PD patients and 1017 healthy controls. Preprocessing was performed on the data by skull stripping, resampling, and bias field correction. The CNN was trained on the data to classify PD-affected and healthy individuals. The results showed an accuracy of 79.3% and a precision of 80.2%. The saliency map showed the salient brain areas involved in classification decisions, including frontotemporal areas and deep gray matter.

The PD classification from three-dimensional MRI scans has been discussed in [12]. This work uses VBM for finding the brain parts affected by the death of dopamine-secreting nerve cells due to PD. Male and female experiments have been done separately, acknowledging the neurobiological differences. Feature selection for the classification has been done to reduce the computational complexity. For men, the best detection levels were accuracy of 99.01%, sensitivity of 99.35% with 100% specificity and precision, while for women, they were accuracy of 96.97%, sensitivity of 100%, specificity of 96.15% and precision of 97.22%. It analyzed the whole brain and identified regions, including the cortex, which concentrated on the striatum.

The work in [13] proposed a unique Ensemble Learning framework with Two-Layer Stacking, which combines early clinical assessment with multimodal neuroimaging features, including T1-weighted imaging and Diffusion Tensor Imaging, into the methodology of the early PD diagnosis. The first layer contains four base classifiers, while the second layer employs Logistic Regression (LR) to finalize the classification. This method proved remarkable with an ability of 96.88% accuracy, 100% precision, 95% recall, and a 97.44% F1 score, thus surpassing the standard ensemble models. The results indicate that the combination of multi-modal and multi-classifier approaches can dramatically improve diagnostic accuracy for early PD detection.

This study [14] proposed a new DL model that incorporates LSTM layers alongside 3D-CNNs to stage Parkinson's disease (PD) progression into four levels using MRI data from PPMI. The model captured spatial and temporal features from pre-processed MRIs and achieved an AUC of 91.9% compared to other models. Preprocessing steps were performed, which included the removal of non-brain tissue and data augmentation to ensure balanced and high-quality input. Such models could have clinical potential in early diagnosis, monitoring disease progression, and drug development. Nevertheless, there were methodological limitations. High model complexity might lead to some overfitting, and the lack of explainability in DL-generated decisions might impede clinical uptake.

Table 2. PD detection using MRI image models

S. No.	Paper Title and Author	Algorithm applied	Dataset used	Performance	Limitations
1	Kaur et al. developed a PD diagnosis model with transfer learning and augmentation techniques [10].	CNN, AlexNet, GAN	PPMI Parkinson's MRI dataset	Accuracy: 89.23%	Potential overfitting due to limited real data.
2	Camacho et al. proposed a DL model for classifying PD [11].	CNN	MNI PD25 Atlas	Accuracy: 79.3 %, Precision: 80.2 %, Sensitivity: 77.7%, Specificity: 81.3 %, AUC-ROC: 0.87	The use of multicenter retrospective data introduces variability in inclusion/exclusion criteria and PD diagnosis, which may affect representativeness,

					particularly in early disease stages; prospective validation is needed for more reliable results.
3	Romero et. al. used MRI scans with machine learning algorithms to diagnose PD [12].	Voxel-Based Morphometry (VBM), Naive Bayes classifier	MRI images	Accuracy: 99.01 %, Precision: 100%, Sensitivity:99.35%, Specificity: 100 %	The study divides the analysis by gender, which may limit generalization to a mixed-gender population. This approach may not fully capture the complexities of PD across both genders.
4	Yang et al. proposed a Parkinson's disease classification method that integrates multi-modal feature extraction with a stacking ensemble learning strategy [13].	SVM, Random Forest, KNN, Artificial Neural Networks (ANN), LR	PPMI Parkinson's MRI dataset	Accuracy: 96.88 %, Precision: 100 %, Recall: 95 %, F1 score:97.44 %	Reliance on multi-modal neuroimaging data (T1WI and DTI), which may not be readily available in all clinical settings due to cost, accessibility, or scanning time constraints, potentially limits its widespread applicability in routine PD diagnosis.
5	Frasca et al. introduced a hybrid DL model to predict PD progression [14].	3D - CNN with Long Short-Term Memory (LSTM)	PPMI Parkinson's MRI dataset	91.9% macro-averaged OVR AUC	Complex and limited interpretability may affect generalizability.

2.3. Spiral / Wave Drawings

PD can be detected by considering the spiral/wave drawings of the people involved, which were observed as research work, as mentioned in Table 3. A machine learning approach was introduced by Abdullah et al. [15] for PD detection, utilizing features extracted from spiral and wave drawings.

The study incorporated ResNet50 and Random Forest with (HOG) by gathering information from a data set made out of samples from drawings by healthy individuals and PD patients. The best performing model, ResNet50, evaluated an accuracy of 89.67% with a loss of 0.245 during validation, and for diagnosing PD, which helped in early detection of this disorder.

This did not include dynamics of the pen, like speed, pressure, etc., which could improve accuracy. These findings focused on future research to exploit the developed datasets and further include sensor and motion-feature derived techniques.

Table 3. PD detection using drawing models

S. No.	Paper Title and Author	Algorithm Applied	Dataset Used	Performance	Limitations
1	Parkinson's disease detection by analyzing spiral drawing using machine learning techniques [15].	ResNet50, Random Forest with Histogram Oriented Gradient (HOG)	Spiral and Wave Drawing Images (Healthy vs PD)	Accuracy: 89.67%, Precision: 90 %, Recall: 90 %, F1 Score: 89 %, Loss: 24.50 %	Limited dataset size, lacks feature analysis like pen speed and pressure in spiral drawings.
2	Ianculescu et al. worked on the early identification of PD by integrating artificial intelligence techniques with medical image analysis [16].	Random Forest	Hand-drawn Archimedean spirals	Accuracy: 95.24%, Precision: 95.67%, Recall: 95.24%	Morphological thinning and unwrapping issues led to the exclusion of some images. Limited generalizability due to inconsistent spiral characteristics.
3	Farhah developed an intelligent classification framework employing DL models to analyze spiral drawings for Parkinson's disease diagnosis [17].	VGG19, InceptionV3, ResNet50v2, DenseNet169 (Transfer Learning Models)	102 spiral drawings of Parkinson's patients from Kaggle	Accuracy: 89%, ROC: 91%	Limited to PD. Did not investigate other movement disorders
4	Huang et al. proposed a DL approach comprised of both spiral and wave hand-drawn images to support early-stage diagnosis of PD [18].	Deep Transfer Learning (VGG19)	Dataset including Handwriting samples (wave & spiral)	Accuracy: 96.67%, Recall: 93%	Small dataset (102 wave, 102 spiral images), Limited to only spiral and wave drawings
5	Dogan et. al. introduced a diagnostic method combining CNN, neighborhood component analysis (NCA), and support vector machines (SVM) for effective PD classification [19].	Hybrid CNN Feature Extraction	Dataset comprised 204 images of spiral/wave drawings.	Accuracy: 99.39% Precision: 99.36% Recall: 99.36%	High computational complexity due to multiple CNNs and fusion. Small dataset size. Overfitting risk is mitigated using Neighborhood Component Analysis (NCA),

The study in [16] was primarily about applying both AI and image processing methods in the PD detection using spirals. It described drawing and transforming them into frequency spectra for feature extraction in the pencil pressure/thickness and frequency domain. The features were fed to ML algorithms; among these algorithms, RF

discovered the highest classification accuracy of 95.24%. The obtained precision was 95.67%, while the recall reached 95.24%. The combined feature set of frequency-based and pencil pressure features consistently outperformed the individual feature set on all evaluation metrics. The most important novelty of this study was its ability to gather data through very simple pencil-paper drawings, avoiding expensive, specific devices. Hence, it was affordable in resource-poor settings.

Farhah et al. employed transfer learning models to analyze spiral drawings for supporting the detection of Parkinson's disease (PD) [17]. A dataset consisting of 102 spirals from diagnosed PD patients was used. Results showed InceptionV3 with 89% accuracy and 91% ROC score, hence the efficacy of DL in early detection of PD through manually drawn spirals was demonstrated. The study restricted its findings to PD diagnosis only without any demarcation from other similar motor disorders, such as essential tremor. Most importantly, data being collected on already confirmed patients restricted the generalizability of findings. The enhanced work might consider a more extensive diversity of samples to improve clinical relevance and robustness of promising approaches.

In the study conducted by Huang et al., deep transfer learning was conducted on the database containing handwriting samples comprised of both spiral and wavy patterns to detect PD [18]. The tested models included VGG16, VGG19, and ResNet variants, whereas VGG19 produced the highest accuracy (96.67%) using cosine annealing and data augmentations such as rotation and flipping. Notably, VGG19 also gave a recall of 93%, a very important metric in healthcare applications. Some limitations of this research included its generalizability as the images considered was fewer. But this study showed a potential application of DL in early PD diagnosis with augmentation and optimization techniques.

An advanced study examined the detection of Parkinson's through handwriting with a hybrid approach, as in [19]. This entailed applying CNN-based feature extraction from models such as DenseNet201, Xception, and NASNetMobile. The features thus extracted were then filtered with NCA to weed out information not relevant to the task. The SVM was then employed for classification. The research was focused on the Parkinson Hand Drawings dataset, comprising 204 images (spirals and waves) captured from PD patients and healthy subjects. Kinematic and spatial features of handwriting were studied to trace symptoms of motor dysfunction. High classification performance was observed, with the model reaching 99.39% accuracy, 99.36% precision, and 99.36% recall. The combination of CNN features followed by NCA and SVM greatly improved results compared to individual CNN classifiers. Moreover, one of the challenges faced by the researchers was that their small dataset led to potential overfitting. The study pronounced the way in which hybrid DL and machine learning models could become trustworthy decision-making support in accepting handwriting analysis for early PD detection.

2.4. EEG Signals

Moreover, PD can also be detected by utilizing the EEG signals, which have been considered in various studies by authors, as illustrated in Table 4. New research investigated DL models to detect PD through EEG signals. One study proposed by Siuly et al., which involved a novel model that integrated a Time-Frequency Representation using a Wavelet Scattering Transform with an AlexNet CNN [20]. Data were obtained from two separate datasets. One dataset from Iowa contained recordings of individuals diagnosed with Parkinson's disease along with healthy controls using a 64-channel system. The San Diego dataset also included both Parkinson's and healthy participants, but recordings were acquired using a 32-channel system.

Both datasets have resting-state EEG signals. The proposed model achieved strong classification performance, with accuracy reaching 95.79% for data collected in Iowa and 99.84% for data collected in San Diego. The architecture outperformed ResNet18, VGG16, and DarkNet19. Its limitations were reliance on resting-state EEG, high computational demand, and small sample size, which might affect generalizability and real-time deployment. The approach showed promise for accurate early PD detection using selective EEG channels, minimizing the need for full-brain recordings.

A method proposed for the diagnosis of PD was presented in the study by authors Khalid and Ehsan in [21]. EEG sub bands were utilized, and features extracted from them were fed into a Gated Recurrent Unit (GRU) classifier. Data on EEG used in this study were obtained from OpenNeuro, UC San Diego, which had been collected from 31 patients, including medicated and non-medicated PD patients. It was found that gamma band activity achieved an overall high sensitivity with an accuracy of up to 98.6% compared to SVM and Multi-channel CNN classifiers. Statistical analysis demonstrated statistically significant differences among the Power Spectral Density (PSD) features in healthy versus PD groups. This study also restricted its investigation to PD only, and other similar disorders were not included. Future research in this field may include studies on more multi-modal signals. Notably, GRU-based analysis presented good outcomes for highly accurate and non-invasive detection using EEG signals for PD.

In [22], a novel method for diagnosing PD employing EEG signal analysis in conjunction with an SVM classifier is presented. Early diagnosis and adoption of more advanced ML methods in EEG signal analysis were given high importance. The dataset included EEG recordings collected from individuals diagnosed with Parkinson's disease as well

as healthy control subjects. The proposed model achieved a diagnostic accuracy of 95.3%, outperforming conventional classifiers such as KNN and RF. Still, the research was conducted on a dataset that may not be representative enough of the larger population for the external validity of the results. It would therefore be much more prudent to do this assessment before concluding on the external validity of the results.

Jibon et al. developed a hybrid architecture combining Autoencoder (AE) and Radial Basis Function Neural Network (RBFNN) to identify PD from EEG data, as in [23]. This method was based on analyzing PSD features extracted from EEG signals that were visually inspected for artifacts. The features were extracted using AE and classified by RBFNN. The EEG data were obtained from UC San Diego, where 31 subjects were selected. Testing was conducted on healthy subjects and on PD counterparts in both medicated and unmedicated states. The proposed model achieved a classification accuracy of 99.5% for distinguishing healthy control subjects. The sensitivity and specificity were calculated at 98.0% and 98.65%, respectively. The evaluation was conducted using a 5-fold cross-validation method. The evaluations showed better performance with the fusion of spectral and connectivity features.

An explainable ensemble-based machine learning architecture was developed for diagnosing PD based on voice features, as evidenced by an experiment conducted in [24]. The UCI ML repository dataset was applied in the study, subjected to data preprocessing, along with augmentation. This stacking model achieved the highest performance among the other ensemble approaches by using the Linear Discriminant Analysis (LDA) feature selection method, giving 97.01% accuracy. To ensure global and local model prediction interpretation, SHAP explainability methods were incorporated. This assisted in building an AI-assisted diagnosis by providing a clearer understanding of the decision-making process. Some methods of optimizing features had resulted in performance degradation. Further, the dataset size limited the generalizability of the findings.

Table 4. PD detection using EEG signal models

S. No.	Paper Title and Author	Algorithm Applied	Dataset Used	Performance	Limitations
1	Siuly et al. introduced a framework for PD detection by transforming EEG signals into time-frequency representations and processing them with the AlexNet CNN [20].	WST + AlexNet CNN	Iowa dataset: 14 PD & 14 HC from Univ. of Iowa (64-channel, 500Hz) San Diego dataset: 15 PD & 16 HC from Univ. of San Diego (32-channel, 512Hz)	Iowa: 95.79% Accuracy, 96.09% Sensitivity, 95.49% Specificity San Diego: 99.84% Accuracy, 100% Sensitivity, 99.67% Specificity	EEG data recorded only during resting-state; requires high computational resources for DL. Limited generalization due to sample size. Lacks real-time validation
2	Khalid et. al. conducted an analysis of PD detection using EEG features with a GRU architecture, aiming to capture temporal dependencies in brain signals [21].	GRU with Power Spectral Density (PSD) features	OpenNeuro EEG dataset by UCSD (31 participants: 16 healthy, 15 PD), 2020	Up to 99% accuracy (Gamma: Acc – 98.6%, Prec – 100%, Rec – 97.4%)	Only EEG data was used. No multimodal inputs like gait or handwriting. Not tested on other neurodegenerative diseases.
3	Allahbakhshi et. al. performed a study on diagnosing PD through ML techniques applied to EEG data [22].	Support Vector Machine (SVM)	EEG signals were acquired with 32 recording channels from PD and healthy people.	Accuracy: 95.3%	The dataset used may not represent the full diversity of the population. The model may require further external validation.

4	Jibon et al. developed a hybrid DL framework that integrates an AE with an RBFNN to detect Parkinson's disease [23].	Autoencoder + RBF Neural Network	UC San Diego EEG dataset (31 subjects: 16 healthy, 15 PD; 32-channel Biosemi EEG; recorded at 512Hz)	Accuracy: 99.5% Sensitivity: 98.0% Specificity: 98.65% F1-score: 98.36%	Relied on a single dataset for both training and testing, which may limit generalizability.
5	Khanom et al. introduced an explainable ensemble ML model designed for PD diagnosis, leveraging optimized feature selection [24].	Stacking Ensemble + LDA Feature Selection	UCI ML Voice Dataset (Little, 2008). Istanbul University Dataset (Sakar et al., 2018)	Accuracy: 97.01%	Some feature selection methods reduced performance. Limited dataset generalizability

2.5. Gait Analysis

Further, PD can also be detected by Gait analysis, which was involved as one of the major factors as proposed in Table 5. For identifying the PD formation, better and more advanced DL techniques have been applied to gait cycle datasets. A study made an attempt to propose a model by bringing together 1D-CNN, GRU, and Graph Neural Networks (GNN) to understand the different temporal dynamics and spatial associations as in [25]. This model was able to use data from wearable sensors for recording the vertical Ground Reaction Force (vGRF) as discrete sequences during the gait analysis. The model demonstrated impressive performance metrics at 99.51% accuracy, 99.57% precision, and 99.71% recall. This study encountered the danger of overfitting because of the limited samples available and a long training time.

An ensemble learning framework called BagStacking was introduced for Gait detection in PD patients using accelerometer data mentioned in [26]. BagStacking synergizes the variance reduction of bagging with the improved predictive performance. When evaluated using real-world accelerometer data, the model achieved a significant improvement of 0.306 in Mean Average Precision (MAP) and significantly improved AUC metrics of 0.88 for start hesitation, 0.90 for turning events, and 0.84 for regular walking sequences. In particular, these results surpassed those of the traditional models' detection capabilities of stacking methods.

A novel method, Fusion of Gait Point Cloud and Silhouette (FuGaPS), was proposed for PD detection by combining model-based and model-free gait features [27]. It integrated FuGaPS representations from videos to enhance the screening of subjects. Feature fusion and classification were done using machine learning models. Experiments on a self-collected dataset of 205 training and 89 test samples showed that LR demonstrated strong performance, achieving an AUC of 0.87, a precision of 0.85, a recall of 0.80, and an F1-score of 0.82. It proved to be more robust for performance when compared against individual methods, improved the representation of movement patterns with limitations of the small dataset, and provided generalization perspectives.

A study was made to diagnose early-stage PD and predict scores that relied on gait parameters [28]. Gait-related parameters, including stride length, gait speed, stride velocity, swing velocity, turning duration, and cadence, were analyzed to distinguish Parkinson's disease patients from healthy individuals. Machine learning models were subsequently trained to perform both classification and regression tasks based on these features. The overall average accuracy was 91%, with sensitivity and specificity being 93% and 90%, respectively. Compared to healthy subjects, early-stage Parkinson's patients demonstrated notable reductions in the metrics involved.

A noninvasive early detection approach for PD was proposed, utilizing gait features specifically extracted from the transition phases of the Timed Up and Go (TUG) test [29]. Here, video recordings were made under controlled conditions to extract kinematic signature features such as shoulder distance, step length, stride length, knee and hip angles, leg and arm symmetries, and trunk angles. These features were filtered in an advanced way and submitted for classification to an SVM machine-learning algorithm. It achieved a high accuracy of 0.89, with precision classified as 0.88 for normal subjects and 1.00 for PD patients.

Table 5. PD detection using gait models

S. No.	Paper Title and Author	Algorithm Applied	Dataset Used	Performance	Limitations
1	Rashnu et. al. designed a deep learning framework for early PD detection using gait cycle data collected from wearable sensors, incorporating CNN, GRU, and GNN architectures for robust temporal and spatial feature extraction [25].	1D-CNN, GRU, GNN	Gait cycle data from wearable sensors from PhysioNet	Accuracy: 99.51%, Precision: 99.57%, Recall: 99.71%	Risk of overfitting due to low sample size, increased training time due to millions of parameters
2	Cohen et. al. introduced BagStacking, an ensemble learning approach that integrates multiple models for detecting PD [26].	BagStacking (Bagging + Stacking Ensemble)	Michael J. Fox Foundation PD Dataset, accelerometer data (available on Kaggle)	MAP (Mean Average Precision): 306, AUC: 0.88	Imbalanced dataset, limited DL integration, potential for optimization in meta-learner and runtime.
3	Tee et. al. presented a screening method based on gait-derived data and silhouette features, aiming to improve motion-based diagnostic accuracy [27].	FuGaPS	A self-collected dataset was utilized, with 205 training samples—111 from non-Parkinson's (NP) subjects and 94 from Parkinson's disease (PD) subjects—as well as 89 test samples, including 39 NP and 50 PD instances.	Precision: 0.85, Recall: 0.80, F1-Score: 0.82, AUC: 0.87	Small dataset size, limited diversity in gait variations. Further testing is needed for broader generalization.
4	Yin et al. applied ML techniques to analyze gait patterns in the early stages of PD [28].	ML Regression and Classification Models	A non-contact gait assessment system was employed to capture gait patterns without requiring physical sensors on the body.	Accuracy: 91%, Precision: 90%, Recall: 93%	Limited to gait parameters, unable to capture non-motor symptoms, and challenges in generalizing to different populations
5	Lim et al. proposed a feature extraction and classification strategy for PD screening [29].	Support Vector Machine (SVM)	Controlled video recordings of the TUG assessment, focusing on the turning phase	Precision: 0.88 (Normal), 1.00 (PD), Accuracy: 0.89, Recall: 0.90 (Normal), 1.00 (PD)	Class imbalance affecting recall for PD class, overfitting observed, and variability in validation loss

3. Conclusion

The primary intention of this study is to utilize various diagnostic methodologies, such as voice recordings, magnetic resonance imaging scans, electroencephalogram signals, spiral drawings, and gait analysis, that may enable the early diagnosis of PD as well as monitoring disease progression. These approaches provide different insights into the motor and neurologic changes occurring with PD. Along with ML and DL models, the ensemble classifiers also proved to be effective and promising in diagnosing and classifying disease progression at an unprecedented level. However, limitations were laid down by the availability of datasets, lack of clinical validation, model interpretability, and so on. Future research will revolve around enhancing the approaches under consideration and effectively proving their applicability to real-world clinical settings.

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