

Automated Parkinson's Disease Detection: A Review of Techniques, Datasets, Modalities, and Open Challenges

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Abstract

Parkinson's disease (PsD) is a prevalent neurodegenerative malady, which keeps intensifying with age. It is acquired by the progressive demise of the dopaminergic neurons existing in the substantia nigra pars compacta region of the human brain. In the absence of a single accurate test, and due to the dependency on the doctors, intensive research is being carried out to automate the early disease detection and predict disease severity also. In this study, a detailed review of various artificial intelligence (AI) models applied to different datasets across different modalities has been presented. The emotional intelligence (EI) modality, which can be used for the early detection and can help in maintaining a comfortable lifestyle, has been identified. EI is a predominant, emerging technology that can be used to detect PsD at the initial stages and to enhance the socialization of the PsD patients and their attendants. Challenges and possibilities that can assist in bridging the differences between the fast-growing technologies meant to detect PsD and the actual implementation of the automated PsD detection model are presented in this research. This review highlights the prominence of using the support vector machine (SVM) classifier in achieving an accuracy of about 99% in many modalities such as magnetic resonance imaging (MRI), speech, and electroencephalogram (EEG). A 100% accuracy is achieved in the EEG and handwriting modality using convolutional neural network (CNN) and optimized crow search algorithm (OCSA), respectively. Also, an accuracy of 95% is achieved in PsD progression detection using Bagged Tree, artificial neural network (ANN), and SVM. The maximum accuracy of 99% is attained using K-nearest Neighbors (KNN) and Naïve Bayes classifiers on EEG signals using EI. The most widely used dataset is identified as the Parkinson's Progression Markers Initiative (PPMI) database.

Keywords

Parkinson's Disease Detection, Artificial Intelligence, Emotional Intelligence, Datasets, Modalities

1. Introduction

Neurological dysfunctions are the second-deadliest reason for death worldwide and the foremost source

of severe long-term disability [1]. Parkinson's disease (PsD) presently influences between 1% and 3% of persons >65 years and is the second-most prevailing neurological disorder, which is prevalent in old

people after Alzheimer's disease [1–4]. PsD is non-curable and impairs the movement of body and the functioning of the human brain [5]. The prevalence of PsD has been predicted to double over the next 30 years [6]. According to 2019 estimates, there were approximately 8.5 million persons worldwide who were affected with PsD. In 2019, PsD resulted in 3,29,000 fatalities, a rise of more than 100% since 2000, and 5.8 million years of impaired life years, a spike of 81% since 2000 [7]. Approximately, 5 million individuals worldwide today experience PsD [8]. Statistically, the heartbreaking pattern that has been proven through research is that when PsD is recognized, it frequently reaches an irreversible stage [9]. PsD has also recently been included in the "Rights of Persons with Disabilities Act, 2016" by the Indian Parliaments [10] to empower and protect the patients from discrimination, optimize opportunities for patients, and make them independent to sustain better life [11, 12].

The disease is an outcome of the changes in the neuronal cytoskeleton of only a few vulnerable types of neurons. PsD occurs due to the decline in the number of the dopaminergic neurons (DNs) in the substantia nigra (SN) of the basal ganglia, which is a portion of the brain situated below the cerebral cortex. Insufficiency of DNs to communicate with other nerve cells affects the motor and nonmotor symptoms [13]. Dopamine regulates both motor and mental actions as well as emotion. The specific origin of PsD is unknown; however, a combination of hereditary and environmental factors is thought to be the condition's cause. Age is a primary risk factor, along with exposure to environmental toxins, particularly pesticides, solvents, and metals, raising the likelihood of acquiring this neurodegenerative disease [3]. PsD is predominantly an abnormal movement condition, represented by bradykinesia (slowness in movements), hypokinesia (decrease in movement amplitude), akinesia (lack of normal unconscious movements), in addition to muscle rigidity and tremor at rest. It may also cause several nonmotor symptoms ranging from cognitive impairment, anxiety, nasal and gastrointestinal issues, etc. [14]. PsD causes various motor and nonmotor ailments that have been defined in detail in Figure 1.

Living with PsD can be overwhelming for most people; hence, measures should be taken to make the life of the patient as well as the family easy. Acknowledgment of the diagnosis followed by adjustment through the grieving stages of emotions like denial, anger, bargaining, depression, and acceptance is crucial at the beginning [15]. Life skills such as

keeping your hopes high, maintaining a positive mindset, and indulging in gratitude, meditation, and deep breathing can keep the spirits high [16]. People with PsD should also exercise regularly because it helps maintain their balance, mobility, and activity, as it promotes the brain's production of dopamine. Research also backs these benefits [16]. Self-compassion also reduces psychical distress such as anxiety, stress, and depression [17].

The symptoms identified by modalities such as electroencephalogram (EEG), electrocardiogram (ECG), gait, etc., develop at a much later stage, causing irreparable damage. On the contrary, emotion deficits are an early symptom of PsD. The components of the limbic loop in the brain play an indispensable role in the maintenance of memory functions, learning ability, and emotional equilibrium, which eventually undergo many pathological changes in PsD [18]. Muscle rigidity, bradykinesia, and tremors occurring in the facial, vocal, and respiratory muscles result in the declined regulation of one's speech and facial expressions, leading to flaws in the recognition, the rendition of emotions, and the external facial features. This is called facial masking or hypomimia [19–21], which is among the early symptoms of PsD and hence recognized as highly important in the diagnosis [22]. Hence, facial expression recognition is used to diagnose PsD. Facial expressions influence social decision-making [23] and in turn adversely impact social life [19, 24].

People with PsD frequently experience low esteem, social incapacitation and biasness, including unfair workplace discrimination and a lack of possibilities for engagement and community participation. A deficiency in visual-spatial learning is observed in PsD patients along with affective disturbances, which are influenced by the emotional deficit [25]. Facial expressions play an important role in conveying our emotions along with identifying the emotional prosody of other people. The lack of emotional expressions in PsD patients makes it difficult to access the complete benefits of the healthcare services. Face masking has a significant impact on communication, which can negatively impact the social engagement and the life-quality of the patients [26]. People with PsD, similar to the general community, require accessible healthcare services, including access to medications and preventive programs, quick diagnosis, remedy, and care. Lack of information and adequate comprehension of PsD among healthcare professionals and the misconception that the condition is contagious, or a normal part of aging, are typical barriers.

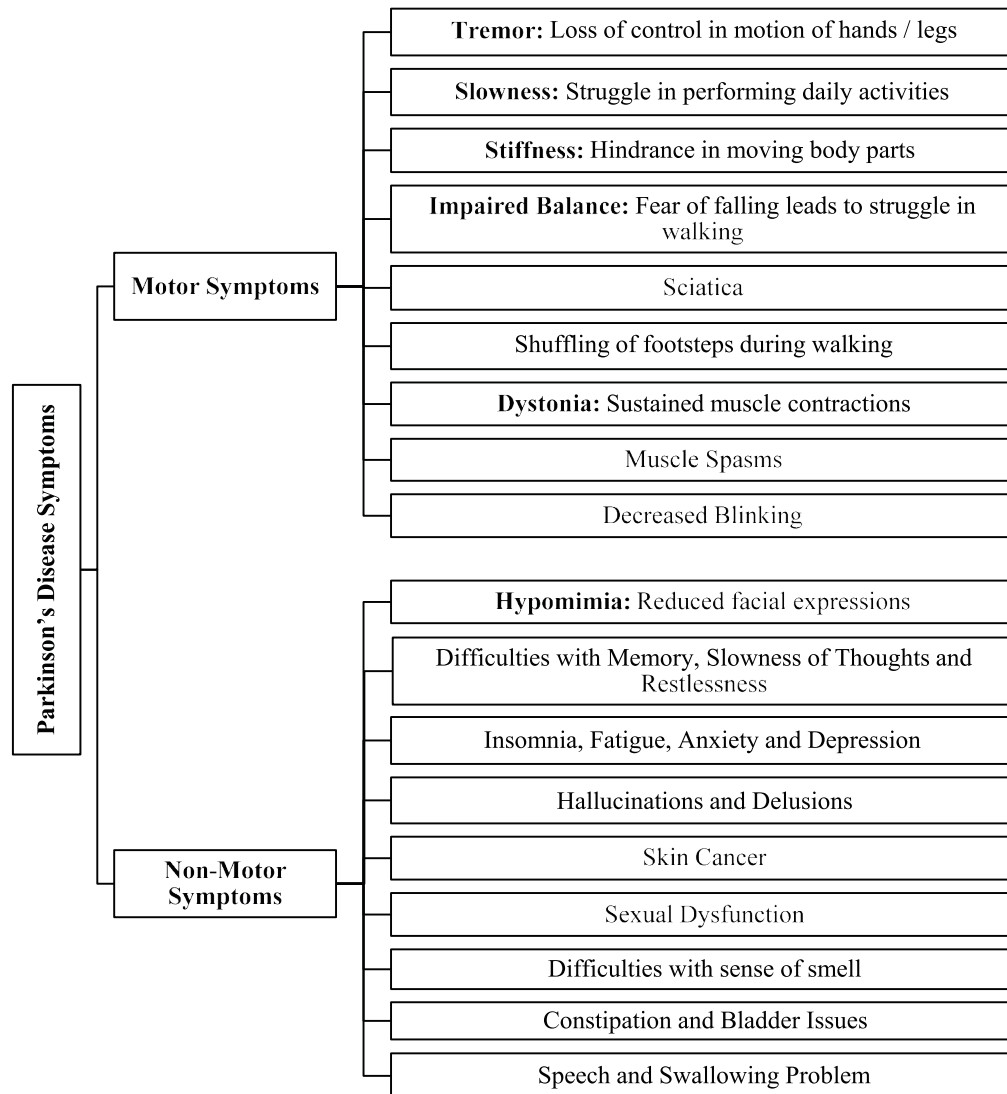


Figure 1: Parkinson's disease symptoms [4, 33, 34].

All these factors contribute to the importance of emotional management in PsD patients, and constant efforts are being made to explore newer ways to diagnose, track the progress, and provide rehabilitation training to the patients efficiently and conveniently. Emotional intelligence (EI) is a predominant, emerging technology, which can be used to detect PsD and enhance the social-life behavior of the patients and their caregivers. EI refers to the ability of recognizing our own and others' feelings too, for motivating ourselves, and for governing emotions well in ourselves and in our relations, as described by Daniel Goleman. Emotional EEG signals, facial emotional recognition, and emotion changes in speech modalities are used to predict PsD using EI.

Generally, methods for recognition of emotions can be grouped in two main categories. Using physical signals such as facial expressions, gesture, speech, posture, etc., or by using internal physiological signals such as the ECG, temperature, EEG, electromyogram (EMG), respiration (RSP), galvanic skin response (GSR), etc. Emotion as well as cognition changes in PsD cases is an early modality for PsD; hence, this area of research is gaining capacity. Early identification and diagnosis of PsD are critical for accessing quick healthcare support and to increase the life expectancy [5, 27]. Hence, emotional intelligence (EI) can be used to effectively diagnose the disease and also help PsD-affected persons in maintaining a better lifestyle.

Various techniques are used to automate PsD detection such as machine learning, deep learning, transfer learning, and EI. These techniques can be applied to various modalities such as magnetic resonance imaging (MRI), SPECT, PET scans, speech, handwriting, gait, eyes, facial recognition, etc. Impaired balance, slowness, rigidity, and stiffness in the legs aid in PsD diagnosis using gait analysis. Symptoms such as vocal tremors, decline in the vocal tract volume, diminished intensity of speech and the pitch-range, reduced tongue flexibility, deterioration in quality of speech, irregular pronunciation, and improper halts in speech are monitored to detect PsD using speech modality [28]. The ultimate goal of handwriting analysis for the diagnosis of PsD is identifying deteriorated handwriting using imagery. The reduced finger grip due to stiffness, slowness, and tremor hampers the handwriting. The pressure, altitude, azimuth velocity, acceleration, jerk, stroke height, stroke width, and movement time are the features used for the detection of PsD [29]. Rapid eye movement sleep behavior disorder is a symptom harming about 70% of PsD patients. Saccade, pupil, and blink responses could be an early biomarker for PsD detection, hence, aiding in early PsD detection [30]. Blood oxygen level-dependent and high-definition susceptibility-weighted imaging sequences in the MRI images are used in PsD diagnosis [31]. Brain can also be monitored with respect to its change in activity through spatial and temporal resolution. MRI has high spatial resolution as it can discern fine details in the brain images. EEG has high temporal resolution; hence, it is able to capture the rapid changes in the brain activity such as the death of DNs. PET indirectly infers the brain activity based on the physiological changes such as blood flow and variations in glucose levels, which is again based on the number of neurons. SPECT is used to evaluate the clinical motor function and the cognitive decline also [32].

The recent developments in computer science, bioinformatics, and personal healthcare have substantially advanced medical research. The COVID wave also raised awareness about the mental-health crises [35]; the need for technological innovation to preserve the continuity of care arose while also lowering the risk of infection and human contact [36]. By incorporating AI in medical facilities, it is possible to improve data collection, disease diagnoses based on symptom classification, and make therapeutic judgments that are heavily influenced by data [37, 38]. All the acronyms used in this paper are listed in Table 1.

The most important applications that may be a future enhancement by utilizing our results are a

PsD detection model with performance metrics—accuracy, sensitivity, specificity, etc., comparable to the clinical findings on large balanced datasets. Further, an efficient PsD progression detection model and an automated model for the accurate diagnosis of multiple neurological diseases with overlapping symptoms are the need of the hour. Also, accurate emotional-state identification in PsD patients is an open challenge on which much work is being done. This can aid in better lifestyle management of PsD patients and their caretakers too.

1.1. Motivation

Substantial research work is being done in the field of PsD detection and management. Although these publications cover a significant amount of work on its symptoms, modalities, detection, cure, management, etc., but some crucial aspects have been overlooked. Table 2 presents the relative contrast of the proposed survey with the state-of-the-art surveys on PsD detection. No existing survey has covered the scope of EI in the detection of the disease, and also only a few modalities are discussed. The motivation of the present paper is to present a dedicated review on the latest PsD techniques, most-used datasets, modalities, and open challenges. It offers a comprehensive survey of almost all the techniques of AI in PsD detection, from both application and methodology views.

In 2020, M. Noor et.al. and H. Loh et al., in 2021, highlighted that the convolutional neural network (CNN) model is widely used and achieves better accuracy in PsD detection. H. Khachnaoui et al., A. ul Haq et al., and M. Alzubaidi et al. presented a correlative analysis of ML as well as DL models and concluded that DL performed better than ML. M. Alzubaidi et al. also identified the best-performing DL models as well as the datasets. According to him, DNN achieved phenomenal results on the VGRF dataset, CNN and FNN achieved outstanding result for image classification, the neural networks gave promising results on voice data, and LSTM outperformed on EEG data. Tanveer et al. proposed CNN and RNN for PsD detection. J. Zhang vouched for SVM and artificial neural network (ANN) on SPECT scan images. M. Shaban also supported the idea that ANNs are most widely used. L. Di Biase et al. highlighted the shortcomings of the algorithms used in 2020. A. Rana et al. obtained the best accuracy to diagnose PsD for voice data using L1-Norm SVM along with K-fold cross-validation, for handwriting samples, using bagging ensemble, and for gait, it was obtained using SVM. Chandrabhatla A.S. et al. and

Table 1: List of acronyms.

Acronym	Meaning	Acronym	Meaning
PsD	Parkinson's Disease	FER	Facial emotion recognition
HC	Healthy Controls	MRI	Magnetic Resonance Imaging
PPMI	Parkinson's Progression Markers Initiative	TNR	True negative rate
TPR	True positive rate	SVM	Support Vector Machine
PET	Positron emission tomography	MSA	Multiple system atrophy
AI	Artificial Intelligence	DL	Deep Learning
ML	Machine Learning	DICOM	Digital Imaging and Communications in Medicine
SPECT	Single-photon emission computerized tomography	EMG	Electromyogram
CNN	Convolutional Neural Network	CRNN	Convolutional Recurrent Neural Networks
SWEDD	Scans Without Evidence of Dopaminergic Deficit	KNN	K-nearest neighbors
ECG	Electrocardiogram	PSP	Progressive supranuclear palsy
LC	Locus coeruleus	LDA	Linear discriminant analysis
SNpc	Substantia nigra pars compacta	DaTscan	Dopamine Transporter Scan
MFCC	Mel-Frequency Cepstral Coefficients	OCSA	Optimized crow search algorithm
OCT	Optical coherence tomography	CCSA	Chaotic crow search algorithm
EEG	Electroencephalogram	RBD	REM sleep behavior disorder
PCA	Principal component analysis	MDS	Movement Disorder Society
ROI	Region of interest	RGNN	Regularized graph neural network
ANOVA	Analysis of variance	FAWT	Flexible analytic wavelet transform
RF	Random forests	Emotion DL	Emotion-aware distribution learning
RBF	Radial basis functions	LIWC	Linguistic Inquiry and Word Count
RQA	Recurrence quantification analysis	MVLL	Maximum vertical line length
MDLL	Maximum diagonal line length	FMI	Face mobility index
STRNN	Spatial-temporal recurrent neural network	LDA	Latent Dirichlet Allocation
FACS	Facial Action Coding System	VGRF	Vertical ground reaction force
AUC	Area under the ROC Curve	EI	Emotional intelligence
MEIS	Multi-factor emotional intelligence scale	FNN	Fuzzy neural network
ANN	Artificial Neural network	GCNN	Graph Convolutional Neural Network
FL	Federated learning	UPDRS	Unified Parkinson's disease rating scale
FDG	Fluorodeoxyglucose	MCI	Mild cognitive impairment
DN	Dopaminergic Neurons	DT	Dopamine transporter
DBN	Deep belief network	LSTM	Long short-term model
TL	Transfer learning	SVR	Support vector regression
Node DAT	Node-wise domain adversarial training	GSR	Galvanic skin response
DNA	Deoxyribonucleic acid	RBC	Red blood cell
WHARMPA	Weighted HARMonization Parameters	RNA	Ribonucleic acid
FoG	Freezing of Gait	CC	Correlation coefficients
MCC	Merkel cell carcinoma	RMSE	Root mean square error

Table 2: A relative contrast of the proposed survey with the PsD detection state-of-the-art surveys.

Author	Year	Conclusion	1	2	3	4	5	6	7	8	9	10	11	12	13
Proposed Survey	2023	Examines PsD patients’ datasets and PsD diagnosis techniques on various modalities while addressing the open research challenges too	✓	✓	9	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Salari et al. [33]	2023	SVM is proposed to be a bridge between psychological research and the clinical facts	✓	✓	5		✓	✓			✓				✓
Shafiq et al. [39]	2023	Flower Pollination Algorithm and Extreme Gradient Boost Algorithm pair obtained the accuracy of 93%	✓	✓	1		✓	✓			✓	✓			✓
Shaban [40]	2023	ANN is the most widely used PsD detection technique and sensory signals, EEG and handwriting are the most utilized data modalities			4		✓	✓	✓			✓			✓
Kumar et al. [41]	2023	Accelerometer is the most widely used sensor for gait analysis for PsD detection	✓	✓	1		✓	✓			✓	✓	✓	✓	✓
Dixit et al. [42]	2023	Review of PsD diagnosis along with an extensive discussion of future scope	✓		6	✓	✓	✓	✓		✓	✓			✓
Khanna et al. [43]	2023	No existing technique is yet suitable for practical use clinically. MRI, PET and SPECT scans are the most popular neuroimaging modalities	✓	✓	3		✓	✓			✓	✓	✓	✓	✓
Zhang [44]	2022	SVM and ANN show best accuracy on SPECT scan for PsD detection	✓		3		✓	✓			✓	✓			✓
Chandrabhatla et al. [45]	2022	Technological evolution in detecting PsD, in-lab to in-home	✓		3		✓	✓	✓		✓	✓			✓

(Continued)

Table 2: Continued

Author	Year	Conclusion	1	2	3	4	5	6	7	8	9	10	11	12	13
Giannakopoulou and Roussaki [46]	2022	ML + IoT can revolutionize PsD diagnosis, mostly used best performing AI models are MLPs, LSTMs, CNNs, other ANNs and ensemble learning techniques	✓		5			✓	✓		✓	✓	✓	✓	✓
Rana et al. [47]	2022	AI has revolutionized detecting early-stage PsD	✓		7			✓	✓						✓
Tanveer et al. [48]	2022	CNN and RNN give better performance than ML	✓		8			✓	✓			✓	✓		✓
A. ul Haq et al. [49]	2022	DL techniques are the most appropriate			4		✓		✓			✓	✓	✓	✓
Rana et al. [50]	2022	Best accuracy to diagnose PsD for voice data was achieved using L1-norm SVM and k-fold cross-validation, for handwritten patterns using bagging ensemble, and for gait analysis by SVM	✓	✓	3			✓				✓	✓	✓	✓
Alzubaidi et al. [51]	2021	Best performing and widely used DL models and datasets according to various modalities are identified			9	✓		✓	✓			✓	✓	✓	✓
Loh et al. [52]	2021	CNN model achieves higher accuracy in various modalities for PsD detection	✓		8				✓			✓			✓
Noor et al. [53]	2020	CNN is used mostly in the detection of PsD			1		✓		✓			✓			✓
Khachnaoui et al. [54]	2020	DL methods show better performance than ML			2			✓	✓		✓	✓			
Di Biase et al. [55]	2020	Very few algorithms are accurate enough to be potentially used clinically for PsD diagnosis and monitoring symptoms			1			✓			✓	✓	✓	✓	✓

1, Symptoms; 2, Causes; 3, No. of Modalities Discussed; 4, Private Datasets; 5, Public Datasets; 6, ML Techniques; 7, DL Techniques; 8, EI Technique; 9, Multistage Classification; 10, Accuracy; 11, Sensitivity; 12, Specificity; 13, Challenges.

K. Giannako-poulou explained the evolution of PsD detection techniques and the role IoT could play in it, respectively. Kumar S. et al. proposed accelerometer data crucial for gait analysis. In 2023, S. Dixit et al. had summarized the present trends and the future prospects in detail. However, a very few authors have covered the causes of the disease, information about the datasets, and the classification of patients into different stages of PsD. Also, most of the authors have worked on a few modalities only. Moreover, this is the first survey to our knowledge in which the prospect of EI being used to detect PsD is being discussed.

1.2. Contributions

The survey's primary contributions are:

1. A novel modalities-based taxonomy for PsD detection is proposed.
2. A detailed summary and comparison of existing PsD datasets is presented.
3. Parkinson's disease-detection techniques are analyzed according to various modalities, and valuable critique on the diagnosis process is supplied.
4. Open research issues and future recommendations are presented.

1.3. Organization and Roadmap of Survey

The roadmap of the proposed survey is depicted in Figure 2. The present paper is arranged in the following manner: Section 2 presents a descriptive outline of the PsD detection techniques using AI based on various modalities. Section 3 describes the techniques for predicting the different stages in PsD. Section 4 highlights the importance, dimensions, and the assessment measures of EI. Section 5 describes the techniques for prediction of PsD using EI. Section 6 summarizes the various modalities and datasets available for PsD. Section 7 and 8 summarize the research gaps and future scope in this area, respectively. Section 9 sums up the article with the conclusion drawn after reviewing all the previous research and review articles.

2. Literature Review of PsD Detection methods using AI

Parkinson's disease can be predicted using many machine learning (ML), deep learning (DL), and transfer learning models. Various modalities have been

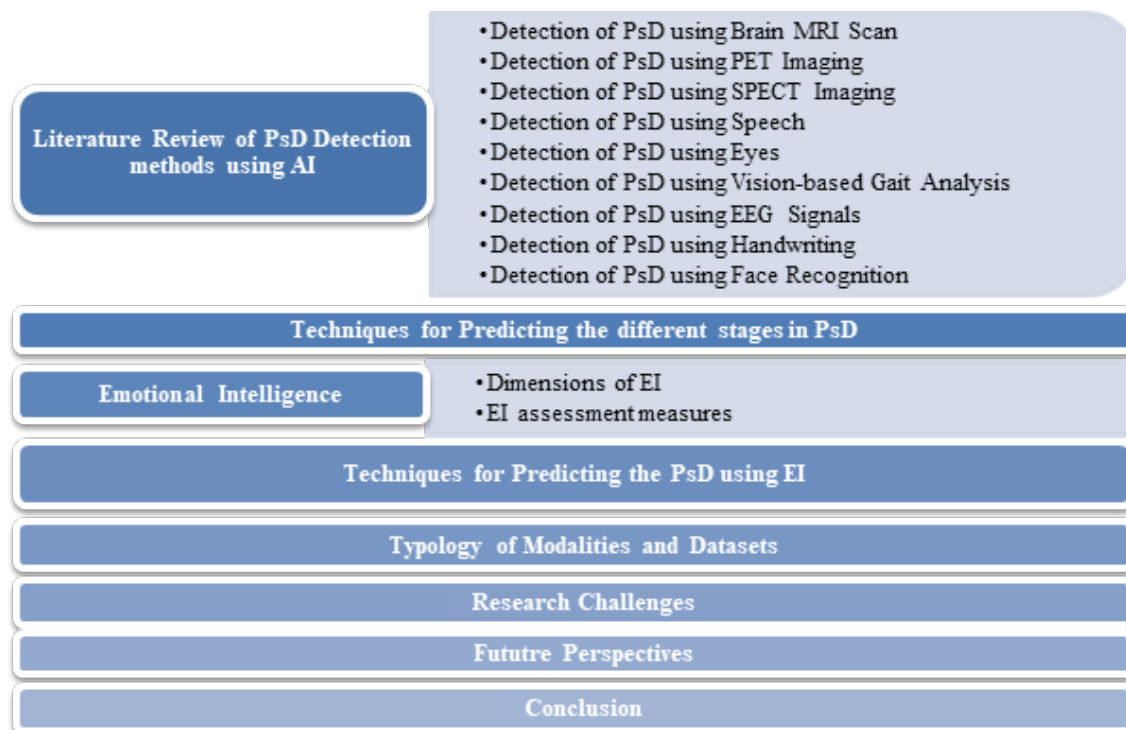


Figure 2: Roadmap of the proposed review.

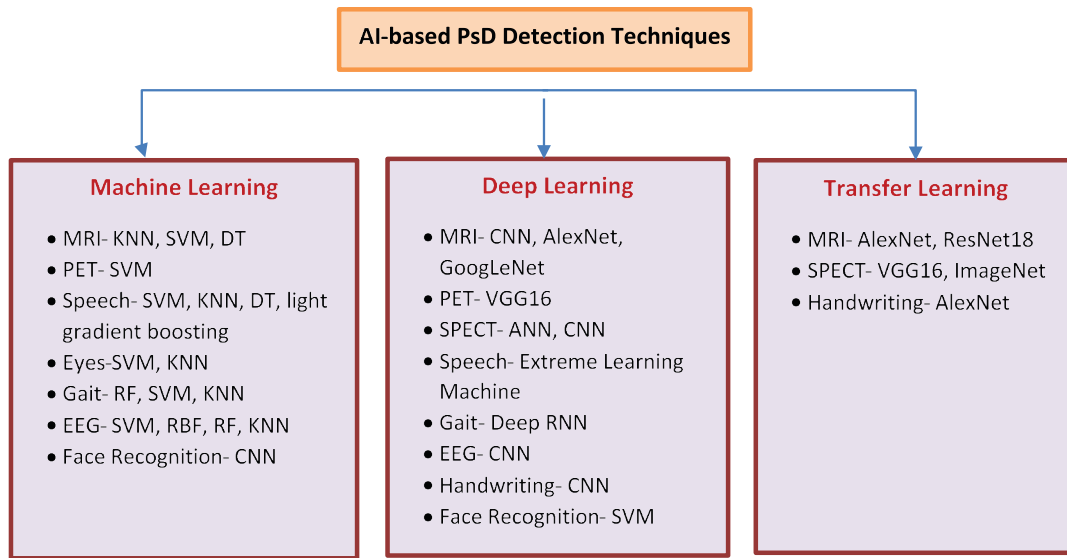


Figure 3: AI-based PsD detection techniques.

researched upon and tested to detect the occurrence of PsD automatically. MRI, PET, SPECT imaging modalities, gait, EEG, ECG, and speech are some of them. Figure 3 lists all the AI techniques applicable on varied modalities. The development and investigation of statistical algorithms, which are able to learn from data and generalize to previously unknown data, allowing them to carry out tasks without explicit instructions, are the focus of the ML, in AI. Models such as SVM, KNN, Random Forest, and Decision Trees are used. DL is a subset of ML techniques that leverages multiple hidden layers and is based on representation learning in ANN. Various CNN models are used to provide good results in diagnosing the disease. TL is used to train models when less labeled data are available, by reusing popular models such as AlexNet and ResNet18 that have already been trained on large datasets.

2.1. Detection of PsD using Brain MRI Scan

Heena Kathuria et al. utilized 3T venous blood oxygen level-dependent and high-definition susceptibility-weighted imaging sequences in the MRI images to find a potential imaging biomarker in PsD diagnosis [31]. Stephanie Mangesius et al. used a multimodal approach integrating serum and MRI biomarkers to characterize all subtypes of parkinsonism, i.e., multiple system atrophy (MSA), progressive supranuclear palsy (PSP), and PsD with higher accuracy for all the three diagnoses [56]. Sivaranjini and Sujatha [57] used a pre-trained AlexNet for 2-D MRI image

categorization from T2-weighted MRI images from the Parkinson's Progression Markers Initiative (PPMI) collection to enhance PsD diagnosis. The accuracy of the suggested AlexNet architecture was 88.90%, the true positive rate (TPR) of 89.30% and the true negative rate (TNR) of 88.40%, respectively. Solana-Lavalle and Rosas-Romero [58] suggested a model employing ML techniques such as K-nearest neighbors (KNN) and support vector machine (SVM). Voxel-based morphometry was used to extract the regions of interest in MRI images from the PPMI dataset. By training an optimized AlexNet model on digital imaging and communications in medicine (DICOM) images from Istanbul University's hospital, Huseyn [59] created a model for the early identification of PsD. Performance of AlexNet and GoogleNet is contrasted along with the distinction of PsD and MSA. Tarjni Vyas et al. used the flair and T2-weighted MRI scans after applying Z-score normalization from the PPMI repository and 2D and 3D CNN were implemented giving the accuracy of 72.22% and 88.9%, respectively [5]. Sabyasachi Chakraborty et al. used the 3T T1-weighted MRI images from the PPMI database to detect PsD [60]. Cui et al. [61] proposed the use of Resnet18 and SVM to improve classification accuracy by using the fusion of image texture features with deep features, and Sangeetha et al. [62] recommended the use of CNN for the classification of PsD and healthy controls (HCs) using PPMI MRI data. A recently investigated imaging biomarker for the detection of neurodegenerative parkinsonism, including PsD, PSP, and MSA, is the loss of dorsolateral nigral

Table 3: Comparative analysis of techniques used to detect PsD using MRI images.

Author (s)	Year	Purpose	Algorithm	Dataset	Output	Merits	Demerits
Sangeetha et al. [62]	2023	PsD Diagnosis	CNN	PPMI dataset PsD: 229 HC: 229	Accuracy = 96%	Preprocessing done and various performance metrics considered	-
Cui et al. [61]	2022	Classification of PsD and HC	Resnet18 + Support Vector Machine	PPMI dataset	Accuracy = 98.66%	Feature fusion improves classification performance	-
Monte-Rubio et al. [63]	2022	Parameters from multiple sites to harmonize MRI clinical data for classification of PsD	Weighted HARMonization Parameters (WHARMPA)	PPMI dataset PsD: 216 HC: 87	Balanced accuracy = 78.60%; AUC = 0.90	WHARMPA encodes global site-effects quantitatively with simple implementation	Unbalanced dataset used,
Hathaliya et al. [64]	2021	To classify PsD and HC patients	Stacked ML model	PPMI dataset	Accuracy = 92.5%, Precision = 98%, F1_score = 98%, Recall = 97%	Detects PsD and measures the disease progression in PsD patients	-
Vyas et al. [5]	2021	Detection of PsD using 3D CNN and compare with the 2D CNN	3D and 2D CNN	PPMI database	Accuracy = 88.9%	Voxel-based morphometry usage is very accurate	Manual feature extraction
Sivaranjini and Sujatha [57]	2021	Detection of PsD	Transfer learning (TL), AlexNet pre-trained model	PPMI MRI images	Accuracy = 88.9%	Improved efficiency of the model using transfer learning	Only one slice of brain image is used
Mangesius et al. [56]	2020	Classification of PsD, MSA and PSP	Decision Tree algorithm	-	Accuracy of classification PsD = 83.7%	Distinguishes PsD, MSA, and PSP with very high accuracy	Does not classify HC and PsD
Chakraborty et al. [60]	2020	Detecting PsD	3D CNN model	MRI scans of 406 subjects from PPMI database	Accuracy = 95.29%, Average recall = 0.943, Precision = 0.927, F1-score = 0.936	The maximum focus was on the substantia nigra region to predict PsD as it is the most-affected part of brain	Specific subcortical structures should be considered

hyperintensity based on MRI data [31]. Table 3 summarizes the learnings from the various recent studies carried out on MRI data, and it is concluded that Cui et al. [61] have achieved the maximum accuracy of 98.66% on the PPMI dataset.

2.2. Detection of PsD using PET Imaging

PsD diagnoses are mostly based on the clinical assessments and hence not easily accessible to all. Also, the rate of incorrect diagnoses is substantial; thus, with the advancement in medical imaging technology, automated PsD diagnosis with high accuracy has become significant. Positron emission tomography (PET) is a type of functional imaging method that scans and measures changes in metabolism as well as in physiologic functions such as blood flow, local chemical properties, and absorption. Radioactive chemicals called radiotracers are used in PET. Distinct tracers are utilized for various imaging objectives according to the target process within the body [65]. Dopaminergic and serotonergic PET imaging helps to monitor the progress of motor and nonmotor symptoms and problems as PsD advances. Metabolic, cholinergic, and β -amyloid PET are effective methods for inspecting the cognitive decay in PsD [66]. Dai et al. [67] used PET scans of PsD patients for computer-aided detection. The sole way for the brain to get energy is through glucose uptake; hence, variations in glucose levels in different parts of the brain can indicate the severity of PsD. According to PET scans, PsD patients have a higher glycol consumption in the parietal cortex and a lower one in the frontal brain, which gets worse as time goes on. PET reveals alterations in the affected brain's glucose metabolism, which may lessen the lesion's distribution.

A useful fluorodeoxyglucose (FDG)–PET-based SVM classifier can accurately detect the advancement of dementia in PsD–mild cognitive impairment (MCI) patients with an accuracy of 74.3%, sensitivity of 95%, and specificity of 91% according to Booth et al. [68]. Wu et al. [69] suggested that radiomic features of 18F-FDG PET images serve as an early biomarker for the detection of PsD using SVM producing an accuracy of $90.97\% \pm 4.66\%$. Modi et al. [13] used the VGG16-based CNN system and achieved specificity of 97.5%, accuracy of 84.6%, sensitivity of 71.6%, and precision of 96.7% on a PET dataset from PPMI. Sun et al. [70] proposed a novel DL-based radiomics (DLR) model to diagnose PsD based on FDG PET images with an accuracy of 95.17%. It can be concluded from the above literature that the DLR model achieved the maximum accuracy of 95.17%. PET is an invasive,

time-consuming, expensive, and uncommon imaging modality used to detect PsD. The major success of PET scans is that it is able to identify cellular level alterations in cells with high efficiency [71].

2.3. Detection of PsD using SPECT images

Diagnosing the PsD-associated dopamine degeneration automatically using SPECT scans is comparable to the diagnosis performed by healthcare experts [44]. A simple, yet fast ANN was recommended by Rumman et al. [72], which was trained on 200 SPECT pictures of brains from the PPMI repository. The model could detect PsD with an accuracy of 94%, sensitivity of 100%, and specificity of 88%. Hathaliya et al. [73] diagnosed PsD and its progression to an accuracy of 88% by training the CNN model on SPECT images. Adams et al. [32] worked on the data of 252 subjects from the PPMI repository and validated that adding DAT SPECT scans and UPDRS_III scores to DL models significantly improves the outcome. Magesh et al. [74] used the CNN and the VGG16-based TL scheme to obtain an accuracy of 95.2% using DaTscan SPECT images. Pereira and Ferreira [75] classified the PsD patients from HC up to an accuracy of 65.7%. Wenzel et al. [76] applied the CNN and ImageNet-based TL, semi-quantitative striatal binding ratio (SBR) analysis to come up to an accuracy of 97%. Ortiz et al. [77] used DaTscan images to detect PsD to an accuracy of 95% using a CNN model. Some of the latest research work done to detect PsD using SPECT images is highlighted in Table 4, specifying the pros and cons of each. H. Khachnaoui et al. [54] reviewed various techniques to diagnose PsD using SPECT scans and concluded that hand-crafted ML algorithms and DL are an active research field. It is observed that Wenzel et al. [76] has achieved the highest accuracy of 97% in identifying PsD on the PPMI dataset. Also, the SPECT scan is found to identify PsD at an early stage [78].

2.4. Detection of PsD using Speech

Speech data are used for PsD identification as the speech defects occur at the early stages of the disease [79]. According to Yadav et al. [28], speech deficits in PsD produce symptoms such as decline in the vocal tract volume, diminished intensity of speech and the pitch-range, reduced tongue flexibility, deterioration in quality of speech, irregular pronunciation, and improper halts in speech. The test results show that the DT group effectively evaluated PD and

Table 4: Comparative analysis of techniques used to detect PsD using SPECT images.

Author (s)	Year	Purpose	Algorithm	Dataset	Output	Merits	Demerits
Hathaliya et al. [73]	2022	PsD classification and monitoring of the DT (dopamine transporter) level inside the brain	CNN-based scheme	58692, 11738, and 7826 SPECT images from PPMI for training, validation, and testing, respectively	Accuracy = 88%	Accurate diagnosis of PsD and its progression	-
Adams et al. [32]	2021	DL algorithm to accurately predict motor-based symptoms	CNN model	252 subjects DAT SPECT images	Average absolute error = 6.0 ± 4.8	Enhanced diagnosis of UPDRS_III score with longitudinal data	Features related to PsD are not identified
Magesh et al. [74]	2020	ML-based early detection of PsD	CNN and VGG16-based TL scheme	642 DaTscan SPECT images	Accuracy = 95.2%	Quick diagnosis for PsD	Dearth of conclusive diagnostic tests for PsD
Pereira and Ferreira [75]	2020	To classify PsD, SWEDD, and HC	CNN models	SPECT and MRI images	Accuracy = 65.7%	Classifies PsD, SWEDD, and HC subjects	Lower accuracy
Wenzel et al. [76]	2019	Robust classification algorithm to diagnose the dopamine transporter	CNN and ImageNet-based TL, semi-quantitative SBR analysis	645 subjects	Accuracy = 97%	Accurate diagnosis of PsD patient with DT analysis	Trained model with few samples
Ortiz et al. [77]	2019	To classify HC and PsD using isosurface-based feature extraction	CNN model	269 DaTscan images	Accuracy = 95%	Low complexity of the input data	Increases overall system complexity

HC with an accuracy of 94.87%. Agarwal et al. [80] suggested that the extreme learning machine (ELM) approach recognizes PsD and HC with an accuracy of 90.7% and a MCC of 0.81. The proposed method achieved 81.5% accuracy when tested against a separate dataset of PsD patients. The SVM classifier was applied by Haq et al. [81] for the accurate classification of PsD patients and HC. For accurate target classification, the L1-norm SVM feature selection was utilized to choose pertinent and closely related characteristics. Based on the value of the feature coefficient weight, it created new feature subsets from the PsD dataset. The best suitable values for the tuning parameters for the classification model were chosen using the k-fold cross-validation method. An accuracy of 99%, sensitivity of 100%, and specificity of 99% were attained on average by the classifier after 10 folds of cross-validation. Z. Soumaya et al. applied the wavelet transform, and the MFCC coefficients are extracted from a dataset of audio recordings of PsD patients and HC while pronouncing the vowel "a." To accurately classify the sick and healthy people, the KNN classifier is used to give an accuracy of 98.68%. It is observed that larger training data yield more precise results [82]. Karabayir et al. [83] stated that ML can detect PsD accurately using noninvasive and cost-effective speech recordings. Light Gradient Boosting produced 84.1% accuracy as compared to other ML algorithms on UCI-ML datasets comprising 44 speech-test-based acoustic features. Soumaya et al. [84] propose applying the Genetic Algorithm and the classifier SVM on voice recordings obtaining the best accuracy of 91.18%. It minimizes the dimension of the features vector and maximizes the accuracy. Reddy and Alku [79] proposed a non-negative least squares-based exemplar-based sparse representation for the PsD classification approach, which performs better than the traditional ML-based methods by obtaining an accuracy of 82.84% on the PC-GITA PsD dataset and an accuracy of 83.08% on the MDVR-KCL database. From the above literature, it can be concluded that the SVM using the k-fold cross-validation method gives the highest accuracy of 99% on speech recordings.

2.5. Detection of PsD using features from Eyes

Rapid eye movement sleep behavior disorder is an often-overlooked sleep disorder harming 70% of the PsD patients. Saccade, pupil, and blink responses

could be an early biomarker for PsD detection according to Perkins et al. [30]. Stuart et al. [85] also asserted that monitoring of the saccades may serve as a potential noninvasive early biomarker for long-term PsD cognitive decline and identification. Raschellà et al. [86] investigated the use of wrist actigraphy for easy and quick RBD detection in the comforts of home, on 26 PsD patients achieving an accuracy of $92.9 \pm 8.16\%$ using ML classification algorithms. Bek et al. [87] identified that the eye movements disclose subtle repercussions of motion on the emotions processing in PsD. Hence, they compared the realization of static as well as dynamic emotional expressions in PsD using eye-tracking. Accuracy and eye movement measures were analyzed using SPSS. Repeated-measures ANOVAs were used to determine the effects of motion and emotions on the participants. The results imply that the older adults with PsD may use motion differently from healthy older adults when recognizing facial emotions. It can be concluded that the use of AI is still very limited and has good scope for further research in the eye-tracking modality for PsD detection.

2.6. Detection of PsD using Vision-based Gait Analysis

Freezing of gait (FoG), i.e., the inability to move, is a typical gait symptom in PsD. Masiala et al. [88] proposed a deep RNN with LSTM cells to detect FoG in PsD with an AUC score of 93%, specificity of 85%, and sensitivity of 89%. A vision-based PsD detection system can be used to assess the presence of PsD using a feature-weighted minimum distance classifier model. Researchers have applied a variety of technologies such as accelerometers, integrated load sensors in shoes, gyroscopes, inertial measurement units, pressure-sensitive walkways or other laboratory setups, and video data collected by camera, smartphone, or any device in-built with video-recording facility to objectively capture gait parameters. Rupprechter et al. [89] used an ordinal Random Forest classifier that was trained to estimate UPDRS severity scores. It achieved high performance. Computer vision-based modality involves two subtypes, i.e., marker-based, and marker-less. In marker-based, the human body model is constructed manually using sensors to extract relevant features, whereas in marker-less, i.e., the appearance-based modality is that computer vision techniques are used to extract the gait parameters [90, 91]. Kour et al. [90] revealed that the SVM

classifier is analyzed to be the most popular among researchers to effectively classify PsD and HC. Using six-angle features in a marker-based motion capturing system for person recognition, Zahra et al. [91] obtained an accuracy of 99.3% using KNN. In the smart healthcare setting, the gait feature selection from the recorded skeletal points is employed to help the real-time PsD diagnosis. In comparison with the current healthcare systems, Sathya Bama and Bevis Jinila [92] asserted that SVM and ensemble learning-based classification models offer faster prediction and accurate classification. The regions of interest (ROIs) are segmented using an enhanced vision-based approach, and gait parameters—namely, spatiotemporal (SPT), linear kinematic and other body motion features—are assessed using statistical tools. Kour et al. [93] have categorized PsD and HC using ML algorithms such as SVM, KNN, Random Forest, and linear regression. KNN outperformed the other models at three severity levels with an accuracy of 90.06%. Pei et al. [94] presented a temporal PAST fusion model, which enhanced the classification accuracy for both PsD and HC classification and PsD level classification on the PhysioBank dataset with an accuracy of 99.18%. Xia et al. [95] proposed a dual-modal model, with each branch having a convolutional network followed by an attention-enhanced bi-directional LSTM; referred to as DCALSTM. It produced an accuracy of 99.31%. We can summarize that the DCALSTM and the KNN achieved the highest accuracies. Also, the motion capture systems are popular and act as the golden-standard methodology for clinical gait analysis, but pervasive gait analysis in home-based environments using wearable systems including pressure insoles, inertial sensors, and EMG sensors is required [96].

2.7. Detection of PsD using EEG Signals

Bhurane et al. [97] used a time-domain technique for the detection of PsD using EEG. An SVM classifier with the third-degree polynomial kernel is used to diagnose PsD automatically utilizing the interchannel similarity features, correlation coefficients (CCs), and linear predictive coefficients (LPCs). Selected characteristics produced using the feature ranking and principal component analysis (PCA) approaches are used in a progressive feature addition manner. A maximum accuracy of 99.1% is attained. Chawla et al. [98] employed a flexible analytic wavelet transform (FAWT). The EEG signals are first preprocessed and then divided in five frequency sub-bands.

Through the analysis of variance (ANOVA), a number of entropy parameters are calculated from the decomposed sub-bands and rated according to their significant level in identifying PsD. Classifiers such as SVM, logistics, radial basis functions (RBFs), Random Forests (RFs), and KNN are used to determine the appropriate feature sets. KNN gives the best accuracy of 99% on Dataset1 of EEG recordings of 20 PsD and HC, respectively. Wagh and Varatharajah [99] proposed an EEG-GCNN model, which substantially surpasses the human and the ML baselines, with an AUC of 0.90. It captured both the spatial and functional associativity between the scalp electrodes. Coelho et al. [100] identified PsD patients using the Hjorth features extracted from the EEG signals. These features displayed a major difference between the HC and PsD, especially when computed in the frontal, central, parietal, and occipital zones. Supervised ML algorithms, KNN and SVM were used, and SVM showed higher accuracy of 89.56% in the classification. Khare et al. [101] uses EEG signals to present an accurate and robust PsD detection model using smoothed pseudo-Wigner Ville distribution coupled with convolutional neural networks producing the best PsD detection accuracy of 100% and 99.97% for datasets 1 and 2, respectively. But, the shortcoming in this model is that the datasets used comprise very few subjects. It can be observed from the following literature that a few studies have managed to achieve the high accuracy of 99% and above, but it needs to be validated using larger datasets.

2.8. Detection of PsD using Handwriting

None of the techniques to diagnose the PsD at an early stage is completely effective. Hence, extensive research is being carried out to identify newer modalities and improved techniques. An optimized form of the crow search algorithm (OCSA) is therefore introduced by Gupta et al. [102] to detect PsD. The OCSA may be used to accurately predict PsD and assist people in receiving the right care at an early stage. The effectiveness of OCSA's performance on 20 benchmark datasets is commendable, and the outcomes have been contrasted with that of the chaotic crow search algorithm (CCSA). The suggested approach is more stable and discovers an ideal subset of characteristics while optimizing accuracy to 100% and lowering the number of features chosen. Nasser et al. [103] applied noise removal and data augmentation by rotation, flipping, contour and freeze and fine-tuning on the PaHaW dataset and achieved

an accuracy of 98.28% using AlexNet classifier with transfer learning technique and they vouch that the spiral dataset is more efficient for Parkinson's detection. Gazda et al. [29] worked on the PaHaW and HandPD dataset and by applying label-preserving and optimal image transformations and skeletonization, they achieved an accuracy of 94.7% using the CNN. The highest accuracy of 100% is achieved by D. Gupta et al., but it is not validated for the various UDPRS stages.

2.9. Detection of PsD using Facial Expression Recognition

Videos and images of both healthy and PsD patient faces are used as input by Face++. Facial expression characteristics (the amplitude of facial expression and shaking of tiny facial muscle fibers) are extracted using relative positions and positional jitter. When the placements of the essential features are applied, an F1 value of 99% can be attained by using an SVM model for the diagnosis of PsD. Doctors may be able to undertake remote diagnostics using the information to better grasp the disease's current dynamics [104]. Sonawane and Sharma [105] observed that hypomimia is a significant biomarker of PsD and the CNN can diagnose PsD with 85% accuracy. Mattavelli et al. [184] achieved an accuracy of 83.34% by using the SPSS statistical software, who asserted the findings that the facial expression recognition, particularly the fear emotion, is critically impaired by

neurodegeneration in PsD and that it appears before other cognitive impairments. It is observed that efficient training of facial expression recognition models requires large-scale training data, hardware advancements, such as GPUs, and lots of high-quality data. Presently, there is much scope of research in this field [106].

The comparative analyses of the highest accuracies achieved in various modalities in PsD detection are shown in Figure 4.

3. Techniques for Predicting the different stages in PsD using AI

There is no single test for assessing the presence, progression, or cure for the disease as described by Liu et al. [185]. We can track the progression of the disease and activity using modalities found in brain scans, cerebrospinal fluid, plasma, and genes. According to Tsoulos et al. [186] finding the appropriate modality and the stage of progression requires years of experience as a doctor so that proper care and medication can be administered. But, in the absence of such a doctor, that is where DL comes into the picture [5].

Several stages of PsD have been identified based on clinical observations and pathological findings of a progressively advancing neurodegenerative process. There is a risk period before the start of neurodegeneration, which is influenced by hereditary and

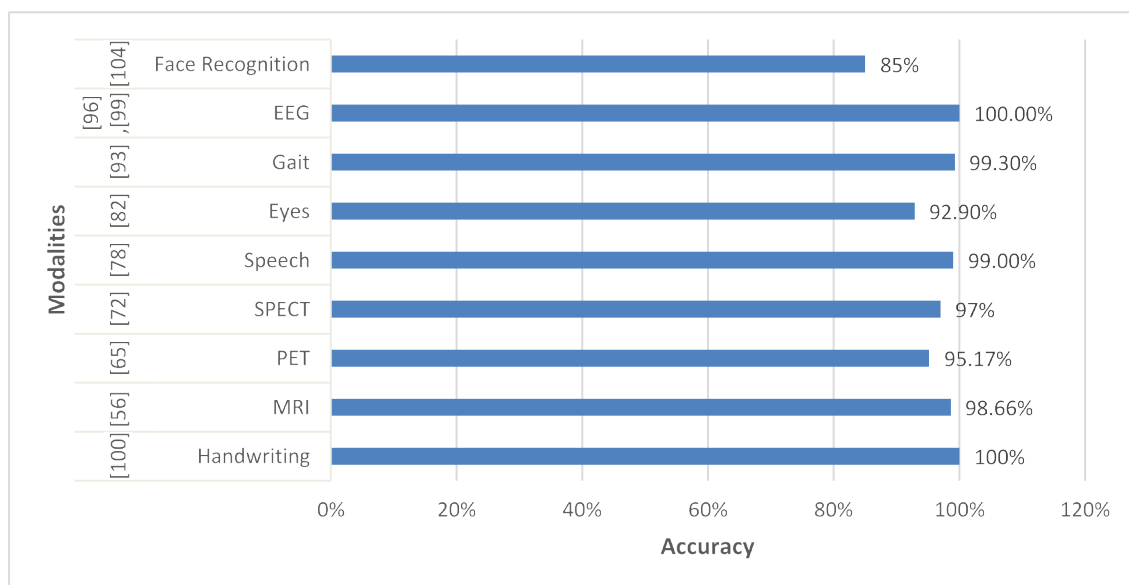


Figure 4: Comparison of the highest accuracies achieved in various modalities in PsD detection.

environmental variables and during which substantia nigra hyper echogenicity can be seen. In the following preclinical period, neurological disease begins to develop before any clinical symptoms or signs become apparent. To accurately identify individuals at each stage of the disease, no markers have yet been developed. The onset of observable neurodegenerative symptoms or indicators characterizes the later prodromal phase. Prodromal phase markers include REM sleep behavior disorder (RBD), autonomic dysfunction, mild motor symptoms, depression (with or without comorbid anxiety), olfactory loss, and pathological imaging markers of the cardiac sympathetic system and the presynaptic dopaminergic system. Despite having a wide range in specificity, these indicators are predictive of clinical PsD. There is strong evidence that the prodromal phase occurs 10–20 years before the clinical diagnosis of PsD. International Parkinson and Movement Disorder Society (MDS) standards characterize the shift to the clinical motor phase of PsD as fully evident bradykinesia with rest tremor and/or rigidity [107]. Table 5 summarizes some of the latest AI techniques applied to detect the PsD progression stages.

3.1. Detection of PsD progression using MRI Data

MRI discloses certain anomalies caused due to the buildup of iron in the brain; hence, it can be used to identify the biomarkers and verify whether the patient suffers from PsD or not. Bhattacharya et al. [187] used a CNN, taking the MRI images of the brain as input, to understand the latent features layer by layer and eventually identifying the required biomarkers for the classification [5]. An incremental SVM has also been used to identify the total-UPDRS and the motor-UPDRS scores. Data dimensionality reduction is accomplished using nonlinear iterative partial least squares, while clustering is accomplished using self-organizing maps. With an accuracy of 94%, CNN can identify PsD and stage it into distinct categories, according to Chakrabarti et al. [108]. They applied min–max normalization on the PPMI database and used a CNN model with five convolutional layers with K-cross field validation to diminish bias.

3.2. Detection of PsD progression using Speech Data

Research has been conducted on the progression of PsD using DL and ML techniques on the telemonitoring dataset. Kathuria et al. [31] asserted that the classification based on the motor UPDRS score performs

better than the classification on the total UPDRS score and thus it can be established as a better measure for severity prediction. The voice data of PsD patients are collected for analysis and normalized into 16 biomedical voice measures using min–max normalization. The DNN identified the two classes—“severe” and “non-severe.” Speech defects in PsD patients are mostly caused by the lowered lung capacity, impaired facial muscle function, impaired laryngeal function, and diminished speaking drive. Many abnormalities in voice and speech result from these changes, including decreased volume, difficulty with volume changes, limited voice modulation (monotonous speech), decreased vocal fold tension, hoarse tone, insufficient articulation leading to slurred speech, and change in speech pace. The condition is known as hypokinetic dysarthria. Phonation, articulation, and prosody defects in speech are caused by injury to the neural pathways and centers that control the nerve impulses of the speech organs. Reduced amplitude and motion tempo of the lips, jaws, and tongue induce alterations in articulation. Reduced accentuation and incorrect consonant articulation lead to babbling. Identification of acoustic features was done using SVR, MLR, and RF. The best performing algorithm was Random Forest Regressor [56]. Sajal et al. [109] combined the tremor and voice data analysis for diagnosing PsD. Wavelet filter banks preserved the tremor signals’ time-localized transient nature and different UPDRS levels were distinguished. KNN outperforms the other models in terms of accuracy, specificity, and sensitivity. Raza et al. [110] used XGBoost on speech signals for monitoring the progression of PsD. Nilashi et al. [111] ascertained that the hybrid of clustering and deep belief network (DBN) with the aid of support vector regression (SVR) for an ensemble of the DBN outputs is capable of relatively better detection of total-UPDRS and motor-UPDRS scores than other learning techniques.

4. Emotional Intelligence

Emotional intelligence (EI) was coined as an ability-based general intelligence in the 1990s. Early dominant work in EI was piloted by Salovey and Mayer (1990), who expressed EI as “the ability to monitor one’s own and others’ feelings and emotions, to discriminate among them and to use this information to guide one’s thinking and actions.” Daniel Goleman defined EI as: “Emotional Intelligence refers to the capacity of recognizing one’s own feelings and those of others for motivating ourselves and for managing emotions well for ourselves and in our relationships.” However, during the past three

Table 5: Comparative analysis of techniques used to detect Parkinson's disease progression detection.

Author (s)	Year	Purpose	Algorithm	Dataset	Output	Merits	Demerits
Kleinholdermann et al. [112]	2021	To predict UPDRS scores	Random Forest regression model	Surface electromyography (sEMG) electrodes data; PsD: 45	Correlation between true and estimated UPDRS values = 0.739	Support the usage of wearables to detect PsD	Other performance metrics not considered
Hssayeni et al. [113]	2021	Severity level estimation (UPDRS-III scores)	Dual-channel LSTM and TL Ensemble	Angular velocity data from inertial sensors; PsD:24	1D-CNN-LSTM used for raw signals and 2D-CNN-LSTM used for time-frequency data with $r = 0.79$, MAE = 5.95	Unobtrusive analysis at home	Fewer subjects
Lu et al. [114]	2021	Detection and severity estimation for PsD patients	OF-DDNet	Video recordings of MDS-UPDRS exams; PsD: 55	AUC = 0.69, F1-score = 0.47, prec. = 0.47, and balanced acc. = 48%	Handles model uncertainty, label noise and small dataset and imbalance issues	-
Raza et al. [110]	2021	Progression of PsD	XGBoost	Speech recordings; l:5875; PsD:42	MAE = 5.09 ± 0.16	Enables continuous monitoring and efficient communication	Uses only voice recordings
Rupprechter et al. [89]	2021	Severity estimation (UPDRS scores)	Ordinal Random Forest classifier	729 videos of gait assessments	Balanced accuracy = 50%, Binary sensitivity = 73%; Binary specificity = 68%	Provides interpretability	3D pose estimation not used

(Continued)

Table 5: Continued

Author (s)	Year	Purpose	Algorithm	Dataset	Output	Merits	Demerits
Abujrida et al. [115]	2020	Detection and severity estimation in walking balance	Wavelet (DWT) domain + fine tree/Boosted trees/RF/ bagged trees/ weighted LR/ KNN/LDA, cubic SVM	Signals from gyroscopes, accelerometers, demographics, and lifestyle data PsD:152, HC:304	Bagged trees Acc = 95%, Prec = 95% AUROC = 0.92 RF: Acc = 93%, Prec = 92% AUROC = 0.97;	Large no. of participants, and amalgam of frequency, time, and statistical features with sway area and lifestyle parameters too	Lack of signal segmentation strategies
Mehrbakhsh Nilashi et al. [111]	2020	Remote tracking of PsD progression	DBN with SVR	Parkinson's telemonitoring dataset; i: 5875	Average output for testing and training sets are 0.521 and 0.537 respectively for RMSE in detecting motor-UPDRS	Supervised and unsupervised learning techniques used	Feature selection techniques are not used
Li et. al. [116]	2019	Diagnosis and severity (H&Y scores) estimation	Random Forest regression	Acceleration and angular velocity signals; PsD:13 HC:12	MAE = 0.166, r = 0.97	Records user's motion information unobtrusively	-
Buongiorno et al. [117]	2019	Detection and severity rating of PsD	ANN and SVM	Postural and kinematics parameters from MS Kinect v2 sensor; PsD:16 HC:14	ANN: Acc. = 95%, SVM: Acc. = 81%, Spec = 78%	Low-cost and easy and fast setup	Only mild vs. moderate severity is measured
Yoon et al. [118]	2019	PsD Severity estimation (UPDRS 0–176 scores)	TL	Phonation and speech recordings; PsD:42	MAE = 2–3 Approximately	Recording done at home, and better accuracy	-
Grammatikopoulou et al. [119]	2019	PsD Severity estimation	Parallel two LSTMs trained with raw joint-coordinates and the combined line distances	Skeletal features of MS Kinect v2 RGB videos; PsD (advanced stage): 12 and PsD (initial stage):6	Acc. = 77.7%	-	Very few subjects, only 2 stages

decades, two fundamentally separate types of EI—often referred to as “trait EI” and “mixed model EI” [120] and a variety of psychometric processes to evaluate these forms have arisen. There are already more than 30 frequently used EI measurements available. A relatively expansive EI literature, blended terminology, and numerous published measures challenge people external to the field [121]. Ability EI originated to relate to a person’s theoretical knowledge of emotions and their functioning, whereas trait EI concerns a person’s perception of their emotional and social efficacy using questionnaires, etc., that quantify the typical behaviors in emotion-relevant situations. The difference between ability EI and trait EI as proposed by Pérez et al. [122] was based solely on the fact that the measure was an assessment of maximal performance, i.e., ability EI, or a self-report questionnaire, i.e., trait EI.

4.1. Dimensions of EI

- **Self-Awareness**—It means recognizing a feeling as it comes. People with greater certainty about their feeling are in better control of their lives.
- **Self-Regulation**—It refers to the ability to manage own emotions and impulses. Thoughtfulness, patience, self-control over impulsive urge, and comfort with ambiguity and change are the major traits. A self-regulated person does not panic and can manage the emotions quite well.
- **Self-Motivation**—Whenever there is a need, there is tension and whenever there is tension, we are motivated to settle the tension and achieve some goal. Emotional self-control is especially important to achieve the goal. If we stay focused and maintain attention, it aids in achieving our goal.
- **Empathy**—It is the ability to put yourself in other’s shoes. It is particularly important as the world is getting too self-centered and materialistic. People high in this dimension can understand other’s needs and wants.
- **Social Skills**—The art of building relationships is largely affected by the skill of managing emotions. The key qualities required are communication, organization, political skill, vision, and cognitive and interpersonal skills.

4.2. Emotional Intelligence-assessment measures

Any characteristic used to measure human intelligence must adhere to the rules of psychometrics, the study of psychological assessment. The EI

assessment must show that it is capable of more than just capturing data on personal attributes or other capabilities. Three techniques are frequently employed to evaluate EI:

- Self-report assessments

The self-report approach is the earliest identified and is the most generously used one due to its ease of application and scoring. Here, the individuals rate themselves, by agreeing or disagreeing with a set of questions. These assessments are beneficial for understanding your perception about your own intelligence and, hence, can be used as a measure of your self-image. However, EI comprises various skills; and these skills are best evaluated by the ability assessments. Sometimes, its effectiveness may be questionable as the person could be biased for his own self.

- Other-report assessments

Since we may be uncertain about our level of EI and how our own emotional states affect others, evaluations based on other people’s reports or Observer Ratings rely on others to gauge your EI. Commonly, the 360-degree instrument is used for it. People who frequently communicate and collaborate with each other are asked to rate each other’s EI. But, since the other person might be biased against you, this might not be a legitimate argument either. Other reports may therefore be biased, but they offer important knowledge and highlight the difference between your own perception and that of others.

- Ability-based assessments

These assessments overcome the threats originating from the former approaches. The pioneer ability-based assessment, the Multi-factor Emotional Intelligence Scale (MEIS), was devised in 1998. This method allowed participants to assess their set of talents or abilities that sum up their EI level. With ability-based or competency-based tests, there is no single appropriate answer. Emotions differ according to specific situations, and each individual responds differently to each context. A consensus study is used to select the best potential solution. The researchers evaluate and ascertain how frequently the respondents choose each of the rating responses. Six fundamental workplace attitude abilities are captured via competency-based assessments such as the Genos model:

- Self-management
- Self-awareness
- Authenticity
- Awareness of others
- Positive influence
- Emotional reasoning

These assessments help individuals comprehend how well they demonstrate self-awareness, empathy, the genuine expression of their feelings, control their emotions in front of other people, build a culture of openness and susceptibility, etc. The Genos model and assessments can be carried out virtually and come with comprehensive and visually appealing findings as well as suggestions for future improvement.

5. Techniques for Predicting the PsD using EI

Emotion and cognition changes in PsD cases are early symptoms of PsD; hence, this area of research is gaining interest, but is still an under-explored area. Using EI in patient populations can open avenues for numerous applications such as trainings to emote properly, evaluating the effects of treatment, and identifying the at-risk individuals [123]. The techniques to diagnose PsD using different modalities, which have been explored till date, are given below.

5.1. Predicting PsD using Emotional EEG Signals

PsD patients apprehend arousal better over valence, and among emotional categories, disgust, fear, and surprise less accurately, while sadness is most accurately identified. Near-perfect PsD vs HC identification is achieved via emotional EEG responses. Overall, the

study shows that (a) analyzing implicit reactions alone allows (i) the discovery of valence-related deficits in PsD patients and (ii) the differentiation of PsD from HC and (b) emotional EEG analysis is an ecologically legitimate, efficient, simple, and long-lasting tool for PsD detection in comparison to expert assessments, self-reports, and resting-state analysis [124]. Another study found that while PsD did not demonstrate any behavioral abnormalities, it did display deficiencies in the processing of emotional data as measured by neurophysiological tests. This demonstrated the potential for distributed spectral power in various frequency bands to offer insightful data on emotional processes in PsD patients. When compared to HC, PsD patients showed lower overall relative delta, theta, alpha, and beta power as well as lower alpha, absolute theta, and beta power at the bilateral anterior regions as well as greater mean total spectrum frequency in EEG signals over various emotional states. Differences in alpha, theta, and beta power asymmetry indices between the right and left hemispheres were observed in the controls. Patients showed bilateral intrahemispheric alpha power imbalance decrease across all regions. During emotional events, discriminant analysis accurately identified 95.0% of the patients and controls [125].

5.2. Predicting PsD using Facial Emotional Recognition

The CNN is used for PsD diagnosis from facial expressions. The CNN includes convolution layers for identifying features and fully connected layers for PsD detection. The diagnosis capability of various facial emotions obtained the most effective output with an accuracy of 96.5% and an AUC of 95.3%. This technique is a noninvasive and reliable method for the diagnosis of PsD [126].

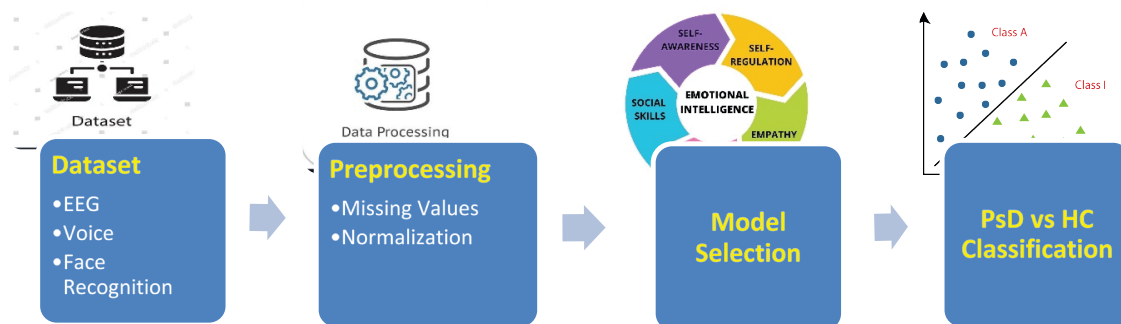


Figure 5: Process flow diagram of PsD detection using EI.

5.3. Predicting PsD using changes of emotions during speech

PsD can be detected by the analysis of emotion changes during pronunciation-defined speech exercises. Using the XGBoost, a balanced accuracy of 69% was attained on the speech data of a Czech tongue twister. It can be employed in clinical practice because the features are explicable. In this research, fear has been found to be the most effective emotion for PsD identification. From a statistical perspective, the characteristics reflecting variations in how people expressed anxiety at the time were extremely important for the PsD diagnosis [22].

Figure 5 presents the process flow of PsD detection using EI. Step 1, the datasets can be taken from a secondary or primary source. Preprocessing techniques such as missing values imputation, normalization, etc. are applied to the raw data. An appropriate model is selected that performs the task of PsD vs HC classification while improving the accuracy, specificity, and sensitivity performance metrics. A comparative analysis of PsD detection using EI is presented in Table 6. It is observed that Parameshwara R. et al. obtained the highest accuracy of 99% using KNN and Naïve Bayes Classifiers on EEG signals using EI.

6. Typology of Modalities and Datasets

Researchers all around the globe are working hard to identify a specific biomarker for PsD detection. For this purpose, various modalities such as ECG, EEG, MRI, etc., are evaluated. Biomarkers such as DNA, RNA, RBC distribution width, cystatin-C, C-reactive protein, urea, vitamin D, and gamma glutamyl transferase are associated as hazardous factors with a multitude of diseases [130, 131].

6.1. Modalities

Speech, handwriting, gait, and imaging modalities such as MRI, PET, SPECT, eyes, facial expression recognition, EEG signals, etc., are the various modalities for PsD detection. Figure 6 defines the taxonomy of PsD detection based on the most widely used modalities.

6.2. Datasets

Datasets have an essential and foundational function in AI-based learning and diagnosis systems.

Table 6: Comparative analysis of PsD detection using emotional intelligence.

Author (s)	Year	Purpose	Algorithm	Dataset	Output	Merits	Demerits
Pegolo et al. [127]	2022	Measuring hypomimia to distinguish between PsD and HC and to classify the emotions	Random Forest showed best results	Frontal face videos; PsD:50 HC:17	AUC values from 94.3 to 91.6; F1 scores from 76.2 to 71.5	A stand-alone methodology for quantifying the degree of impairment	Imbalanced data
Parameshwara et.al. [124]	2022	PsD detection	KNN and Naive Bayes Classifiers	EEG data; PsD: 20 HC: 20	Acc = 99%	Non-invasive use of emotional EEG signals	Inadequate number of PsD patients with mild-to-moderate severity, relation in EEG and motor symptoms is unknown

(Continued)

Table 6: Continued

Author (s)	Year	Purpose	Algorithm	Dataset	Output	Merits	Demerits
Dar et al. [20]	2022	EEG based emotional classification	ELM (extreme learning machine)	PsD dataset, AMIGOS, and SEED-IV datasets	Acc = 83.2%	Implemented on cross-subject and cross-dataset, robust to real-time applications	Datasets with fewer number of subjects
Anusri et al. [126]	2021	Early detection of PsD using facial emotional intelligence	Alexnet and VGG16	PPMI dataset PsD:188 HC:50	Acc = 96.5%	Early diagnosis justified using different performance metrics	Imbalanced dataset
Sechidis et al. [128]	2021	Assessment of PsD speech characteristics	Machine learning	Speech dataset	NA	Main focus is on happy and sad emotion only	No dataset of PsD and HC exists thta has labeled emotions
Justyna and Burget [22]	2020	Analysis of Emotional changes during quick pronunciation exercise	XG Boost	Video recording of speech exercise PsD:70 HC:45	Acc = 69%; sadness and surprise are negatively correlated with PsD	Seven emotion classes are considered	Low accuracy
Yuvaraj et al. [125]	2014	To discriminate PsD patients and HC while emotional information processing	Discriminant analysis	EEG scan; PsD: 20 HC: 30	Acc = 95%	Distributed spectral powers in EEG frequency bands supply information about emotion processing in PsD patients	Fewer number of subjects
Zhao et al. [129]	2014	Classification of emotions through speech in PsD patients	Naïve Bayes, Random Forest, and SVM	Recorded speaking short statements	Acc = 3.33%	First automatic classification of emotions in the voice of PsD patients	Low Accuracy

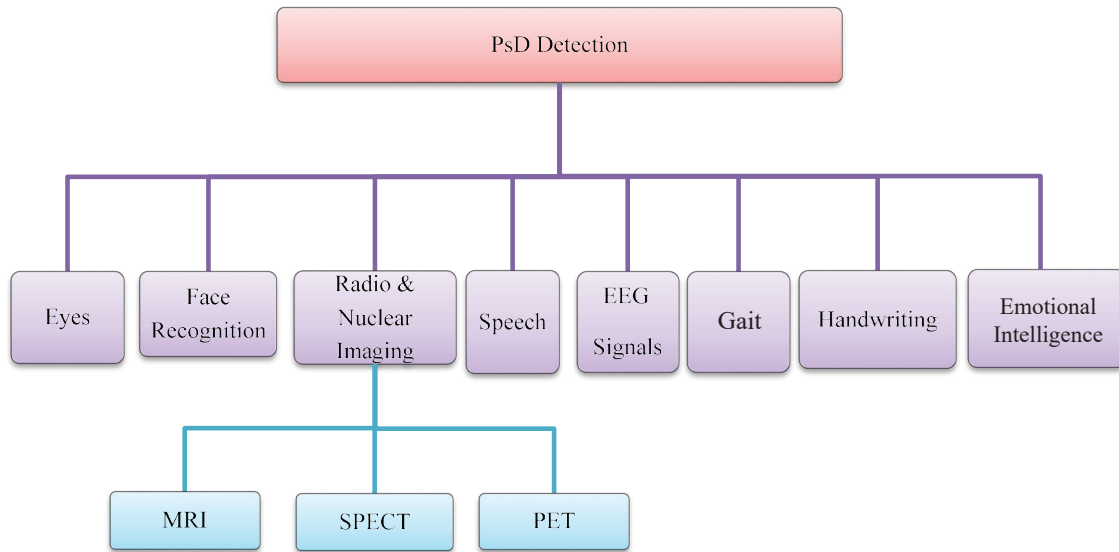


Figure 6: Taxonomy for detection of Parkinson's disease according to different modalities [42, 48].

Various forms of data inputs for distinguishing the PsD patients from HC are reported in the literature. Over the years, a variety of datasets have been compiled and made accessible to professionals and aspiring AI and ML researchers for the purposes of analysis and experimentation. This section provides a comprehensive overview of the public and private PsD datasets available for each of these dataset categories.

6.3. Public Datasets

Several research studies have been carried out for the collection of Parkinson's datasets based on various modalities. Publicly available datasets promote research extensively as the data are free to use for all and are presented in Table 7.

6.4. Private Datasets

Private datasets fill a major void in the research datasets by offering desirable properties in terms of modalities, constraints, and quality at the same time. Table 8 presents all the private datasets in detail.

7. Research Challenges

As per our literature survey, certain research gaps that need special attention have been identified and considerations for developing techniques for detecting the occurrence of PsD have been undertaken.

i. Fewer benchmark datasets to detect PsD patients and their emotional states

Detection of PsD along with their emotional states is a recent innovation and is thus far from being a fully developed research area. The development of standardized benchmark datasets is an extremely vital component of every automated diagnostic model. Due to the absence of standard datasets for PsD detection, especially in emotional data, researchers have constructed their private datasets under varying laboratory-controlled environments, which are further not suitable for all AI models. These datasets moreover do not contain any standard features for assessing an algorithm's efficacy. Extensive research should be directed toward the creation of accurate, standardized, and publicly accessible datasets that will aid researchers in validating their proposed models [90]. Any attempts made in this regard will go a long way toward advancing research for automated PsD detection.

ii. Fewer number of subjects and imbalanced datasets

The cardinality of the dataset is one of the major issues in the detection of PsD. Due to the lack of larger number of PsD patients' data, it is difficult to train DL models effectively. Access to PsD patients and their active participation are a challenge. Gender disparity, unmatched demographic data, and severity level ignorance led to imbalanced datasets [8, 90]. The

absence of easy dataset-acquisition technologies also makes it difficult to automatically classify healthy and terminally ill individuals. As a result, accurate and efficient classification continues to be a problem [34].

iii. Nonavailability of automated models for PsD Detection using EI

A model that can diagnose PsD using the EI data of the patients is still unavailable. AI is applied to modalities such as EEG and facial expression recognition to recognize the emotions of a person and, in turn, also detect PsD, but they are limited in terms of accuracy and generalizability.

iv. Variability in expressing emotions

Effectiveness of the remedial treatment toward emotional impairment in PsD is a highly challenging issue, as patients typically lack the ability to determine and also communicate to the therapists their exact personal emotions to receive successful treatment. Factors such as environment, mood, and socio-cultural background also influence the variability in the emotions of a person. Hence, EI could be a game changer for gaining deeper understanding about the emotions of the patients and correspondingly aid in diagnosis and treatment too.

v. Overlapping symptoms of PsD with various other diseases

PsD has symptoms that are similar to essential tremor, dementia with Lewy bodies, corticobasal syndrome, MSA, normal pressure hydrocephalus, and progressive supranuclear palsy [70]. Hence, it is very difficult to get 100% accuracy with a single modality; thus, the need for a PsD detection model using hybrid modality.

vi. Confidentiality

Enormous data are required for training and testing the AI models. So, datasets of PsD patients from various origins are collected and used for the detection of the disease. This raises issues like security and confidentiality. The privacy of the patients should be maintained so that the vulnerability of the patients' sensitive personal data is not exposed to discrimination.

vii. Lack of interpretability of models

Most of the effective AI models come from extremely complicated or ensemble models, which are

notoriously opaque (black-box). Medical professionals adopt evidence-based practice, which integrates the most recent research with clinical expertise and patient situations. The use of an unintelligible AI model in medicine creates moral and legal questions as there is no justification or reasoning behind the decisions made. Therefore, ML interpretability or explainability is a crucial requirement for using such techniques in high-stakes situations that occur in industries such as banking or medicine. The goal is to curtail the adjustment between model accuracy and interpretability by inventing techniques that result in clear and understandable AI models [180].

viii. Manifold modeling

As PsD is a complicated disorder, its diagnosis in the early stages must carefully consider multiverse data. Traditional computational tools face substantial challenges in determining how to incorporate disparate datasets such as clinical, genomic, genetic, social demography, neuroimaging, and environmental exposure data. The simplest method for dealing with assorted data is to convert every type of data into a vector format before it is processed and then cautiously concatenate all of the vectors specific to each subject into disease diagnosis and phenotypic prediction.

ix. Lack of implementation of Data Aggregation

Large PsD datasets are few in number, and various researchers and hospitals throughout the world produce disparate data, which cannot be combined for our benefit as they are incompatible. Federated learning (FL) allows the distributed computation of ML models on various distinct, isolated data sources, without transferring any particular data to a centralized location thus, maintaining data anonymity and security [181, 182]. FL can prove to be beneficial in smart healthcare applications for both the heterogeneous and homogeneous data [183]. To address important challenges such as data privacy, data access rights, data security, and access to heterogeneous data, FL enables numerous researchers to develop a single, strong ML model without sharing any data. But, still no work like this has been done in the field of PsD.

x. Lack of validations using various performance metrics

Most of the researchers have validated their models on the basis of accuracy only. However, metrics

Table 7: Comparative analysis of PsD public datasets.

Dataset Name	References	Instances and subjects	Attributes	Datatype	Merit	Demerit	Used Device /Sensor
Parkinson's Disease dataset	[132–134]	I-197, PsD:23, HC:8	23	Speech signal	No missing values	Fewer instances, unbalanced and only suitable for binary classification	Recorder
PhysioNet/Vertical Ground Reaction (VGRF)	[55, 135–138]	PsD:93, HC:72	-	Multi-channel recordings from force sensors	Disease severity is also monitored	-	8 sensors under each foot
PPMI database	[5, 108, 139, 140]	PsD:600, HC:400	-	MRI Images, DaTscan, PET, etc.	Most widely used database of PsD datasets	Imbalanced dataset	Tesla scanner
Parkinson's telemonitoring/Oxford PsD Telemonitoring Dataset	[141, 142]	I-5875, PsD: 42	26	Voice recordings	No missing values	Suitable only for binary classification	Telemonitoring device
Daphnet Freezing of Gait Data Set	[134, 143, 144]	I-237, PsD:10	9	Gait monitoring data	Realistic activity monitoring	Very few subjects in dataset	Acceleration sensors at the hip and leg
Parkinson Dataset with replicated acoustic features dataset	[141, 145, 146]	I-240, PsD:40, HC:40	46	Voice recording replications	No missing values	ML cannot be applied	Recorder
Parkinson Speech Dataset with Multiple Types of Sound Recordings Dataset	[147, 148]	I-1040, PsD:20, HC:20	26	Sound recordings	Useful for classification as well as regression	Fewer subjects	-
Parkinson's Disease Classification Data Set	[149–152]	I-756, PsD:188, HC:64	754	Speech recordings	Features extracted through many speech signal processing algorithms	Imbalanced dataset	Microphone

(Continued)

Table 7: Continued

Dataset Name	References	Instances and subjects	Attributes	Datatype	Merit	Demerit	Used Device /Sensor
Parkinson Disease Spiral Drawings Using Digitized Graphics Tablet dataset	[153, 154]	7 I:77, PsD:62, HC:15	7	Handwriting-Spiral drawings	Three different kinds of tests to collect data	Fewer subjects, and imbalanced dataset	Wacom Cintiq 12WX graphics tablet
NewHandPsD dataset	[155, 156]	PsD:31, HC:35	-	Handwriting	Balanced dataset	Fewer subjects	Smart pen (BiSP)
PC-GITA Spanish dataset	[157, 158]	PsD:50, HC:50	-	Voice samples	A well-balanced corpus with respect to age and gender	Recorded under optimal recording conditions	Fast Track C400 sound card and a Professional microphone
NTUA Parkinson Dataset	[158, 159]	I:44007, PsD:55, HC:23	-	MRI and DaTscans	Sufficiently large dataset	Imbalanced dataset	-
Neurovoz	[160–162]	PsD:47, HC:32	-	Spanish speech samples	No Noise	Fewer subjects	AKG C420 headset microphone coupled with a preamplifier
OpenfMRI	[163, 164]	37 studies with 1411 subjects	-	MRI and EEG scans	NIFTI format	-	-
PsD-BioStampRC21 dataset	[165, 166]	PsD:17, HC:17	-	wearable sensor accelerometry data	24-hour monitoring data	Fewer subjects	MC 10 BioStamp RC sensors
Italian Parkinson's Voice and Speech	[167, 168]	PsD: 28, HC: 37	-	Voice and Speech data	-	Fewer subjects	-
Physio Bank	[94, 169, 170]	PsD: 93, HC:73	-	Database of Gait	Multichannel recordings, demographic information, and disease severity	-	Ultraflex Computer Dyno Graphy, Infotronic Inc. sensors
Neurocon	[171, 172]	I: 303, PsD: 27, HC:16	-	T1 and resting-state MRI dataset	Includes both T1 and resting-state scans	Fewer subjects of only initial stage PsD	1.5-Tesla Siemens Avanto MRI scanner

Table 8: Comparative analysis of PsD private datasets.

Dataset/Source/ Author Name	References	Instances and subjects	Attributes	Datatype	Merit	Demerit	Used Device /Sensor
Hospital Universiti Kebangsaan Malaysia, Kuala Lumpur	[124]	I: 1440 PsD: 20 HC: 20	-	EEG signals	Non-invasive detection	Fewer subjects	14-channel wireless Emotiv Epoc headset
Wearable Bio mechatronics Laboratory at Western University	[173]	I: 409,380 PsD: 13	-	Video recordings while performing the trials	Resting, postural, and action tremors are monitored	-	Wearable assistive devices
Tuncer T.	[174]	I:756 PsD:188 HC:64	-	Vowel voice recordings	High classification performance even with heterogeneous dataset, less expensive	Imbalanced dataset	Microphone
M. Lu	[114]	I:200 PsD:55	-	Video recordings of MDS-UPDRS exams	Both gait and finger tapping experiments are performed	Less data	-
Pacific Parkinsons Research Centre (PPRC)	[175]	PsD:20 HC:21	-	Resting EEG	High Performance metrics	Fewer subjects	64-channel EEG cap and a Neuroscan SynAmps2 acquisition system
Iakovakis et al.	[176, 177]	PsD:18 HC:15	913	Keystroke dynamics information	Combined discriminative potential of enriched keystroke variables	Fewer subjects	Touchscreen smartphone
Hospital at Sun Yat-sen University	[178]	I:7000 PsD:40 HC:30	-	EEG signals	Large number of instances	Fewer hyperparameters	64-electrode Geodesic Sensor Net (Electrical Geodesics Inc.)
RMIT University, Melbourne, Australia	[179]	PsD:41 HC:40	-	Voice samples	all recordings were normalized	Fewer number of samples	Apple iPhone 6S plus

such as sensitivity, specificity, F1-score, and RMSE are equally important and could present more clarity [33, 44].

8. Conclusion

As evident through research, there has been a concerning rise in the number of Parkinson's patients across all age groups, especially, the elderly, and the acute symptoms of the disease impair the life quality exponentially gradually. The absence of a single reliable test for diagnosing this neurological disorder, and the complete dependency on the doctors influenced the development of various AI techniques to diagnose PsD. The present paper provides a descriptive evaluation of the state-of-the-art AI- and EI-based techniques for PsD detection and diagnosing the disease severity. It also summarizes the disease symptoms, various modalities identified for research on PsD, public and private datasets available for research, the current open research challenges, and future perspectives. The AI systems are trained to categorize the input data into predefined labels or classes as they learn from the patterns in the vast amounts of historical data. EI uses the self-report assessments, observer ratings assessments, and ability-based assessments to assess the EI of a person. Until now, no study has incorporated the direct use of EI scores to classify PsD from HC. But researchers are extensively identifying models to identify the emotions of the people and thereby classifying them as healthy or a patient on the basis of these emotions. Hence, they are basically applying AI to the varied emotions of a person to identify any unusual behavior. The EI technique is highly suitable for PsD patients as by detecting the emotions of a person, the caretakers can handle the patients in a better manner by identifying their real needs while identifying the disease too. So, the applicability of EI is much more. We conclude by emphasizing on the importance of early onset detection of the disease and the role of emotions in the life of a PsD patient, its deficit, and how a feasible diagnostic system established on noninvasive identification of psychological discomposure can promote noninvasive treatment and enhance the quality of life for PsD patients. It is observed that the MRI, speech, and EEG modalities have each shown promising accuracy of about 99% upon using the SVM classifier. A 100% accuracy is achieved in the EEG and handwriting modalities using CNN and OCSA, respectively. An accuracy of 95% has been achieved in PsD progression detection using Bagged Tree, ANN, and SVM.

The highest accuracy of 99% is achieved using KNN and Naïve Bayes Classifiers on EEG signals using EI. AI and EI techniques produce accurate and comparable results on the EEG dataset for the PsD detection. Also, the most widely used dataset is the PPMI database.

Factually accurate and early PsD detection is very crucial. Hence, in future, incorporating ensemble learning strategies, federated learning, and TL in PsD diagnosis can improve the performance of AI-based PsD detection techniques. Automated emotional intelligent models could further pave way for the early detection and curing the PsD patients judiciously. An efficient model to classify PsD from other diseases with overlapping symptoms while validating through various performance metrics is an open challenge and the future scope of our research. Using IoT technology and wearable devices to collect psychometric data of patients can open newer avenues to diagnose PsD. Also, all the AI-based detection techniques are not capable to elaborate on the basis of the classification; hence, explainable AI could be a fulfilling amendment capable of providing valid reasoning to the results too.

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Conflict of Interest

Author declare that there is no conflict of interest.

Data Availability

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