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Review

A Comprehensive Review on AI-Enabled Models for Parkinson's Disease Diagnosis

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Abstract: Parkinson's disease (PD) is a devastating neurological disease that cannot be identified with traditional plasma experiments, necessitating the development of a faster, less expensive diagnostic instrument. Due to the difficulty of quantifying PD in the past, doctors have tended to focus on some signs while ignoring others, primarily relying on an intuitive assessment scale because of the disease's characteristics, which include loss of motor control and speech that can be utilized to detect and diagnose this disease. It is an illness that impacts both motion and non-motion functions. It takes years to develop and has a wide range of clinical symptoms and prognoses. Parkinson's patients commonly display non-motor symptoms such as sleep problems, neurocognitive ailments, and cognitive impairment long before the diagnosis, even though scientists have been working to develop designs for diagnosing and categorizing the disease, only noticeable defects such as movement patterns, speech, or writing skills are offered in this paper. This article provides a thorough analysis of several AI-based ML and DL techniques used to diagnose PD and their influence on developing additional research directions. It follows the guidelines of Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR). This review also examines the current state of PD diagnosis and the potential applications of data-driven AI technology. It ends with a discussion of future developments, which aids in filling critical gaps in the current Parkinson's study.

Keywords: Parkinson's disease; computational intelligence; deep learning; diagnosis; machine learning; smartphone; augmented reality; virtual reality

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1. Introduction

PD is a chronic movement illness that impacts the whole body. Around the world, 7 to 10 million people are suffering from PD [1]. By 2030, there will be 8.7 million to 9.3 million instances of Parkinson's disease worldwide, according to the most current forecast from the European Parkinson's Disease Association [2]. The impact of PD on voice patterns is a symptom that has received little attention. In this disease, the range of speech phonation motions (lips, tongue, and jaw) is limited (hypokinetic), and, as a result, vowels become centered, i.e., formants with particular rates have lower rates, whereas formants with low rates have higher frequency ranges [3]. In addition to movement abnormalities, Parkinson's is associated with non-motor symptoms, such as restlessness at night, tiredness, and so on. It was recently discovered that almost all patients have non-motor symptoms in addition to the traditional motor symptoms, which vary depending on the severity of the disease [4]. Tremor, stiffness, postural instability, and bradykinesia are all motor signs of PD caused by insufficient dopamine signaling caused by dopamine-producing neurons being destroyed in the substantia nigra portion of the brain [5].

There is no solution for the illness, while therapy for its motor symptoms is available. There are currently just a few diagnostic tests for Parkinson's. When it comes to treatment options, the stage and severity of Parkinson's are critical factors to consider. The topic of forecasting Parkinson's symptoms and their severity is also examined. Both of these responsibilities are intended to aid decision support systems in assessing patients' health, reviewing current therapies, and, if necessary, recommending a new therapy plan [6]. This paper focusses on different indicators of parkinsonism. We have also focused on various ML and DL techniques applied in various research studies related to this disease . Table 1 presents the list of abbreviations used in this manuscript along with their full form.

Table 1. List of abbreviations used in this manuscript along with their full form.

Acronym	Definition
A3C	Asynchronous Advantage Actor-Critic
Acc	Accuracy
ADAM	A Stochastic Optimization Variant
AD	Alzheimer's Disease
AE	Auto Encoder
ANN	Artificial Neural Network
BFS	Base Feature Selection
CNN	Convolutional Neural Network
DCNN	Deep Convolution Neural Network
DBN	Deep Belief Network
DTW	Dynamic Time Warping
DNN	Deep Neural Network
DRL	Deep Reinforcement Learning
EHR	Electronic Health Record
ELM	Extreme Learning Machine
ELEP	English Language Empowerment Programme
FD	Future Directions
FNS	Fuzzy Neural System
FC-RBF	Fully Complex-Valued Radial Basis Function Networks
FoG	Freezing of Gait
GA	Genetic Algorithm
GRU	Gated Recurrent Unit
HC	Health Control
HD	Huntington's Disease
ICDs	Impulse Control Disorders
IH	Idiopathic Hyposmia
LR	Logistic Regression
LSTM	Long Short-Term Memory
LSVM	Lagrangian Support Vector Machines

Table 1. *Cont.*

Acronym	Definition
McFCRBF	Meta-cognitive fully complex-valued RBF network
MRI	Magnetic Resonance Imaging
ML	Machine Learning
MSE	Mean Square Error
OC	Open Challenges
OPF	Optimum Path Forest
PD-MCI	PD–Mild Cognitive Impairment
PD	Parkinson Disease
PET	Positron Emission Tomography
PPMI	Parkinson's progression markers initiative
PCA	Principal Component Analysis
RBM	Restricted Boltzmann Machine
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RBF	Radial Basis Function
SAE	Stacked Autoencoder
SVM	Super Vector Machine
SVD	Singular Value Decomposition
TCN	Temporal Convolution Networks
TFR	Time-Frequency Representation
VGFR	Spectrogram Detector and Voice Impairment Classifier (DEEP LEARNING MODEL)
VEGF	Vascular Endothelial Growth Factor
VGRF	Vertical ground reaction force

1.1. Motivation

The assessment and projection of future research paths in the field of AI-based PD diagnosis is the main objective of this survey. Recent studies have only focused on machine learning and deep learning aspects of Parkinson's disease detection. They have been often superficial in their methodology, but, in our survey, we compile it in such a way that it would be useful even for early researchers who are interested in this domain. There is no single paper that has discussed the combination of ML and DL with mobile-based technologies. This comprehensive study will provide an in-depth analysis of ML and DL models for automated Parkinson's disease identification and to further advocate models as a possible mobile-based application for medical decision support systems.

1.2. Contribution of This Survey

The following is a brief overview of our contribution:

In this study, we looked into the use of ML and DL in diagnosing Parkinson's Disease. We have discussed various datasets related to PD detection and management.

- Review of new techniques such as extreme learning machine, DBN, the deep generative model, and others, as well as older computational intelligence techniques such as Random Forest, ANN, DNN, KNN, and others to identify early traces of Parkinson's disease.

- The studies on ML and DL techniques in PD are summarized in a thorough tabular format. The model, major contributions, and model constraints are all provided in the summary.
- We have also included the latest mobile technology and applications which can be used for assessment as well as for identification of PD. This review explicitly discusses the open challenges and future directions in Parkinson's diagnosis and disease management.

Table 2 presents a comparison of the present review with previous surveys or other similar review articles.

1.3. Survey Methodology

1.3.1. Search Strategy and Literature Sources

This work presents the many research findings and studies on using ML and DL techniques to detect PD that have been published in significant electronic database search engines, including IEEE, PubMed Central, Science Direct, etc. Figure 1 illustrates the search terms used in the database queries. It was observed that the number of studies discussing PD diagnosis using DL techniques has steadily grown in recent years. We used Prisma technique for article selection.

Search String

("artificial intelligence" OR "machine learning" OR "deep learning") AND ("smartphone" OR "augmented reality" OR "virtual reality") AND ("Parkinson Disease diagnosis" OR "types of Parkinson") AND (“open challenges in Parkinson” OR “future work”)

Figure 1. Search terms used in database queries.

1.3.2. Inclusion Criteria

The articles were chosen for inclusion based on their applicability. Only English language articles were considered, and inclusion was based on the originality of the review's topic and the articles' suitability for inclusion. All full-length publications that used ML and DL techniques to treat patients with Parkinson's and related outbreaks were seriously considered for inclusion.

1.3.3. Elimination Criteria

The following items were not considered for this review: editorials, letters, practice guidelines, reports with only abstracts, papers without abstracts, dissertations, theses, short papers (less than five pages), commentaries, preprints, and articles unrelated to the fields of machine learning and health care research. Abstract screening was used for the first phase of exclusion, while full-text and data extraction were used for the second round. The articles were rejected because they were irrelevant, or poorly written. We included ML and DL research papers from 1 July 2006 to 15 October 2022.

Table 2. Comparison with previous surveys/Comparison with other similar review articles (H—High-level discussion, M—Moderate-level discussion, L—Low-level discussion, N—Not available).

Reference	Summary	Shortcomings of the Reviews	ML	DL	OC	FD
Our paper	This research provides a thorough analysis of methods based on AI for PD diagnosis. Different computational-based methodologies for PD prediction are also briefly described.	-	H	H	H	H
[7]	The use of smartphones and tablets to track the individual at home appears to be the most viable path toward understanding PD, according to this report. It also discusses how e-health research kits are continually being improved.	The majority of works utilize signal or graphics information, necessitating some type of AI-supported decision-making system that needs further improvement.	H	N	H	H
[8]	This study's main finding was how frequently CNN was used to diagnose Parkinson's. On the other hand, DNN is applied more often to identify neurogenerative illnesses.	High-dimensional CNNs, such as 2D and 3D-CNN, that would have given reliable findings for big and multimodal neuroimages, have not been deployed.	N	H	H	H
[9]	The risk factors, pathophysiology, and personality characteristics in patients with PD with ICD are the main topics of this review. According to the results, both extrinsic and intrinsic factors play an important role in how behavioral difficulties arise.	Additional prospective studies with bigger sample sizes are required to identify the risk factors causing behavioral alterations in PD patients with ICD.	N	N	N	H
[10]	According to this survey's findings, 90% of patients with PD have a vocal impairment. Using speech datasets, several studies can be conducted to automate the diagnosis of PD.	It does not include extreme machine learning and genetic algorithms which can be incredibly useful for PD detection	H	N	H	L
[11]	Information from 91 studies that investigated the use of neural nets, primarily DL algorithms, for the early identification of Parkinson's disease was collated for this review. The information covered voltage sensor data, biological voice data, and pictures for both PD and HC subjects.	Many different types of disorders can cause PD, each with its own set of symptoms. Therefore, from a clinical standpoint, they have overlooked classifying disorders.	H	H	M	H
[12]	This review's primary goal was to identify existing ML-based work to diagnose PD using handwriting patterns, voice characteristics, and gait datasets. It also sought to identify the most effective method for diagnosing the disease with a high rate of accuracy.	Existence of a dataset imbalance in the study.	H	H	M	L
[13]	They address how ML can help with earlier detection, the interpretation of medical imaging, the discovery and development of new treatments, and much more in this review.	Due to data constraints, the majority of ML pipelines in practice begin with meticulous data curation, which takes time and professional assistance.	H	H	H	M
[14]	This study aims to investigate some information and the status of sensor-based methods for the identification of PD. It also addresses ensemble methods for integrating sensor-based data to create ML models for customized risk prediction.	They do not discuss dimensionality reduction algorithms in ensemble techniques, which would allow the application of several classification models on data spaces for better disease classification.	H	M	H	M
[15]	They did a thorough analysis of 217 research papers that discussed the use of different ML techniques and DNN designs to diagnose PD. They also carefully looked through and examined the researcher's architectural plans.	The discussion about the recent technology is very limited.	H	H	H	M

1.3.4. Results

From Google Scholar, IEEE Xplore, Springer, and other literary sources, a total of 282 distinct articles were obtained; 41 articles were excluded after title and abstract screening. An additional 62 papers were eliminated after a full-text review of the remaining 241 articles, leaving 179 articles for consideration in the final review [16–190]. The results are shown in Figure 2. Figure 3 presents the overall structure of this review.

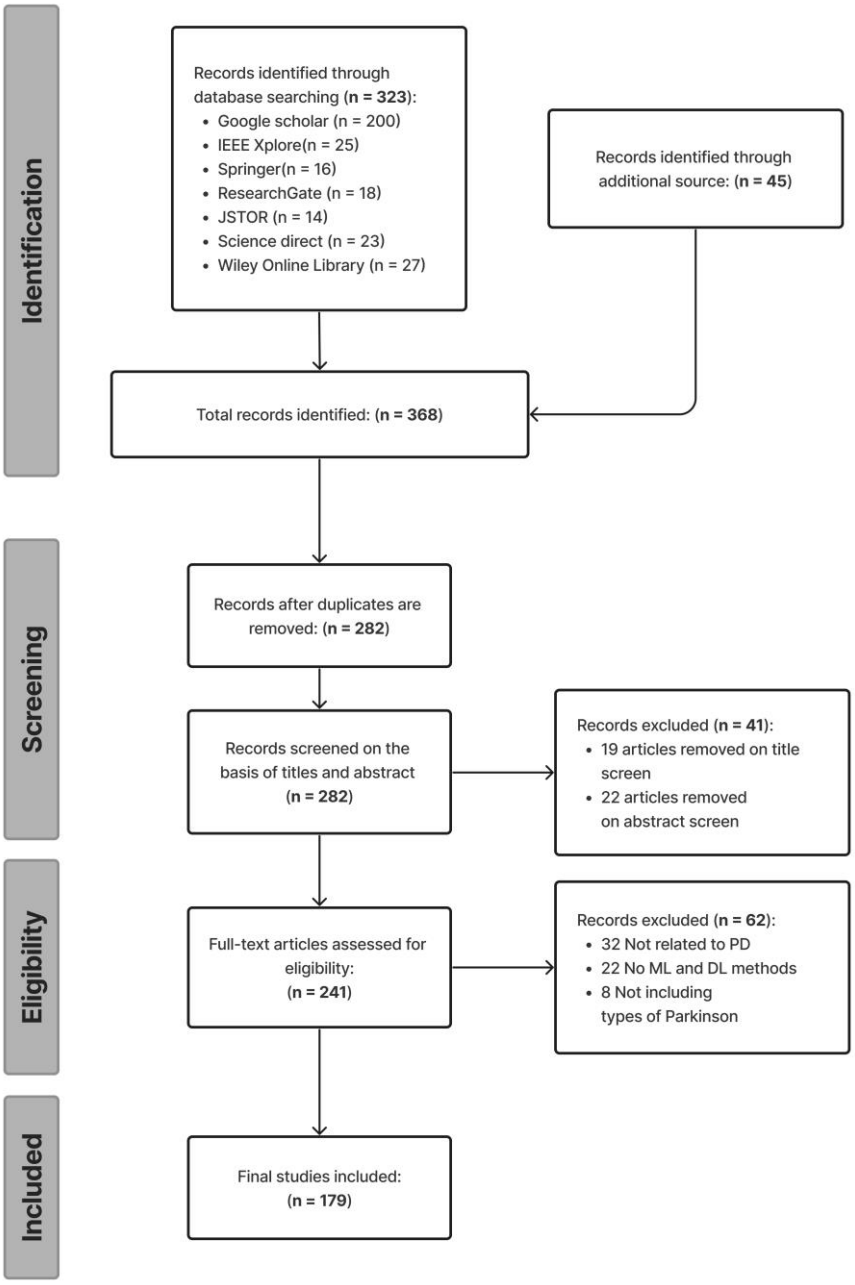

Figure 2. Selection of articles based on PRISMA technique.

Figure 3. Structure of this review.

2. Parkinson's Disease Diagnosis

A thorough history and physical examination should be part of the differential diagnosis of Parkinson's disease (PD). Referring challenging or dubious cases to a mobility disorder specialist for additional assessment is recommended. Since there are no conclusive tests to confirm the diagnosis of PD, a clinical diagnosis must be made by a physician after considering the patient's past medical history, evaluating their symptoms, and ruling out other conditions, such as multiple-system atrophy, DLB illness, and fundamental movements. Figure 4 illustrates an overview of Parkinson's disease diagnosis.

2.1. Motor Symptoms Monitoring

The key motor aspects of Parkinson's are akinesia (lack of action, trouble beginning motions) and bradykinesia (slow movements). Rigidity is linked to the patient's sensation of stiffness, and clinicians can quantify rigidity by looking at a muscle's resistance to passive stretching. The presence of a subset of motor symptoms is required for the clinical diagnosis of parkinsonism; hence, the diagnostic approach accommodates patients with varying motor health statuses. An individual with the disease can "freeze up" and would be unable to walk for a brief amount of time. Furthermore, categorization into the three primary severity groups (mild, moderate, and severe) was further separated into dichotomous issues, in which binary classifiers outperform and pick various sets of non-motor indicators [16]. Loss of scent is one of the non-motor indications and symptoms of PD, including anosmia, nerve damage, urinary incontinence problems, bowel problems, depression and anxiety, sleep issues (insomnia) leading to daytime sleepiness, cognitive issues, psychotic episodes, fantasies, and depression. The majority of current therapeutic practice is devoted to the

pharmacological treatment of motor complaints. It takes years to develop and has a wide range of clinical symptoms and prognoses.

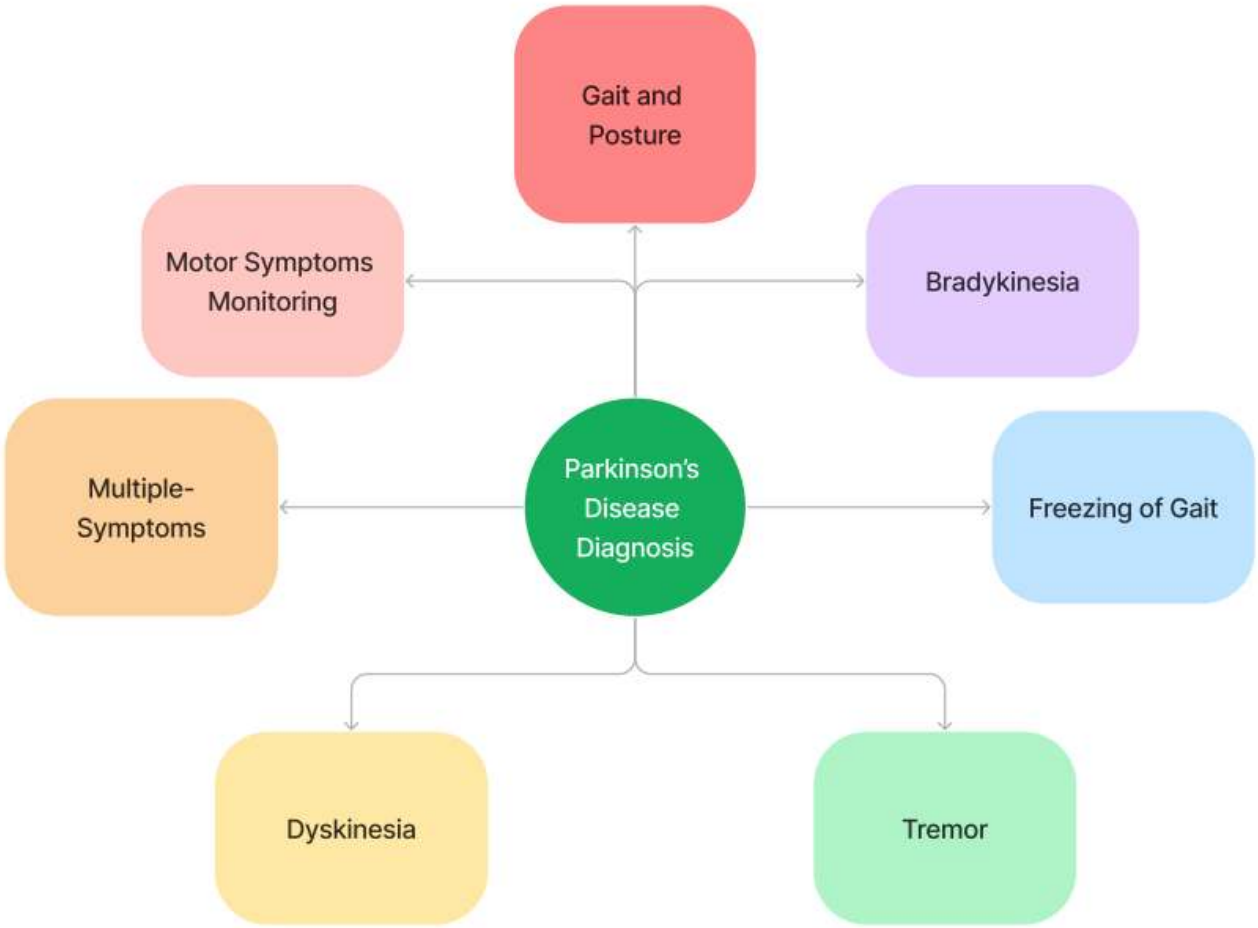

Figure 4. Parkinson's disease diagnosis—overview.

There is no single scenario or course that can depict the whole range of motor and cognitive symptoms that Parkinson's patients encounter. Moderate motor-predominant PD strikes people while they are young (in their 50 s or 60 s). Even though the signs are more noticeable than in the light engine version, these people can nevertheless work and live busy lives. People may have moments when the medicine effectively cures motor symptoms, but they may have levodopa-induced dyskinesias as the condition worsens. These people can suffer off time towards the conclusion of the dosage when the motor symptoms reappear. Patients' sickness advances over time to a more severe stage, yet they normally survive for a long period before becoming disabled [17]. No language, on the other hand, can reflect the severity of movement abnormalities, corroborating previous findings. Fine-grained speech impairments are independent of coarse-grained motor functioning, according to the UPDRS-III and other studies [18]. It takes years to develop and has a wide range of clinical symptoms and prognoses.

2.1.1. Gait and Posture

With no uniformity in the study or justification for why a trait was included in the illness assortment, gait features in the literature greatly vary. Previous research has experienced several problems, such as people who had more serious conditions, a limited sample size, and a lack of real-world data to identify the ideal gait features. As a result, the findings are less generalizable, valid, and applicable.

As a result, substantial trials for Parkinson's classification in patients with less severe illness employing a set of clearly interpretable and quantifiable gait features are required. Step size, speed, breadth, step time, swing time, posture time, and their corresponding variability and asymmetry are the distinguishing features of gait. Deficiencies are a prevalent symptom of parkinsonism that develop early and progress over time. The current method for defining gait impairment is a univariate method, which makes understanding the role of various gait parameters challenging. Therefore, a top priority to increase the use of gait traits as a technique to enhance illness diagnosis and management is to identify the best combination of gait attributes to detect PD more effectively [19]. For research purposes, the PhysioNet repository provides access to a large database of physiological parameters. In this deep-learning-based study, by using two separate symptoms linked with PD, gait and speech loss, a neural network is utilized to identify the disease. Patients with significant gait problems are at risk of falling and losing their functional independence. Each subject's 16 recorded sensor readings are turned into a spectrogram picture, which portrays a pattern by graphing the sensors' fluctuating signal levels [20]. Ground reaction force is the pressure that the ground applies to a body that is in contact with it. VGRF is the strongest factor of the ground reaction force during walking, producing forces that are larger than one body weight (BW) per step. For gait analysis and characterization, the VGRF signals contain significant information.

As a result, this method easily might be applied to other gait clinical trials in a clinical context. Rather than storing discriminative similarities between Parkinson's and control gaits, the algorithm in this case might save specific subject gait features. For future research, going into the DNN layers and analyzing what they have learned might be interesting. This type of research would help us learn more about PD gait and its characteristics [21]. In the early phases of the syndrome, gait is characterized by reduced leg speed and amplitude, as well as reduced arm swing [22]. Patients in the Fox Insight study said that jogging or mowing the lawn could trigger tremors, and phone analyses of gait metrics generated from this raw sensor information were also shown to be erroneous for people living in congested locations. [23,24]. Abdulhay et al. [25] compared various ML methods to investigate gait and tremors. They used peak detection and pulse length to extract numerous gait data, and their accuracy for Parkinson's diagnosis was 92.7%. Other specialists have spoken about the advantages of utilizing wearable sensors to track gait characteristics, as well as signal processing and machine learning techniques for extracting useful information from data. This type of data helps assess the technology's potential impact on PD research and practice. We can better understand PD by merging speech and gait analytic data. As a result of their capacity to automate pattern identification with high precision, ML and AI technologies are becoming more popular [26]. The purpose of [27] was to pinpoint the specific gait characteristics that could help distinguish Parkinson's from other neurological diseases. According to the results, Levodopa significantly enhanced gait speed and stride length. Other investigations have looked into the relationship between gait variability and walking speed. Gait speed does not affect swing time variability. Clinical scaling systems, such as the UPDRS and others, can be used to quantify these stages. Using a Parkinson's patient's gait data, an attempt can be made to determine this stage. This can be used not just to determine one's stage, but also to track the disease's progression. In this scenario, using an advanced gait analysis tool could help clinicians diagnose patients more quickly. This research developed a new intelligent Parkinson's detection mechanism that analyses gait data using deep learning algorithms. Because one of the earliest signs of this condition is a change in stride, physicians would benefit from a sophisticated gait classifier. In this clinical environment, their study goal was to develop intelligent technology that could recognize PD indicators, and disease incidence rates were predicted using gait data (depending on the UPDRS) [28,29].

2.1.2. Bradykinesia

Bradykinesia is characterized by a loss of conscious motor function, as well as sluggish or frozen motions. It is most usually a sign of PD or a drug adverse effect. It is one of the most obvious signs that physicians check for when diagnosing PD [30]. It frequently develops in the initial stages of the disease [31] and is specific to the disease of the basal ganglia [32]. Actions may be delayed (bradykinesia), decreased (hypokinesia), or altogether abolished (akinesia) depending on the degree.

Facial muscular bradykinesia is another kind of dyskinesia that affects the face. During the assessment phase, while various body segments are at varied levels of repose, the consistency of rest tremors is assessed using a single score for all tremors [33]. Overall, medicine improved bradykinesia and tremor measurements, whereas treatment worsened non-motor indicators. Dopaminergic drugs have many positive benefits, such as reducing bradykinesia and stiffness, but they also have some bad impacts, such as hypersomnolence and impulsive control issues [34]. By utilizing bradykinesia and rigidity derived from recent clinical and pathological studies, the positive predictive value of diagnosis can be raised to above 95% [34]. The challenge of automated Parkinsonian detection utilizing a transfer learning process with residual networks was presented by Passos et al. [35]. They studied two different types of drawings, which were fed into an RNN for supervised classification. The OPF also had the best results, with a 97% accuracy rate.

2.1.3. Freezing of Gait

FOG is a kind of akinesia characterized by the inability to begin or maintain movement. Motion blockages are a typical sign of Parkinson's, and they can affect any of the body's extremities, as well as the face. According to its definition, it refers to a condition where there is a brief, episodic disappearance or considerable diminution of forward movement of the feet. The sensation usually lasts for a few seconds after it arises and then vanishes. It is a typical reason for people to trip and fall [30]. It is a common gait problem in people with advanced PD. FoG episodes have been associated with falls, which disrupt daily activities and reduce the quality of life. For patients with advanced diseases, it is a prevalent gait condition. Falls have been linked to episodes, which disrupt everyday activities and lower quality of life. It is usually resistant to pharmacologic therapy, requiring the use of effective non-pharmacologic treatments. It is the sort of gait impairment that is common in Parkinson's patients. It causes patients to feel as if their feet are stuck to the ground and that they are briefly unable to re-establish gait. These attacks might last for anything from a few seconds to a minute. It can emerge everywhere, although it is particularly common during turns, before gait begins, in small spaces such as doors, and in stressful situations. Mazilu et al. [36] used a three-axis accelerometer to track body acceleration in PD patients to discover FoG events. Offline, freezing appearances were recognized by comparing the collected data across freezing and regular gait. In this study, from 11 PD patients, asynchronous accelerometer data from the left shank were assessed. It was shown that leg movement during FoG events included high frequency elements in the 3–8 Hz range that were not present in normal gait or voluntary control sitting. It attained a sensitivity and consistency of up to 89%.

Another significant challenge is recognizing and analyzing PD-related movement patterns, such as gait start and gait freezing, which are all typical illness markers. According to one medical study, 90% of people with the disease exhibit vocal impairment, making it critical to analyze speech data to distinguish healthy people from those with the disease. Various symptoms are important in the diagnosis, treatment, and therapy of PD. Three symptoms are present: difficulty starting or maintaining walking, complete immobility, and staggering with swift steps [37]. About half of PD patients experience this extremely debilitating symptom in the latter stages of the illness [38]. Miljkovic et al. [6] devised a mechanism for FoG identification, employing six wearable accelerometers and two gyroscopes in their latest study. The approach is created via filtering and feature extraction, and it is then classified using four ML techniques. The four phases of the method include

missing data restoration, low pass filtration, feature extraction using a sliding window, and classification. The study included sixteen people, five of whom had been diagnosed with PD and had a history of FoG. The suggested method is intriguing, since it can be completely incorporated into clinical practice and has a classification accuracy of 96.11%.Heremans et al. [39]used a DNN with three levels: input, hidden, and output on the UCI speech dataset. The classification accuracy for preparation was 94.4%, whereas for testing it was 62.7%. The findings of this study show that 15 years after first evaluations, dopamine non-responsive issues predominate, with frequent falls occurring in 81% of patients. At ten years, 71% of patients showed substantial PIGD motor deficits, the majority of which were caused by non-dopamine-responsive characteristics, including gait freezing (FoG) [40]. This study made considerable use of ML techniques to identify workable models and the most essential combination of spatial and temporal gait factors for early disease identification. The best classification models for the dataset were LR, SVM, and RF. The algorithm's performance increased by 10% once features had been chosen. RF had the greatest testing classification accuracy of 97%. These characteristics not only improved results, but also helped physicians to gain a better understanding of ML. The results are a first step toward demonstrating the promise of ML as a complement to clinical practice, but additional outside validation is required to support these results [41]. They assigned the method a poor grade; however, it removed the incidence of inaccurate FOG forecasts and the statistics only included 46 FOG events [42]. The current research examined data from additional patients to increase the viability and robustness of FoG detection using EEG (electroencephalography), yielding a specificity and sensitivity of 82.7% and 86.6%, respectively [43]. A relationship between FOUL and FOG appears to exist in some cases of PD [44,45].

2.1.4. Tremor

Tremor is described as a progressive loss of muscle control that causes quivering (uncontrollable shaking) in numerous body parts [46]. Several characteristics are crucial in determining the identification, treatment, and therapy of PD. Tremor is a limb twitching that is involuntary and oscillatory. Rigidity in motion is induced by increased muscular tone. Loss of balance and unexpected falls are caused by postural instability. Because of these mobility issues, people with PD show different gait characteristics from healthy people. One of the most significant components of disease management appears to be tremor diagnosis and classification. Body posture detection is also essential because automated systems only based on their base frequency have difficulties distinguishing the two. Motor assessment of PD is the evaluation of tremors combined with bradykinesia, as well as evaluations of tremors in the mouth, jaw, bottom lip, arm, or leg [143].

The UPDRS scale is an unreliable method for assessing and discriminating tremor severity, and clinical examination and tremor incidence determination require the presence of at least one neurologist. It is critical to create a method or piece of equipment that can assess the intensity in Parkinson's patients. Frequency and intensity of tremors are two main parameters that have been cited in most previous publications for objective categorization of not only Parkinson's tremors, but also other forms of tremors [47].Their gait is characterized by a forward flex posture, quick shuffling, shorter step lengths, and prolonged support intervals, among other characteristics [48]. Periodicity, irregular cycle, and deterministic behavior are some of the noteworthy and different aspects of gait pattern, which involves the succession of periodic and rhythmical patterns of foot motions. Periodicity, irregular cycles, and predictable behavior are some of the notable and distinct aspects of gait patterns. Finally, to identify the stages of Parkinson's, only supervised linear classifiers have been used. Nonlinear classifiers, on the other hand, can be utilized to generate nonlinear correlations, especially when tremor data and gait patterns are used [49]. Each stage of the disease is distinguished by different symptoms of shared motor characteristics. While, in the off state, people with PD feel sluggish, inflexible, and have more tremors. Symptoms are much less severe in the on state, and tremors may go away altogether. Dyskinesia manifests itself as a series of spontaneous motions, some of which include the wrists [50]. Tremor

and voice loss, on the other hand, can only be noticed when around 70% of susceptible dopaminergic neurons have perished as a result of PD [51]. A recent study proposed a two-part model for classic tremors, with the cerebellothalamocortical network acting as the tremor's driving power and the basal ganglia as its trigger [144].

2.1.5. Dyskinesia

Dyskinesia is the incapacity of people with PD to control their muscle movements. Twitches, jerks, twisting, and writhing are examples of such movements. Dyskinesia can affect the arms, legs, and chest, among other body regions. There are various sorts of movements, and the timing and frequency with which they emerge vary from person to person with Parkinson's disease. Dyskinesia can last for the majority of the day in some people. Others may only notice it after they have taken their prescription, or right before their next dose is due. When levodopa levels in the bloodstream are very low and dopamine levels in the brain are at their peak, people with Parkinson's disease may suffer this adverse effect. The neurotransmitter dopamine is created in the brain. PD symptoms appear when dopamine is very low. Even though the symptoms are more noticeable than in the mild motor-predominant version, these people can nevertheless work and live busy lives. People may have moments when the drugs successfully cure motor symptoms (on-time), but they may have levodopa-induced dyskinesias as the disease progresses [17]. More UPDRS components will be compiled, and the addition of other four Parkinson's characteristics, such as rigidity or dyskinesia, will be explored as enhancements to the current study [47]. A previous study made efforts to tackle the use of wearable sensors to count distinct types of PD symptoms, only using bimodal distribution or unimodal sensors [52].

Bind et al. [16] created a system for diagnosing and categorizing Parkinson's patients categorized on their postural behavior, which they analyzed with a L2 norm metric and SVM. Twenty-four people were evaluated both before and after treatment. To test their postural balance, each patient was subjected to the following analytic methods: eyes open on the force platform (firm surface) first, then on foam placed on the force platform second (FO). When individuals stood on a solid surface with their full attention, the number of people with dyskinesia increased from 66% to 77%. This study looked at a variety of machine-learning-based strategies for predicting PD. Ahlrichs et al. [30] were able to detect dyskinesia with a 96.8% accuracy rate. A total of thirteen people were recruited for the research. While executing a set of programed tasks in a controlled setting, each subject gave around 2.5 h of acceleration data. During the recording process, six tri-axial acceleration detectors were attached to the subject's body. Several section sizes were empirically tested. The fifteen-minute portions provided the most accurate results (i.e., 96.8%). However, accuracy was reduced to around 80% when one-minute timings were used. DNN has been utilized by several other writers to better capture time-based characteristics. They have 91% sensitivity and 93% specificity for detecting dyskinesia. The DNN is fed a collection of features collected from a two-second sliding window. A five-point FIR filter is also used to filter the outputs of each artificial neuron. Long-term pharmaceutical use has also been linked to the development of dyskinesia or uncontrollable movements. The intensity of these variations can be lessened with customized treatment programs. In this study, they focused on the assessment of the disease state in PD because it is a crucial aspect of improving the condition's management in clinical practice. Participants provided around 4500 hourly labels for a total of approximately 5500 h of accelerometer data (80% diary compliance). Dyskinesia manifests itself as a series of spontaneous motions that may include the wrists. Importantly, the recorded data contains realistic physical exercises that have a major impact on the recorded signal, as well as the manifestation of illness states. They introduced an upper layer (randomly started, = 0.01) to the generative model during the fine-tuning phase. This top-layer had four SoftMax units that correlated to four interest classes: sleeping, off, on, and dyskinetic [50].

2.2. Speech Monitoring

Dysarthria is a symptom that significantly differs between cohorts. This kind of heterogeneity could be attributed to subject-level and task-related cognitive factors. A crucial classification difficulty is the proper representation of voice and speech data for PD diagnosis. To use these resources for PWP (People with Parkinson's), accurate clinical monitoring tools must be used. According to research, around 90% of PWP suffer voice impairment and speaking issues. Loudness, decrease, breathiness, roughness, and increased vocal tremors are the five major clinical symptoms of dysphonia in humans. Looking at the frequency of time in speech recordings can provide all of these characteristics [53]. Abayomi et al. [54] indicated that a quick and easy data augmentation method based on spline and pchip interpolation has been shown to be successful in the diagnosis of PD, particularly if the sample is of voice impairment. Dopamine is a neurotransmitter that allows the brain to effectively communicate when it comes to managing feelings, behaviors, consciousness, physical movement, and speaking ability. Analyzing and classifying patients' speech signals is thought to be a way to diagnose PD early by distinguishing characteristics and aspects of their voices [55]. The goal of the study was to see if speech difficulties may be detected in the early stages of PD, before the traditional symptoms appear, and if those at risk of the condition can be identified from the general population using acoustic and classification analyses. In it, speech articulator motions (lips, tongue, and jaw) are limited in range (hypokinetic), and vowels become centralized; i.e., formants with high frequencies are likely to have a lower frequency, whereas consonants with lower frequencies tend to have higher frequencies [56]. Speech monitoring and repair assessments significantly separated the groups and were linked to linguistic performance tests [57]. One typical PD characteristic is hypokinetic dysarthria, a combination of neuromuscular speech disorders that impair understanding, self-image, and productivity. There has been no study that has looked at this idea while controlling both task-related and specific topic cognitive factors, while avoiding previous flaws. Monolith, monologs, and inappropriate pauses are all prevalent deficiencies in the prosody area. Disturbances in the basic frequency of vocal-fold vibration and language latencies cause such changes. Notably, restricted characteristics, such as the pronunciation of particular vowels against particular consonants, are frequently used to actualize speech regions [18].

Speech signals can be used to diagnose the disease. Affected individuals have a lot of speaking issues. Reduced speech intensity, variation in frequency components, hoarseness in voice, and inconsistency in speech articulation (hypokinetic dysarthria) were among the speech impairments. Due to the presence of non-stationary and discontinuity in the speech signal, extracting and classifying speech features has always been a difficult problem [58]. An important classification difficulty is the appropriate interpretation of voice and speech data to identify PD. The depletion of neurotransmitters, notably dopamine, results in a variety of symptoms, including speech, vision, mobility, urine issues, weight loss, sadness, anxiety, panic attacks, sleep abnormalities, and so on. Dysphonia, hypophonia, monotonic, and dysarthria are some of the vocal and speech problems that PWP suffer from [59]. The most common symptoms are dysphonia, which is present in over 90% of patients, and gait unpredictability, which is a distinguishing criterion for the development of this condition. As a result, enhanced speech signal processing technology for PD symptoms has sparked a lot of interest [60].

2.3. Handwriting Analysis

The complicated process of handwriting requires intellectual, visual, and fine motor skills. Handwriting difficulty is still one of the earliest symptoms that lead individuals to seek medical attention, despite not being explicitly included in the diagnostic criteria for PD. The majority of PD sufferers display faulty handwriting. Recent research has revealed that auditory cueing has a good impact on handwriting proficiency, but visual feedback has conflicting results. The degree to which a handwriting assignment is beneficial can be determined by comparing its fluency with and without the provision of feedback. Since the

development of kinematic analysis via the use of digitized tablets, research on handwriting in PD has experienced a significant revolution. The traditional PD handwriting anomaly known as micrographia is now included in the spectrum of "PD dysgraphia". When a disease is still in its initial stages, this study may be employed as a clinical marker [23]. In their study on micrographia [61], McLennan picked patients who had notable, noticeable micrographia and took handwriting examples from them. The chosen patients were required to submit samples of their handwriting from both during their advancement of PD. According to reports, serial signatures from rejected checks were the most prevalent sources. They commented that the "type of information did not lend itself well to quantification", but that this limitation is now addressed. The research by M. Ranzato et al. [62] focused on the identification of PD using RBMs and features extracted from handwritten pictures. To satisfy the RBMs, the photographs were digitized and pre-processed. The Fuzzy OPF was contrasted to the regular OPF, KNN, and SVM classifiers in this context. The "HandPD"1 dataset, which is made up of images from handwritten tests, was used in this study. The second dataset contained activities from specific tasks collected from healthy people (the control group) and patients during handwriting assessments. They used data from spirals and meanders to create 368 photos, 296 of which were from patients and 72 from the control group. The fundamental idea behind using such photos is that patients often notice varied levels of tremors, which are frequently connected with illness progression.

2.4. Face Video Analysis

There is a lot of interest in utilizing machine learning to help with disease diagnosis, and the present results are promising—often, the claimed accuracy percentage only using speech or accelerometer data is in the mid-90s [63]. However, because the experimental methodology involves distinguishing between (possibly erroneously) diagnosed PD patients and healthy controls, these findings should not be taken at face value (HCs). In the realm of smart recognition, the ability to identify individual attributes is a global security problem [64]. Ref. [65] suggested an LSTM model that will aid in providing patients with more thorough care and assisting medical professionals in better comprehending the dynamics of the disease in real time. Additionally, it aimed to ease the burden on doctors' recurrent patient diagnoses and the issue of enrolling patients who have mobility issues. Various algorithms have been created in recent years to address the security issue, but there is still a need for quick and efficient biometric recognition. Biometric recognition is the process of automatically recognizing an individual's qualities based on anatomical or behavioral features. Extrinsic biometric features and intrinsic biometric features are the two types of biometric recognition approaches [30]. When compared to intrinsic traits, extrinsic features are more visible and have more negative aspects. The retinal surface, for example, is influenced by the high intensity of light used to extract iris characteristics [31]. Face identification accuracy is further impacted by brightness differences, facial style, blood vessel obstruction, and position [32]. Face recognition systems [38], motion detection systems [66], and other applications are among them. Additionally, it enhances the effectiveness of DL approaches and the general uniformity of training outcomes. In the so-called "small data problem" [67], where only a small quantity of information is accessible for ML model training, the latter is particularly crucial.

2.5. Brain Imaging

Cho et al. [19] used an advanced computer-based method to analyze brain MR imaging of subject areas with suspicious characteristics of Parkinson's to contribute to individual diagnosis, based on the idea that diseases linked with systematic changes in brain MR scanning are too uncertain to be noticed by visual inspection. This is a very cost-effective procedure that is supposed to supplement, not substitute, current treatments for obtaining an early and accurate diagnosis of the disease, because existing MR imaging data is repurposed with modern information processing. They presented the study as initial evidence for the feasibility of performing SVM personalized classification of DTI data of Parkinson's,

indicating the need for further prospective and more extensive follow-up studies. Although brain MR imaging is frequently used in diagnostic procedures, it is mostly used to rule out other conditions, such as regular hydrocephalus and chronic subdural hemorrhage.

2.6. Using Multimedia Approaches

A lot of studies [68–70] have built PD detection mechanisms using various types of datasets. The data were evaluated, and information was extracted using feature identification techniques (image, text, audio, and video). In many studies, simple body sensing data (text), speech data (audio), image features (pictures), and motion sensors are all examples of simple body sensor values. These studies have not focused on building machine learning and deep learning techniques for managing inter datasets. In the future, this research could be broadened to include multimedia data processing to create a more successful PD identification system. In the performance review, the proposed DMVDA algorithms had the lowest MAE and the best disease identification rate [71].

2.7. Stage-Wise Prediction of Parkinson

In the beginning, the person only experiences minor symptoms that do not affect daily life. Shen et al. [179] developed a methodology for sparse feature learning in PD early detection. During stage 1, only one side of the body has tremors and other movement symptoms [180]. Balance is not harmed in stage 2. Furthermore, the person's posture may start to shift, and walking difficulties may start to emerge or worsen [181]. Loss of balance is the defining characteristic of the middle stage/stage 3. Motor symptoms become worse. Though physically capable of living independently, the person's everyday activities are now restricted in a functional sense. Stage 4 symptoms are completely formed and quite incapacitating. The person can still stand and walk unaided, but, for safety reasons, they may need to use a cane or walker [180]. The most advanced stage of Parkinson's disease is stage 5. Advanced leg stiffness can also result in freezing when standing, which makes it impossible to move or stand [181]. Various stages and symptoms of Parkinson's disease are presented in Table 3.

Table 3. Various Stages and Symptoms of Parkinson's Disease.

S. No.	Stages—Parkinson's Disease	Symptoms—Parkinson's Disease	Patient's Appearance	Impact on the Patient
1	Stage 1—Only one half of the patient's body is affected	Mild tremor and rigidity, slight changes in facial expressions, little challenges in posture, balance, and walking.		Does not affect the daily activities and life style of the patient.
2	Stage 2—Full patient's body becomes affected; however, the patient is still able to balance himself/herself. Affects the midline of the patient's body; namely, neck and trunk.	Challenges in walking and balancing. Pitiable posture, stiffness, tremors, and trembling may be more noticeable. Noticeable changes in facial expressions and sometimes difficulties in speaking.		Daily tasks of the patient become more challenging and time consuming.

Table 3. *Cont.*

S. No.	Stages—Parkinson's Disease	Symptoms—Parkinson's Disease	Patient's Appearance	Impact on the Patient
3	Stage 3—Impaired balance, but the patient remains independent	Loss of balance, reduced reflexes, tremor, rigidity, slowness of movement, falls, and dizziness. Freezing and muscle cramps.		Daily tasks of the patient become significantly impaired; however, the patient completes basic daily activities at a slow pace.
4	Stage 4—Walking and standing with external assistance	Substantial decrease in the movement and reaction times of the patient.		Patient requires external assistance for daily activities and independent living is not possible.
5	Stage 5—Debilitating stage	Stiffness in the legs, unable to stand or walk. Freezing upon standing, confusion, loss of smell, hallucinations, delusions, constipation, poor reasoning and memory. Loss of body weight, disturbances during sleep, problems in eyesight		Patient is bedridden or confined to a wheel chair.

In order to create an automatic stage classification of PD, supervised machine learning techniques can be used to understand the inherent correlations between high-dimensional spatiotemporal data using a training dataset, and then apply the knowledge acquired during training to a fresh dataset [182]. Several scientists have investigated the effectiveness of ML systems to categorize the phases of PD based on UPDRS using the UCI voice signals [183]. Non-motor symptoms include things like Rapid Eye Movement (REM), olfactory loss, and sleep behavior disorder. The development of machine learning models will be crucial for stage-wise prediction of this disease, and will be very helpful in forecasting it. Based on stage-wise classification, the proposed method is intended to predict all motor and non-motor features. Parkinson's patients were classified using the Random Forest Classifier, and 96% accuracy was reached using the fewest voice features possible to make the diagnosis [184].

3. Datasets for Parkinson's Disease Diagnosis

Another obvious sign of PD is a decline in handwriting skills, which are commonly observed in most PD patients but are not considered diagnostic criteria for the disease [60]. One of the three widely used PD handwriting datasets, the PaHaW dataset [72], HandPD [7], or NewHandPD [64], were used in thirteen experiments on deep learning algorithms that sought to diagnose PD using handwritten drawings. The spiral sketching test is one of the tests included in all three databases, and is one of the drawing and writing tests present in all three databases. Dataset can also be created by assessing equal number of people with PD and HC as done in [154]. For each modality (such as MRI, EEG, voice, etc.), DL studies may utilize a distinct dataset to develop their models. For instance, instead of using the public dataset, PPMI, MRI studies may choose to use a private dataset. As a result, it could be challenging to compare the effectiveness of two DL models that were trained using different datasets [73]. No restrictions on drop-out (or bias investigation), report of inclusion/exclusion criteria, or relationships between prodromal markers were found in [74]. Table 4 shows the list of various Parkinson's disease diagnosis datasets.

Table 4. List of Various Parkinson's Disease Diagnosis Datasets.

Reference Number	Year	Dataset Used	Availability	Dataset Size	Details about the Dataset	Data Type
[155]	2009	Track HD	Open Dataset	366 individuals	Genetic information and HD detection were connected	physiological, intellectual, quantitative motor, oculomotor, chromosomal, and psychiatric evaluations
[156]	2011	PPMI	Open Dataset	64 early patients,196 HC, and 65 REM patients	PD Biological markers	medical record, biological material, and pictures of the brain
[157]	2008	Predict HD	Proprietary Database	438 pre-HD patients	Genetic information and HD identification were connected	MRI, smell recognition, verbal learning/memory task, tapping test, genetic information, and cognitive assessment
[72]	2014	PaHaW	Open Dataset	37 PD, 38 HC individuals	Archimedean spirals and writing for PD	Altitude, x-y dimensions, tilt, height, and the state of the in-air and on-air surface
[158]	2019	OASIS	Open Dataset	1098 individuals	Identification of AD	CT, PET (Positron Emission Tomography)
[159]	2005	Gait in Parkinson's disease	Open Dataset	93 PD and 73 HC patients	Step in PD	recordings of force sensors
[160]	2017	PDMultiMC	Proprietary Database	16 PD and 16 HC individuals	Written words, spoken words, and eye tracking in PD	Settings for digital tablets and speech
[161]	2008	ADNI	Open Dataset	ADNI-GO: 200 early 400 MCI, and 200 AD patients	identification of AD and pre-AD; tracking the condition's development	Biomarkers, medical, chromosomal, MRI, and PET
[162]	2013	AZTIAHO	proprietary database	50 HC and 20 AD patients	Biological markers of AD in voice	Speech Database
[163]	2012	NTUA	Open Dataset	There were 78 people, 55 of whom had PD, and 23 HC patients	Hand gestures in PD	Testing using MRI and Dopamine Transporter Scan scans

4. Machine Learning and Deep Learning Models for Parkinson's Disease Diagnosis

4.1. Need for Machine Learning and Deep Learning Models for Parkinson's Disease Diagnosis

To maximize ML's generalization capabilities in neuroscience, many sorts of validation processes will be required. Testing different and new data on the same training model at the same time is the next step in attaining the best diagnosis accuracy. ML approaches have been widely utilized to predict PD across a variety of datasets. Furthermore, picking features for a new training model each time prevents the model from being automated and put into practice. Finally, ML algorithms that allow for incremental data updates and re-learning must be researched further. When large-scale labeled datasets are available, CNNs have already shown tremendous achievements in terms of navigating classification challenges in recent years [75]. The combination of ML models with feature selection methods enables the evaluation of the relative value of characteristics in a wide feature space to choose the most distinguishing ones, which is difficult to manually do [76].

The accuracy rate of deep learning techniques improves as the size of the dataset grows. However, to reproduce absolute speech data features from raw datasets, appropriate speech-processing algorithms must be devised. Traditional DL algorithms must also be updated for changing auditory information [71]. Old PD diagnosis requires a large number of observations in everyday activities, fine motor skills, and other brain features; however, this method is inadequate for detecting the disease early. ML and AI approaches have a lot of potential for categorization, according to previous research, and the classification system increases the validity and consistency of the diagnosis, as well as minimizing errors and boosting the efficacy of the process [26]. There is not a certain test for screening Parkinson's because the medical approach is dependent on the patient's signs and symptoms, or, specifically, because every patient has their own set of symptoms. To do so, we will need new techniques for permanently recognizing the disease in its early stages, in order to take advantage of the most effective medical treatment available. For this purpose, automated analysis using learning classification algorithms is extremely intriguing [77].

4.2. Machine Learning Techniques

4.2.1. Artificial Neural Network

ANNs are often depicted as networks of interconnected "neurons" capable of calculating values from inputs/outputs and of pattern recognition and machine learning. Bind et al. [16] suggested using an ANN to diagnose PD in a dataset of ill and healthy patients using a boosting committee machine. Neural networks with backpropagation filtering techniques employ a majority voting scheme. Indeed, 75.4% of the 195 samples tested positive for PD, with the rest being healthy. Sachdev and Kim [78] studied the gait characteristics of 93 PD patients and 73 healthy adults. The disease has been discovered to utilize multiple biomarkers, which have been used in various investigations to identify the onset of the condition and its associated issues. To diagnose the effects of PD, Pereira et al. [64] used a Multi-Layer Perceptron ANN. They also contemplated utilizing a feature selection method based on meta-heuristics to detect such diseases. Despite studies showing the potential for using SVM to automatically identify PD from vocal factors and provisionally supporting the use of ANN and SVM together for the rapid recognition of PD, in this research, ANN was used for FS before classifying speech-related qualities using the augmented LaGrange synthesis of SVM, which maximizes margin min-maxi. Therefore, the use of internal FS to enhance early PD diagnosis using speech-related statistics is a vital contributor to the work [79].

AM García [18] developed the Multi-Layer Perceptron with a back-propagation learning method and RBF to forecast PDs [80]. The model for this module is based on ANN, another DL paradigm. It is divided into four layers, each of which has 64, 32, and 16 neurons. The dataset is supplied as a CSV file, from which it learns the non-linear trends in signal values and teaches itself. Tensor flow and Kera are also used in its development. When the issue is properly categorized or tiered into hierarchical levels, a tree functions well in diagnostic testing. Classification results are often good if sufficient data is provided to

train ANNs. In many physiological settings, this is not the case; hence, they frequently overfit the provided data, which decreases generalizability [81]. The researcher's model [82], on the other hand, lacks explanations and poorly performs when compared to theirs, due to the fundamental nature of DL models. Furthermore, the method can determine the severity of the disease in addition to Parkinson's diagnosis, which may be more valuable to patients and physicians. A technique based on SVM and ANN was proposed by Rizvi et al. [83]. The ANN-based approach has a precision of 92.31%. They then discussed the dataset creation technique they used, as well as the models they chose (classifiers). The adoption of more resilient designs, such as layering various models to construct an ensemble, might counterbalance the prejudice of each model and supplement the automated diagnostic, as evidenced by the 83% diagnostic accuracy gained in this study. It would also be worthwhile to investigate TCN considering their impressive findings in several sectors of research. Finally, to increase ML diagnostic performance, more information from patients and healthy controls is required [84]. In [85], researchers used a variety of speech signal processing techniques to clinically extract significant characteristics, which were subsequently fed into several artificial learning systems to generate correct PD classification options.

4.2.2. Naïve Bayes

The NB Classifier is a probabilistic classifier that assumes the presence of one class characteristic that is unrelated to the presence of other factors [86]. For writing tasks and spiral drawing, they employ an NB algorithm, with different metrics for each challenge. With an accuracy of 83.2%, the fourth task has the greatest classification accuracy [46,87]. It is sometimes referred to as a probabilistic predictor because of the probabilistic relationship between the category and the attributes. It does not have a deterministic relationship and is very extensible. The training is carried out in linear time by calculating a closed-form expression, as opposed to the iterative approximation used by many other classifiers. It has shown the lowest accuracy (71.79%) in detecting the presence of PD [88]. With more training data, the classification accuracy of this algorithm will drop. According to the best training data chosen by the PSO algorithm, the greatest accuracy in the potential classification for PD diagnosis may be reached with only eight training data. Researchers have proposed a new PD diagnostic model based on a PSO algorithm, and a combination of Naive Bayesian Classification and other algorithms. The PSO approach was used to select the best training data for Naive Bayesian Classification. By picking the best training data and avoiding those that produce a drop and decline in classification accuracy, the algorithm achieved a classification accuracy and PD diagnosis of 97.95%. This classification accuracy demonstrates the proposed method's advantage over existing disease diagnostic models. Furthermore, it should be noted that, based on the findings of the paper, it is not always essential to present a new classification method to improve classification accuracy; rather, it can be significantly improved by choosing the best training data and eliding the improper training data [89]. Naive Bayes only takes the total motor score into consideration, which may not account for patient variability as two individuals with comparable total motor scores may have completely different symptoms. As a consequence, they used the aforementioned ML methods to forecast the outcomes of each sub-symptom, then combined the findings into a single prediction. This strategy is known as symptom aggregation (SA) prediction [90]. Using a subset of attributes provided by a wrapper of the same learning method, the top-scoring classifier, NB, achieved scores of 91% accuracy, 88% sensitivity, 95% precision, and a 0.952 AUC value. Although the NB's algorithm's assumptions are contradicted by its data and characteristics, the algorithm's success is logically justified, which encourages its use. Researchers have also tried using alternative classifiers, such as random forests, with comparable or slightly worse outcomes. There were 5875 occurrences and 26 characteristics in the data. For data visualization, classification (majority, k-nearest Neighbor, and SVM), evaluation, and unsupervised learning methods, the dataset was obtained and run using orange software v2.0b (hierarchal clustering). Weka v3.4.10 was used to accurately classify instances (classification) using Bayes Net and Naive Bayes. It

had the lowest accuracy (69.23) [91]. Alemami and Almazayedh [92] designed and verified classification algorithms; their findings revealed that the automated classification method, NB, and KNN reached a high degree of accuracy of 93.3%. For reliability assessment and the time it took to complete the set of data, comparative categorization tests on multiple datasets inside an item were used to discover the optimal classifier model. The Bayesian theory is a mathematical model based on the arithmetic of levels that forecasts relevant beliefs. Bayes Net and Naive Bayes are the most active learning techniques, using a random sequence structure within each class. Network categorization refers to a collection of algorithm-based categorization methods [93]. Some learning schemes, such as NB, are extremely effective as classification approaches, but they are challenging to apply as regression schemes [94].

4.2.3. Decision Tree

There are two research phases in the data mining module. The first involves applying association rule mining algorithms to analyze the patient's status using raw patient data, therapy, patient profiles, and other publicly available data as part of the rule discovery process. The progress of automated symptom detection based on patient time series is the second step. This forecast is based on decision trees, and it aims to be more accurate than the prior study [6].

The fact that decision trees express rules is one of the most appealing features. Humans can easily grasp rules when they are written down. Nilashi et al. [95] attained the highest accuracy of 82% utilizing a decision tree on gyroscope data acquired with the Shimmer. To classify it, they employed the J48 decision tree included with the Weka software. Scholars from all across the world are interested in how medical datasets might be used. Kim et al. [96] employed datasets for decision rule discovery by creating decision trees after using PCA. They employed CART at this stage and applied these strategies to all clusters. According to clinical practice guidelines, they imposed the first split rules as the primary source of damage. Following that, the most effective criteria and thresholds for forecasting future total UPDRS scores were established. To prevent too many finely-grained sickness conditions with inadequate visits, they guaranteed that the minimum number of trips residing in the disease condition was not less than 100. Using Enhanced Decision Trees, they were able to obtain up to 95% reliability on the sample; however, there is still potential for development. With additional development, the model's accuracy score might approach 99%. For instance, more data analysis of the features might be required to remove some of the identical features and only utilize the qualities that are intricately connected to the description [97].

4.2.4. K-Nearest Neighbor

The patient populations with the smallest sample sizes, which are those with significant cognitive deficits, show the lowest classifications. The classification is quite appropriate for the remaining groups, where a particular diagnosis is needed to make future healthcare plans. These results imply that the degree of cognitive impairment in PD patients can be assessed using EEG parameters derived from a daily clinical practice exploratory research approach [98].For each test sample, K-Nearest Neighbor (KNN) is a fundamental classification algorithm that produces the most comparable clusters among the K closest examples in the training set [99].

Bind et al. [16] developed a classification strategy based on KNN to predict voice signals to detect Parkinson's sickness or healthy patients using a Parkinson's speech dataset with various audio recordings. It had an accuracy of 80%. To handle the problem of categorizing Parkinson's patients' speech, data mining techniques, including Random Forest, Ada-Boost, and K-NN, were used by AH Al-Fatlawi et al. [55] With an accuracy rate of 90.26%, the K-NN technique was discovered to be the most effective of the three. These studies used a variety of speech signal processing techniques to clinically extract significant characteristics, which were subsequently fed into many AI systems to generate reliable PD

classification decisions. Because of its simplicity and ease of use, KNN is similarly effective. The performance of the algorithms mentioned in this paper is inextricably linked to the quality of the attributes extracted from the data. While manually identifying adequate features to characterize the intrinsic aspects of speech (audio) data is difficult, utilizing a DL technique, the latent characteristics of the data can be autonomously discovered. A method for identifying PD using speech sounds has been proposed by RWR de Souza [100]. The fundamental frequency, jitter, and HNR, as well as additional statistical metrics based on these properties, were used as inputs to the proposed model. Several selection methods were used, including correlation rates, Fisher's Discriminant Ratio, and ROC curves, to extract important features from the entire feature collection. The KNN classifier outperformed the other classifiers in terms of accuracy, sensitivity, and specificity (with an accuracy rate of 93.82%) [85], producing the best results. In higher-dimensional layouts, on the other hand, KNN performs better. When it comes to the training stage, the traditional OPF beats the KNN, SVM, and Fuzzy OPF in all circumstances. Tiwari [80] suggested a fuzzy k-nearest neighbor-based technique for PD categorization. They investigated and developed a support vector machine-based technique for PD diagnosis. Nearest data generates instances that correlate to locations in an n-dimensional environment using Euclidean distance.

4.2.5. K-Mean Clustering

K-mean is a known approach for separating PD patients into subgroups, such as those with tremor predominance vs. those with fast motor control loss and cognitive issues. An overfitted system may have too many customizable variables, causing unpredictability or other confusion in training examples to be misinterpreted as true disease-related architecture. Because the model's intricacy may be indefinitely raised to achieve high accuracy, this is a common challenge in statistical ML. With encouraging findings, some researchers have used dynamic handwriting analysis to categorize persons with PD. Regardless of the amount of sickness indicated by the patients, they all focused on the healthy/unhealthy binary distinction. In other words, the Parkinson's disease sample is thought of as a distinct cluster in which every member has the same level of PD severity. The goal of this study is to determine whether and how dynamic handwriting traits can identify PD sufferers at a preliminary phase [99].

4.2.6. Random Forest

Novel PD data with a class-balanced distribution were classified using the RF classification and the SMOTE method, modeling the data using the data points using multiple decision trees. New predictions were created by combining the findings of each decision tree and giving that category to the data point that was predicted by the majority of the trees [58]. Medication doses, time variables, and preoperative symptom-specific levodopa response were all shown to be strongly linked with clinical outcomes [90]. In this study, researchers computed an important score for the characteristics in a two-class (PD/Normal) classification framework to determine their value. This technique involves drawing out n observations with a replacement for each decision tree, omitting 37% of the data on average. These are the 'out-of-bag' statistics, and they can be used to figure out how important certain qualities are. The RF model, which was used to assess feature importance, had an accuracy of 99.03%, a sensitivity of 99.51%, and a specificity of 98.1%, indicating that it did a good job of distinguishing PD from HC. The proportion of PD observations that were not recognized was exceptionally low (less than 10%, or 0.5%), showing that the machine learning model was able to identify complex patterns in the data and aid in identification. In [101], researchers demonstrated that the Synthetic Minority Oversampling Technique (SMOTE) improves minority class detection in order to address the class imbalance issue in PD stage-wise segmentation. By measuring the differences between the samples that were generated and demonstrating the lack of replication or overlapping, the method was validated.

4.2.7. Support Vector Machine

Ref. [48] included several statistical features collected from time-series gait data were examined before being decreased using a correlation matrix. The top seven feature vectors were then extracted and classified using a kernel-based SVM decoder and a Gaussian radial basis function. The findings showed that the seven features used for SVM had a precision of 83.33%, a high PD detection rate of 75%, and a low false positive rate of 16.67%. In an unlimited dimension space, an SVM creates a hyperplane that may be used for classification or regression. The classifier with the least errors is the one with the biggest gap between data points. It is used to classify the extracted characteristics. Leave-one-out cross-validation is used once more for training. Research has been conducted for resting tremors, but they also looked at postural and mixed tremor performance [102]. An algorithm was developed to categorize feature vectors that included probability, as well as other data, using other statistics. El Maachi et al. [21] looked at the spatiotemporal characteristics of patients with neurological illnesses, as well as control participants. They calculated statistics, such as fuzzy entropy, skewness, and kurtosis, for each time series. RF, SVM, MLP, and KNN were among the ML classifiers utilized. The best result was produced with an SVM after optimization with a features selection approach. Their method used the SVM algorithm to carry out the PD patient assessment to meet the requirements of the mobile app. In conclusion, the PD speech recognition system uses SVM and SVR for speech diagnosis and severity evaluation, respectively. Experimental results have shown that SVM and SVR worked best for recognition and severity rating. The categorization task's recall rate was achieved at 97.03%, and the regression task's mean absolute inaccuracy could approach 3.7699, which was acceptable given that UPDRS values vary from 0 to 199 [82].

The traditional bootstrapping or leave-one-out validation methods have been developed for classification with a Support Vector Machine (SVM) for examining the validity and statistical significance of the PD connections to variables [91]. The topic of forecasting PD symptoms and their intensity was also examined. Both activities were designed to aid decision support systems in measuring and reviewing the care of individuals [6]. For PD diagnosis, Aich et al. [26] employed a feature selection approach, as well as a machine-learning-based technique. They observed that by using reciprocal information-based feature extraction and an SVM as a classification strategy, they were able to achieve 92.75% accuracy. Support Vector Regression was used to forecast the course of PD. They discovered that the suggested technique aided in enhancing the precision of PD development. The gap between the training images and the category border was maximized using SVM. It created a hyperplane for every data point that was represented by a collection of feature values and assigned a classifier to it [86]. In this paper, SVM used a linear kernel for Parkinson's detection. The examples in the training dataset were utilized to maximize the gap. The hyperplane was described as a plane that maximized the total lengths between the margins [60].

4.2.8. Ensemble Models

Ensemble models demonstrated that some of the features employed can detect indications of PD while being undetectable to human ears. This is a very hopeful discovery for the field, as it suggests that a large robust model could someday outperform humans. This also demonstrates the importance of voice phonation. Characteristics could be included in a set of non-invasive indicators for PD [103]. Dropout achieves the same result as the bagging ensemble strategy for a large number of DL models while maintaining low computing costs. The primary idea underlying dropout is that each time a new instance is input to the model, only a random subset of the network is used; consequently, the only parameter to tune is the likelihood of deleting a neuron [46]. Using structural MR images, ML was employed to differentiate PD from progressive supranuclear palsy (PSP), and a method based on resting-state brain networks was used to tell patients with Parkinson's disease and those with very mild cognitive impairment apart. Additionally, studies on whole-brain functional connectivity have been conducted to learn more about the disorder [63].

There are different distributions for people who are healthy and those with PD. However, because these patterns have a lot of volatility and overlap, it is impossible to diagnose based on just one aspect. For the detection of Parkinson's illness, Tiwari [80] created an ensemble technique that combined PCA, rotation forest ensemble with SVMs, and sparse multivariate regression. They investigated whether ensembles of regression trees may provide better results for PD prediction than single regression trees, and whether RvC ensemble approaches can help with this method. To predict motor and total UPDRS, classifier models with the proposed ensemble technique were used. Even though the theoretical analysis indicated that the weights should be effective for the proposed ensembles, they discovered that the technique had significant RMSEs. They investigated the reasons behind this tendency. They found that, although the prediction error should be zero in theoretical calculations, in practice, the average classification errors for several datasets ranged from 20% to 40%. This indicated that they might have given inaccurate results a disproportionate weight. As a result, the weights did not provide the intended benefit [94].

4.2.9. Limitations of the ML Models

Although earlier research has examined the application of machine learning in the diagnosis and evaluation of Parkinson's disease (PD), studies have only been able to analyze data from wearable sensors, kinematics, and motor functions [30,104,105]. The lack of adequate or accurate descriptions of techniques or findings, as well as some research's failure to accurately report the number and kind of subjects utilized or how ML models were implemented, trained, and assessed, were problems seen in many of the included research. Rarely did authors cite another publication instead of providing essential information, such as the number of patients and their medical conditions. Several papers did not provide this information in the main text, which could make it more challenging to replicate the findings [106–109].

4.2.10. Inference of ML Models

In summary, the realization of machine-learning-assisted diagnosis of PD yields high potential for a more systematic clinical decision-making system, while the adaptation of novel biomarkers may give rise to easier access to PD diagnosis at an earlier stage. Machine learning approaches, therefore, have the potential to provide clinicians with additional tools to screen, detect, or diagnose PD. Table 5 presents a summary of studies on machine learning models for Parkinson's disease diagnosis. Figure 5 illustrates the machine learning models for Parkinson's disease diagnosis used in this review.

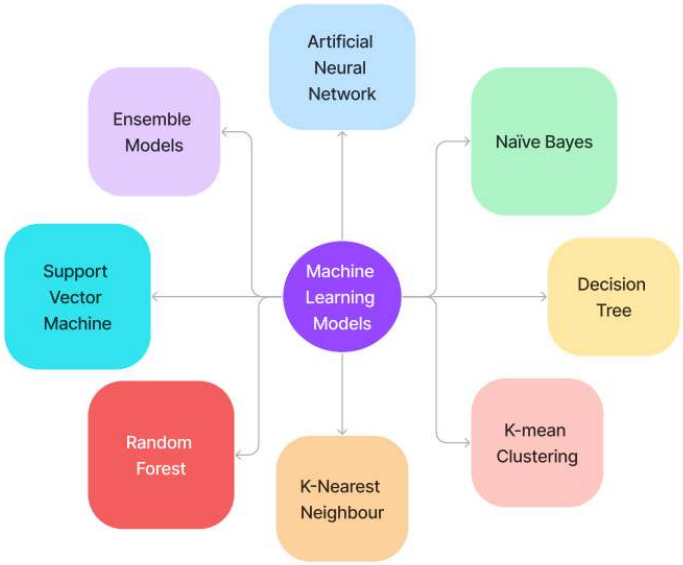

Figure 5. Machine Learning Models for Parkinson's disease Diagnosis used in this review.

Table 5. A Summary of Studies on Machine Learning Models for Parkinson's Disease Diagnosis.

Reference	Machine Learning Approaches Used	Dataset	Model is Pre-Trained	Feature Extraction Approach	Limitations	Performance Evaluation Metrics
[164]	Neural Network	Voice Database	Yes	Linear Discriminant Analysis	The testing database did not include any healthy classes, which shows that the data is unbalanced. Information about feature extraction was lacking.	Acc = 0.95
[165]	K-nearest neighbor and Decision Tree	Speech, audio, and hand PD database	Yes	Improved cuttlefish algorithm	Unable to merge the models of HandPD and Voice Datasets.	Acc = 0.92
[72]	SVM with RBF kernel	Handwriting Dataset for PD	No	NCP Method	They chose to only concentrate on PD and the HC group in this investigation. Various illnesses also need to be examined.	Acc = 0.81 specificity = 0.809 sensitivity = 0.84
[166]	Super vector machines	Sound Database	Yes	Bacterial Foraging Optimization	The surrounding environment of a bacterium has a great impact on the search capabilities of a BFO algorithm. Additionally, parallel computing techniques could increase computational efficiency which was not used.	Acc = 0.975
[167]	SVM-MLP	EEG database	No	Constant Fourier Transform	It only offers a solution for data that is linearly segregated.	Acc = 0.1
[168]	PBL-McRBFN + RFE	MIR BRAIN IMAGES	Yes	Voxel-Based Morphometry	A decision model's performance degrades due to the high dimensionality of MRI data and the scarcity of samples.	Acc = 0.87
[110]	Bayesian approach	Acoustic characteristics are taken from duplicate recordings	Yes	Gibbs sampling method	The dependency nature of the data being mostly ignored, voice recording replications have not typically been addressed for PD discrimination.	Acc = 0.86
[169]	PBL-McRBFN	ParkDB database.	Yes	ICA	-	Acc = 0.95

4.3. Deep Learning Models

4.3.1. Recurrent Neural Networks

To enable the hard customized prediction task, Che et al. [111] presented an RNN design to calculate the commonalities connecting the health records segments with a DTW-similar architecture that brings superior alignment for periods with substantial temporal changes. According to these findings, the RNN representation with the ADAM algorithm produced the finest classification results on both voice sets. These outcomes demonstrate the advantages of LSTM and ADAM optimization together. The model was evaluated using a variety of criteria and was tested on two different speech datasets. The accuracy was 95.8%, retention was 100%, accuracy was 92.3%, and the F-score was 96% on the first dataset [46]. RNNs are used to process sequences for text mining because they keep track of past hidden layer processing memory. Because the training converges more quickly and recognizes long-term patterns in the data, LSTM is far superior to basic RNN units [112]. DL methods and word embedding models have been explored to interpret and analyze user perspectives on Parkinson's illness [113]. Multiple nodes are found in the RNN's hidden layer [114].

4.3.2. Deep Autoencoder

An autoencoder is a program that can be used to learn representations, reduce complexity, and condense data [115]. In unlabeled data learning and voice identification applications, an autoencoder [116] has been widely used. The input data, dense nodes, and reconstructed surfaces can all be created as a three-layer neural system [53]. To learn about patient representations, deep learning techniques were used. To assess EHR in an unsupervised manner, Si et al. [117] employed a DNN made of using a layer of noise reduction autoencoders, collected stable structures and common trends in the data, and produced a medical diagnosis. DNNs have the potential to exist as a better classifier for PWP speech than traditional approaches. In contrast to traditional methods, DNNs not only use autoencoders (AEs) to lower the dimension of features, but also use the SoftMax layer to categorize the samples. AE attempts to maximize its data as the network's data, which may result in distinct input representations [27].

4.3.3. Long Short-Term Memory

The rear-diffusion method is used by LSTM for training. In an LSTM network, there are three valves. The input, forget, and output gates are the three gates. To select whether input data should be activated and changed in the store, the input gate employs a logistic function. For both the DNN and LSTM studies, the performance indicators obtained for each of these systems were utilized to assess statistics quantifiers, such as average, mean, variance, and so on. The efficiency of the LSTM model was 99.03%, with a standard deviation of less than 1%, which means that most accuracy measurements were around 97.96%, which is significantly better than the results of the majority of previous research in this sector. The DNN algorithms showed a range of min and max levels of accuracy of 90 to 97%, which was better than earlier research, but not as good as the LSTM models. With the greatest accuracy of 97.12% and 99.03%, on the same dataset, the DNN and LSTM-based prediction models performed better than all other models, indicating that these are trustworthy models for detecting PD [83].

4.3.4. Deep Neural Network

A DNN is composed of several basic components that are built on top of each other. Most of these simple structures perform irregular operations, like rescaling information to depict it in a different dimension, which helps uncover concealed features in the data [118–120]. The DNN proposed in this research is made up of two basic components that are coupled together: SAE, as well as a SoftMax predictor. SAE [121] is formed when the required number of autoencoders is combined. Among the most effective optimization techniques for instructing the neural network in this study is the Limited Memory BFGS optimization algorithm. Over OPD and PSD datasets, the suggested DNN is contrasted with innovative methods, including SVM, NB, and DT classifiers.

The following are some of the benefits of the suggested classifier:

1. The suggested DNN classification model can uncover latent characteristics, significantly improving the classifier's execution.
2. This classification model can be used to remotely diagnose and monitor Parkinson's disease. As a result, PWPs only need to visit the clinic once in a while.
3. It could be capable of monitoring and treating PWDs in creating useful biomarkers for diagnosing PD at a preliminary phase because speech difficulties are one of the earliest indications of PD.
4. Due to its high selectivity and responsiveness, the DNN model may be employed as a trustworthy PD sorter [59].

4.3.5. Deep Belief Network

DBNs (Deep Belief Networks) are a form of DNN that models high-level representation in the database with complicated composition using several computational levels [122]. These processing levels are linked by connection weights, but there are no connections

between them. As a result, it is a generative graphical model [123] that is made up of numerous layers of hidden units.

The evident surface is something that will collect the data (pattern characteristics) and will be altered at many processing levels. The quantity of packages in the viewable gradient increases to 16 neurons when 16 of the features collected by [124] are taken into account. Because the algorithm will categorize the waveform into each of the two risks, normal (0) or sick (1), only one system is necessary for the output layer. According to G. Hinton [123], the number of training examples, their complexity, and duplication might impact the number of these components. The DBN technique is a sort of NN approach. The layers are completely connected; however, there are no connections between the inner layers. These processing levels are linked together by connection weights, but there is no connection between them. As a result, it is a visual model made up of many surfaces of concealed neurons [125]. In this direction, large sets and few parameters are required for high-redundancy training instances, as more variables could result in overfitting [119]. There is not an ideal value; instead, choices are typically made through trial and error inside a range. Studies indicate that when estimating the number of concealed units in a network, the technique should begin with one level, add another, and finish before reaching the prediction error, while others believe that a system with two [126] or three concealed surfaces is adequate to handle most challenges.

Supervised learning approaches must be used to adapt them to efficiently handle the input data. The data were separated into two categories in the sample. The first category consisted of the training sample, which accounted for 74% of every test. The last representatives were utilized to test, validate, and assess the correctness of the system. As a result, the system's overall accuracy was 94%. This percentage was sufficient to produce a trustworthy system capable of diagnosing patients. A DBN-based diagnosis algorithm for Parkinson's was provided. Early PD could be detected by recognizing the patient's voice. DBN improved diagnosis with 94% accuracy, according to the findings. This result demonstrates that DBN was able to achieve the highest level of accuracy with that dataset [55].

4.3.6. Deep Convolutional Neural Network

Traditional PD detection approaches are typically handmade and need a high level of knowledge. The CNN uses an alternating convolution and pooling layer structure instead of completely linked hidden layers. They have been utilized in speech and audio processing for a variety of applications, including pathological speech categorization, audio activity recognition, voice identification, and more. CNNs are meant to handle datasets from multiple matrices, such as a three-channel color picture (RGB) or two-dimensional arrays that correlate to the TFR (Time-Frequency Response) of sound transmissions. In the study by Vásquez-Correa et al. [127], they created a CNN comprised of four convolutional layers, which offered a comprehensive investigation of PD patients' motor skills using architectures established on a combination of CNN and TFR that incorporated data from language, writing, and pace symptoms. The suggested approach simulated patients' difficulties in starting and stopping muscular activity in the upper and lower arms, as well as in speaking. Three main studies were conducted: (1) classifying patients with PD and HC subjects; (2) classifying patients with PD at various phases of the disease according to total points; and (3) classifying PD patients at distinct phases of development according to specific impairments in the bottom and top limbs, as well as speech, using MDS-UPDRS-III sub-scores.

The hidden projections of the neural network may be interpreted using the extracted features discovered by the CNN trained on multimodal input. The CNN's initial convolutional layers, which were trained with speech TFRs, exhibit substantial disparities between PD sufferers and HC. The last layer of the CNN is trained using handwriting, producing similar results. It appears to be a good fit for modeling PD patients' difficulty in starting and stopping distinct limb motions, allowing for the reliable categorization of PD

patients and HC controls. Furthermore, the proposed designs appear to have the potential to classify various phases of the illness. Their suggested CNN directly and automatically creates feature representations using parallel convolution layers matching each feature set. This was the first research to use a CNN with comparable surfaces to identify PD. The use of parallel convolution layers allows feature representations to be extracted from a variety of data. Multiple kinds of data can be sent into the system as inputs at the same time using parallel convolution layers. This allows us to use multi-modal data in the categorization of PD [85]. Abayomi-Alli et al. [54]'s investigation of the effects of feature extraction and data processing techniques examined the CNN LSTM and the SVM-based classification strategy.

Scholars have proposed utilizing a wrist-mounted accelerometer and gyroscope to collect tremor data, with CNN networks used to classify the data. The approach was tested on 92 patients and was found to be 85% accurate. The learned features are obtained by convolving the input data with a variety of filters during the training process [102,128,129]. They used a CNN to analyze spiral and meandering hand sketching characteristics in PD patients and found that the accuracy for 128 $\times$ 128 meander pictures was 87.14% and 77.92% for 128 $\times$ 128 spiral images [64]. Ref. [130] suggested a data augmentation method using a combination of GANs and Alex-Net that will successfully produce high-quality MR images and increase the performance of the classification model. A useful reference is provided by this work in medical image evaluation using DL. Srivastava [4] created a hybrid CNN-LSTM model in which the CNN learns well from spatial features from stride data and the LSTM trains well from the sufferer's time factors to forecast the intensity of the condition. When compared to base models for classification, this spatiotemporal model provided better results. By calculating an anemic person's blood count test results using optimal CNN and SAE with GA, they divided anemia patients into three groups. It demonstrated that their model was 98% more accurate than baseline models [131]. They demonstrated that CNNs can learn useful information and beat raw data outcomes. This initiative also aims to create a public dataset that could be accessed by scholars all over the globe to promote PD-related research. They suggested acquiring pen-based features using CNN, which can examine data using a succession of levels, each of which is responsible for learning a distinct and finer depiction. Furthermore, this paper did not include any work that dealt with automated PD diagnosis using deep learning techniques, which proved to be the case for vital contributors of this study. The significant addition to this research was the availability of a dataset containing signals gathered from sick and healthy persons using a smart pen. In another paper [64], they used a CNN-based technique to classify meanders and spirals created by control and PD sufferers. In addition, they ran a separate experiment on the original data that should be used as a reference point. They used the OPF classifier, which is a quick and parameter-free supervised ML algorithm. Varied CNN models, and also pictures with various qualities and training data set sizes, were used in the experimental portion. The results of CNN were compared to the uncategorized raw data classified by the OPF, and they were found to be very encouraging, as CNNs were able to learn essential characteristics to distinguish patients from healthy people, producing excellent results throughout the databases.

DCNN has considerably increased picture categorization and detection performance. Deep learning algorithms for segmentation, tumor identification, and disease classification have recently been applied to medical pictures. Scientists have used TFR and CNN to describe PD patients' articulation deficits. J.C. Vasquez-Correa et al. [132] identified PD and HC participants using voice recordings in three languages: Spanish, German, and Czech, with a degree of precision ranging from 70% to 85% based on the language, suggesting that learning techniques have the potential for analyzing the speech of patients. The proposed CNN model can be utilized to discriminate between HC's and Parkinson's patients with minimal or no signs. This work demonstrates the diagnostic use of speech in Parkinson's disease (PD) and raises the possibility that speech may provide a comprehensive picture of the disease, enabling tailored medicine by improving the efficiency, dependability, availability, and cost of PD care. The findings showed that the suggested deep CNN model,

which would be built on domain adaptation and uses a fine-tuning method, can diagnose PD with a precision of 91.17%. One of the most crucial elements of the research is that it may diagnose PD illness over a broad range by merely studying the vocal qualities of patients at various stages of the disease. ImageNet and LeNet are two alternative CNN designs. Scientists found that ImageNet had the highest accuracy for meanders and OPF had the best accuracy for spirals, both at 83.77%. A reduction in the levels of fluid dopamine produced by brain cells called neurons is another sign of PD. It can be discovered using dopamine transporter imaging techniques, such as FP-CIT SPECT. A deep CNN model was created for the automatic classification of cardiac and ocular artifacts in magnetoencephalography (MEG) data. Based on CWT images, CNN classified MER segments into artifacts and clean signals using its deep transfer learning model, which had been trained on millions of images. Their work was the most accurately completed (ACC = 88.1%) [133].

4.3.7. Deep Generative Models

Deep Generative Model (DGM) designs are challenging to implement due to their tremendous mathematical complexity. Several organizations have been working on systems that incorporate the core architectures of deep learning, making learning, configuration, and other uses of these tools in massive amounts of data easier [134]. Addressing these obstacles through analytical means would have a substantial impact on the treatment of PD and other neurodegenerative disorders, where evaluation faces similar issues. In ubiquitous computing, their system includes a standard analytic pipeline for activity recognition. The collected data is first segmented using a sliding window process, followed by the extraction of a hand-crafted collection of characteristics from each frame. These characteristics are then utilized to train a succession of RBMs in cross-validation trials. To improve classification performance, a SoftMax top layer is added to the learned generative model, which is then finetuned using conjugate gradients. Importantly, this first stage of training is exclusively driven by the goal of learning a predictive model of the training examples and does not rely on any input data labels. Advances that address the particular constraints of this issue setting would have a substantial social impact, since realistic evaluation tools will assist not just people with PD but also those with a variety of other degenerative diseases. Aside from the potential effect, naturalistic environments present a distinct machine-learning problem that might serve as a new testbed for the development and assessment of unattended and semi-supervised learning algorithms [50].

4.3.8. Deep Boltzmann Machine

Passos et al. [135] addressed the topic of a fine-tuning DBM to reconstruct binary pictures using meta-heuristic-driven optimization strategies. When compared to a random search, the experimental findings from three public databases demonstrated the validity of applying such strategies to optimize DBMS. They also demonstrated that when two out of three datasets were used, DBMs might develop better accurate estimates than DBNs. Wilcoxon signed-rank analysis was also employed to look at the similarities between each optimization approach, as well as the exchange between the computational burden imposed by each heuristic algorithm and its efficacy. Several sets of qualities with multiple variables were gathered from two datasets of hand-written artworks created by both PD patients and healthy persons using the RBM, a power probabilistic heuristic net. These qualities were subsequently included in the OPF method, which offered sample classification and performed better than the outcomes of previous methods [136].

The Continuous RBM successfully learns a deep cortical signal representation. For some patients, the CRBM model detects HVS (High-Voltage Spindles) before the ground truth; the lower the specificity, the sooner the HVS is detected. Because of the signal-to-noise ratio per channel or the existence of HVS, data quality can greatly vary from one rat to the next. The continuous RBM's properties offer a variety of benefits, and there are currently several ways to improve it. It is an unsupervised generative model that may be used as a predictor and can learn ideal frequencies to detect. It can extract quasi-

components, but the data must be separable. To assist hidden units in extracting different components, a knowledge of the model's architecture is required. Directly working on the Diffusion Network to eliminate the time lag produced by the usage of an observation window is another viable improvement option. Refs. [137,138] looked at two different types of drawings with two different resolutions, that were subsequently fed into RBM algorithms for supervised categorization. It addressed the topic of automated PD detection using characteristics learned by RBMs. It was discovered that RBMs with more hidden layers allowed for faster learning convergence, although this does not always indicate better performance on the test set. In addition to Discriminative RBMs, studies intend to use DBNs and DBMs for categorization in the future.

4.3.9. Deep Reinforcement Learning

Reinforcement Learning (RL) discipline optimizes subsequent choice tasks based on predetermined outcomes. It is one of the three branches of machine learning (along with supervised and unsupervised training). Researchers have discovered that the RL method generates a pharmaceutical schedule that is equivalent to that of physicians. They used a multivariate regression model to establish that health assessment ratings and medications had a significant enough level in forecasting future UPDRS III. Then, utilizing the statistically relevant factors and decision tree regressor, they created 28 distinct illness conditions that correlated to another overall UPDRS III score. RL can help PD patients improve their pharmaceutical strategy by suggesting treatments that are both efficient and effective. When general neurologists and primary care physicians deal with difficult cases where the appropriate drug combination is in dispute, this model will be tremendously useful. This effort marks the start of the creation of an AI-physician ecosystem that is collaborative [128]. They use deep RL to resolve the resultant model (DRL). The ideal treatment strategy that minimizes the patient's symptoms is determined by the recommended policy. Their findings reveal that the prototype strategy beats the static a priori therapy plan as part of alleviating patient symptoms, demonstrating that DRL may be used to supplement medical decision-making for chronic illness treatment decisions.

A3C is a DRL method that employs an actor to interact with the surroundings and a critic to learn about function and policy. The A3C approach makes use of numerous concurrent agent threads engaging with environment replicas, each of which asynchronously updates a world net [139]. In medicine, they have demonstrated stronger learning from positive reinforcement and poorer learning from negative reinforcement, whereas individuals who were not on medication showed the reverse trend. Patients who were not on medication performed much better at negative reinforcement than normal age controls (HC), implying that PD enhanced some components of RL. Dopamine may alter learning expression, according to a recent update to typical RL models. The active and passive routes, which learn from positive and negative reinforcement, have independent learning rates and factors that can influence the OpAL model. Enabling dopamine to influence the decision parameter can lead to a bias toward picking stimuli primarily learned through the direct or indirect pathways, giving greater weight to the rewards or punishments acquired. Dopamine and PD had no impact on the presentation of positive or negative reinforcement when immediately tested after learning or 24 h later. Over 24 h, dopamine during learning boosted the consolidation of RL memories. The initial PST had a low level of accuracy, and the changes made to it had a significant impact, improving learning and novel pair precision, as well as the number of avoid-B decisions made by participants. This emphasizes the impact that tiny adjustments to these sorts of jobs may have. The previously observed effects of dopamine and PD on RL were not replicated in this paper, suggesting that the impact is modest [140].

4.3.10. Extreme Learning Machine

An ELM has a very quick learning rate. The input weights are chosen at random using SLFNs, and the output weight is analytically calculated. Not only are the hidden node

parameters free of the training examples, but they are also independent of one another. It may be possible to generate the concealed node without considering the training data. All nonlinear piece—wise constant functions are compatible with ELM. PD has been predicted using the newly developed Meta-cognitive Fully Complex-valued Radial Basis Function (McFCRBF) network. When contrasted with a real-valued ELM and the FC-RBF network, the effectiveness of the Mc-FCRBF used to predict PD demonstrates that it predicts the illness better. The meta-cognitive product's self-regulatory learning process is credited with enhanced quality [141]. Nagasubramanian and Sankayya [71] tested ELM algorithms for PD categorization. The sigmoid function was used in the extreme training algorithm, and it was quick to operate. In an ELM system, the real-valued inputs and objectives were applied to the network. Regarding precision, the Mc-FCRBF network performed better than the ELM and FC-RBF networks. Consequently, BCGA-ELM could effectively distinguish between troublesome and ideal solutions. The results of the experiments clearly showed that the suggested technique could provide a similar solution for the PD classification issue for various random initializations. They intend to conduct a medical investigation of the 19 genes they chose in their upcoming research [78].

4.3.11. Limitations of the DL Models

To assist physicians in their choices, this in-depth analysis highlights the information on diagnosing Parkinson's disease (PD). It is acknowledged that gathering real-world data from patients is the most difficult endeavor in the healthcare sector compared to other study sectors. The medical datasets collected for any neurodegenerative condition are typically unbalanced.

- Given that the imbalanced dataset today influences the results, handling it is quite difficult.
- In addition, due to advancements in deep learning techniques combined with nature-inspired methodologies, there is a latent potential to leverage multimodal datasets to enhance PD's prediction accuracy.
- Although using the right criteria to assess ML models' performance in PD classification is important, there is still room for improvement.

4.3.12. Inferences of DL Models

A variety of studies have been conducted to determine the viability of various machine learning methods. Cross-validation methods were used to choose the most crucially dependable models. Most of the designs followed non-motor features, but some models employed motor aspects that were more enhancing than others. Using these kinds of models to detect diseases has many advantages. In other cases, PD was detected by analyzing the affected people's handwriting. The other means of identifying the same is through missing data. Therefore, each of these approaches deals with a separate set of conclusions and seeks to provide a thorough examination of this specific subject in a variety of ways. This study evaluated several papers on methods based on deep learning and machine learning for the diagnosis of Parkinson's disease (PD). To identify Parkinson's disease and increase the model's accuracy, a lot of research has been done on speech signals using machine learning approaches. However, there may be a need to investigate additional modalities, such as speech signals, for the diagnosis of PD. It has been determined from this survey that several ML and DL algorithms can be improved and that there is a need for additional research to increase accuracy and facilitate fast decisions.

By combining deep learning-based algorithms with experienced doctors, the rate of PD early detection can be raised. In the field of health care today, these deep learning models have a positive influence. To achieve high accuracy in the diagnosis of PD, deep learning models need to be enhanced. Finally, we think that parameters besides specificity and sensitivity might be used to provide even better guidelines for PD diagnosis specialists. The issues with improving the classification of Parkinson's disease may be resolved by these suggestions. Table 6 shows a summary of studies on deep learning techniques for

Parkinson's disease diagnosis. Figure 6 depicts the deep learning models for Parkinson's disease diagnosis used in this review.

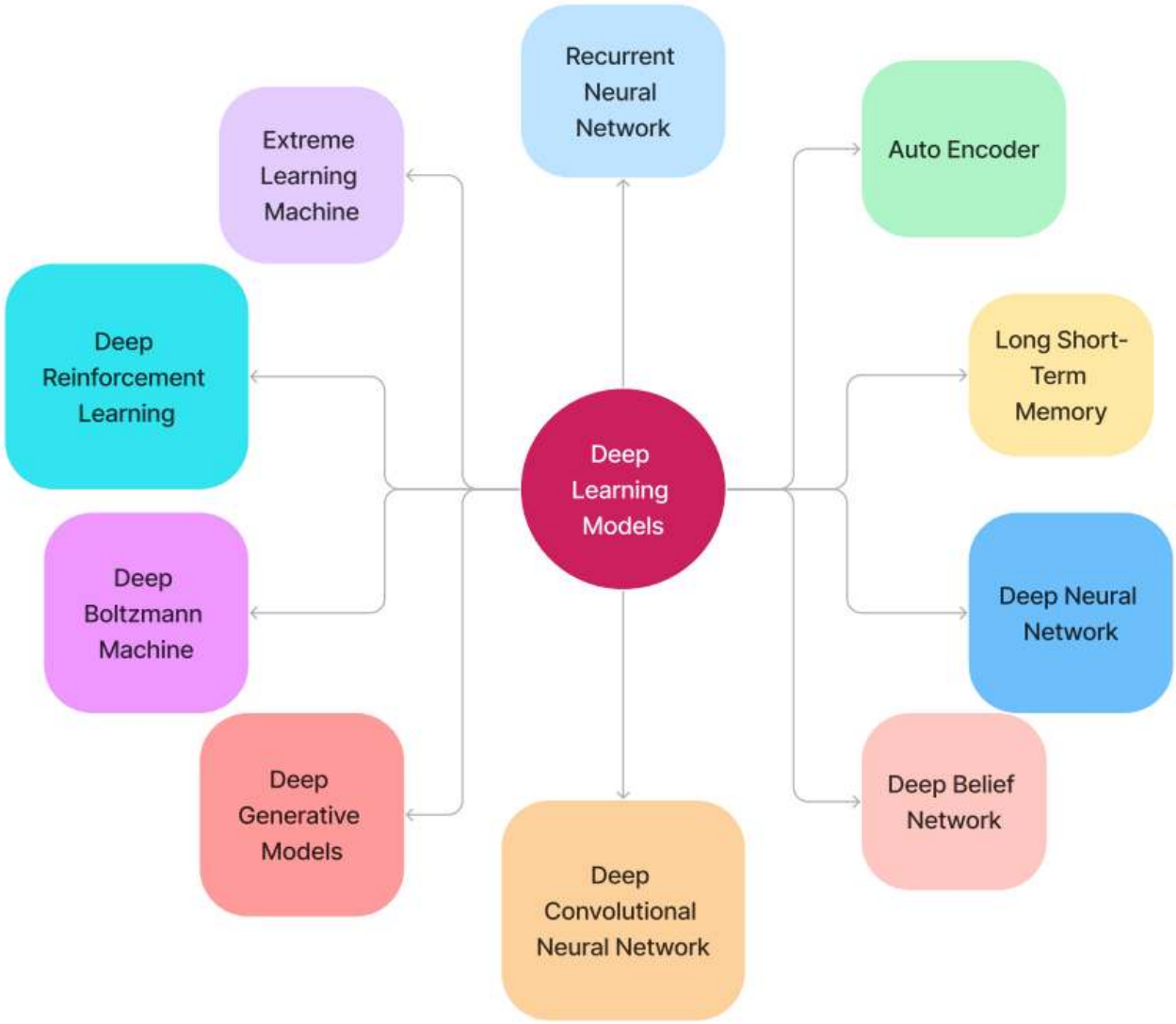

Figure 6. Deep learning models for Parkinson's disease diagnosis used in this review.

Table 6. A Summary of Studies on Deep Learning Techniques for Parkinson's Disease Diagnosis.

Reference	Learning Model	Dataset	Selected Features	Main Contributions	Limitations	Performance Evaluation Metrics
[170]	Convolutional Neural network	PaHaW dataset, HandPD dataset	Handwriting images	Presented an effective method for identifying handwriting degradation brought using static photographs of handwriting samples. With the NewHandPD dataset, this accuracy is the greatest ever obtained.	To validate this method, additional datasets and various network designs must be examined.	Acc = 0.94
[171]	Radial Basis Function Networks	93 PD; 73 HC	Gait features	GRF, a kinetic gait feature, can be used to distinguish between individuals with PD and HCs. As sensing devices and gait data analysis methods progress, the proposed method, which used GRF sensors, can be easily utilized in the clinical prediction of PD.	The test of the suggested approach's generalizability is constrained by the limited size of the current database.	Acc = 0.96
[172]	Convolutional Neural network	20 PD; 20HC	Ground reaction force	The LRP research reveals that bodily balance, where increasing degrees of the disease hinder patients' ability to walk without being at risk of falling, is a significant factor in diagnosing PD.	Lack of a plan for individualized longitudinal tracking to find the intensity of PD progression.	Acc = 0.83
[173]	Convolutional Neural network	NewHandPD dataset	CNN-Based Features	Using an end-to-end deep transfer learning technique, they were able to transfer already acquired knowledge onto the realm of handwriting samples with positive results.	There was an absence of a dataset of difficult tasks with other clinical factors that will help in not just identifying PD early but also figuring out how severe it is and how levodopa and other medications affect it.	Acc = 0.99
[174]	complex-valued artificial neural network	23 PD; 8 HC (Little, 2007)	(mRMR) attribute selection algorithm	The primary innovation in the research design is the implementation of a hybrid method, mRMR + CVANN, which combined a powerful classifier with an efficient feature selection method.	The program's data rate must be decreased and its efficiency must be raised to increase usability.	Acc = 0.98
[175]	Extreme learning machine	23 PD; 8 HC (Little, 2007),	22 biomedical voice measurements	The recommended GA-WK-ELM PD diagnosis process has several benefits including the ability to generalize, the ability to find the best wavelet kernel with the ideal w, x, and y parameter combinations, and the direct use of feature vectors.	-	Acc = 0.97
[176]	Artificial Neural network	93 PD; 73 HC (public)	Statistical features	In this study, the suggested strategy restricts the number of alternative symbols per data point so that the frame of encoding is fairly close to the center pixel.	The NR-LBP method approaches the candidate codes as numeric values, taking their maximum, median, average, or other quantitative metrics.	Acc = 0.98
[177]	Enhanced probabilistic neural network (EPNN) back propagation	189 PD; 415 HC (PPMI)	motor, non-motor, and neuroimaging features	This study shows how combining motor and non-motor information might enhance multiclass classification.	-	Acc = 0.98
[178]	13-layer 1D-CNN	20 PD; 20 HC (private)	end-to-end EEG signals	This study is the first to identify PD using EEG data using a thirteen-layer CNN architecture Despite the small number of participants, they were able to achieve high accuracy.	The created model should be tested in the future on a sizable subject population to detect PD in its initial stages.	Acc = 0.88
[179]	Deep Belief Network	125 PD; 225 HC (private)	laconic representation of PET images	The GLS-DBN model accurately classifies patients into diagnostic groups and provides a measurable biomarker that can spot early PD with minimum image analysis.	The learning rate was calculated by trial and error, and the network structure's parameter values were refined by numerous tests, increasing the algorithm's temporal complexity	Acc = 0.90

5. Open Challenges

5.1. Challenges in Computational ML Models

We should look into the challenges associated with training ML models using unclean data collected from the public as well as the area of sound signal processing. We must also prove that the experimental method of classifying healthy and diagnosed individuals differs from how a neurologist makes a diagnosis. We must provide insights into the behavior of these models, not only present data as a performance metric, and show that machine learning can outperform physicians in precise phonation analysis, potentially uncovering novel indicators for PD.

5.2. Challenges in Computational DL Models

- A DL model is a closed system that trains from data that can be used to imitate the dataset acquisition. As a result, explanations are frequently insufficient to fully comprehend its mechanism. Images from different datasets have diverse appearances due to non-standardized reference sources. This is a significant difficulty when using DL to analyze brain imaging.
- The use of large training datasets is critical for generating better results with DL approaches, and the lack of them is among the major hurdles in the application process. It is used in neural mapping to protect patients' confidentiality. At the same time, labeling those data is a major challenge that requires professional guidance.

5.3. Challenges in Integrating Parkinson's Disease Diagnosis Data

- Medical data consists of patient longitudinal records that span from a few months to years during their regular visits. Dealing with conflicting patient records is one of the most difficult aspects of working with longitudinal data. Because many patients leave out or fail to show up for evaluations, there is a discrepancy in data, causing statistics to be skewed. Another issue is that patient data is missing for a few medical practitioner assessment exams that are not provided at the time. Lipton et al. [142] also employed forward and backward filling within a one-hour window for each visit to resample all missing values. When the whole variable record was lacking, they substituted a clinically normal value as determined by specialists.
- Realigning and combining complex multi-source and multi-site PD databases is also a challenge. In Parkinson's, collecting such data is difficult since there is such a scarcity of cohorts having extensive, well-curated information. As a result, one major requirement is the growth or duplication of projects like PPMI or PDBP, ideally with a model that provides an unrestricted approach to the underlying information; the expense of this data type gathering is high, but it is an essential resource in their attempts to understand PD.

5.4. Challenges in Merging Omics Data with Various other Sources of Information, Such as Electronic Health Records and Wearable Sensors Data

- The evolution of wearable devices to monitor people with PD has largely emphasized the motor elements of the condition, which are also assessed by clinical scales, but with less sensitivity and specificity. Even though there have been recent improvements in quantifying motor symptoms like tremors, these outcomes frequently only show limited quantitative consistency with evaluations of life quality.
- Non-motor impairments are frequently sources of disability and patient priorities (e.g., depression, anxiety). The majority of health data are now kept on paper and are controlled by medical centers, many of which have poor communication capabilities. Some health files have already transitioned from paper charts to electronic health records, but these EHRs are primarily digital copies of their paper-based forebears and do not include all of the technical alternatives that are presently available to help clinical decision-making. Strong and comprehensive data protection laws and

regulations are also expected to lower the danger of data leakage to a minimum and raise the user acceptability of EHRs.

5.5. Challenges in Precision Medicine and Identification of Personalized Treatment

While the impact of ML is tied to the advised transfer learning model, the choice of research is based on the doctor's capacity to employ the established technique during health examinations. Additionally, the success of the suggested technique would indicate an improvement in healthcare outcomes, as well as reduced costs for the national health system. Developing and disseminating expert systems for these tasks is undeniably a technological and scientific problem. Due to the increasing growth in patients every year and the complexity connected with this brain condition, PD demands specific consideration when it comes to constructing automated diagnostic systems. The programed DL classifier can help in the official diagnosis of a patient's PD severity, allowing practitioners or neurologists to provide further treatment options and consultation.

5.6. Data Isolation Challenges

It is critical to use ML and DL approaches to separate Parkinson's symptoms from other things. The dataset employed in these procedures, in particular, must be well evaluated. Nagasubramanian et al. [71] looked at a variety of Parkinson's datasets. They were mostly concerned with picture datasets. For the development of their research, they employed DNN and believer networks. The majority of studies present in this survey employed speech characteristics or picture databases to identify PD indications. Motor dysfunction research continues to present the scientific community with a variety of clinical concerns [75].

5.7. Data Management Challenges

- The BEAT-PD data challenge was created to test innovative strategies for predicting PD development. Its goal was to see if illness intensity and development could be determined using passive sensor data collected in everyday life. Participants had access to raw sensor time-series data that might be utilized to forecast individual medication status and symptom intensity. Cleaning and curating data is difficult, but discovering patterns from it is much more difficult. Quoc V [120] outlined the problems of big data, as well as the importance of big data technologies in the biomedical field. It is challenging to create a stereotype MRI database because it is a remnant of a training method that might end in a statistical product. The issue can be alleviated by introducing a large dataset into the system, assessing the relationship between retrieved characteristics, and fine-tuning the system's variables. It is still a work in progress to predict NLD in actual time from visual observation.
- Stream processing, on the other hand, is a parallel computer approach for processing substantial amounts of data. When we use ML techniques to gain value from large data, maintaining data quality is a major difficulty. According to researchers, unbalanced data is a prevalent difficulty in categorization. The most difficult task is the cleaning and curating of the data. Each file must be separately examined, and any duplicate or administrative data not necessary for the research should be eliminated. When we combine all of these broad properties, we obtain a massive sparse matrix. The goal of the research should be to uncover and display the connections between different traits.
- Because it is time series data, the complication is raised even further. Compiling and layering data are difficult tasks. The information is skewed, unbalanced, and contradictory. There are many missing values when data is pooled. Only 30% of the data is accessible. Databases from healthcare research and behavioral investigations of PD are now quickly developing, with little awareness or integration of the qualities obtained. Recognizing the significance of each characteristic collected through PD identification and therapy is critical, and the research serves to emphasize the data's reliability difficulties and ways to address them. We can expand their study in the

future by allowing them to add more qualities and identify their involvement in PD [143].

5.8. Data Sparseness Challenges

- The major goal of [8] was to enhance the reliability of the current state-of-the-art in-patient diagnosis and avoid patient misinterpretation, and the experimental findings showed that the goal was met. However, because the diagnosis may be conducted in a variety of ways, there is still a lot of room for advancement in technology. The findings of this study advised against using less accurate approaches for diagnosing Parkinson's and the usefulness of telemonitoring apps.
- The PPMI is a pioneering prospective in clinical research that examines PD cohorts using a variety of data sources, including sophisticated imaging, biologic samples, and clinical and behavioral evaluations, to determine the circumstances of PD development in individuals. The data is scarce, inconsistent, and continuous, with a lot of temporal facts encoded in a clinical situation that supports the lengthy progress route of PD, making learning even more challenging.
- Che et al.[111] dealt with data anomalies and imputed the bulk of incomplete data. For the bulk of the missing data, they used the latest occurrence carry forward method. They substituted the patient's first observed record if the patient's initial record was missing. Table 7 presents the open challenges for Parkinson's disease diagnosis. Figure 7 depicts the open challenges for Parkinson's disease diagnosis.

Table 7. Open Challenges for Parkinson's Disease Diagnosis.

References	Challenges in Computational ML Models	Challenges in Computational DL Models	Challenges in Integrating PD Diagnosis Data	Challenges in Precision Medicine and Identification of Personalized Treatment	Data Isolation Challenges	Data Management Challenges	Data Sparseness Challenges
[50]	×	✔	✔	✔	×	✔	✔
[145]	✔	×	✔	✔	✔	✔	✔
[95]	✔	×	✔	✔	✔	✔	✔
[146]	×	✔	×	×	×	✔	✔
[8]	×	✔	✔	✔	✔	✔	✔
[64]	×	✔	✔	✔	×	✔	×
[4]	×	✔	✔	✔	✔	✔	✔
[147]	×	×	✔	✔	×	✔	×
[148]	✔	✔	×	✔	×	✔	✔
[7]	✔	×	×	✔	×	×	×

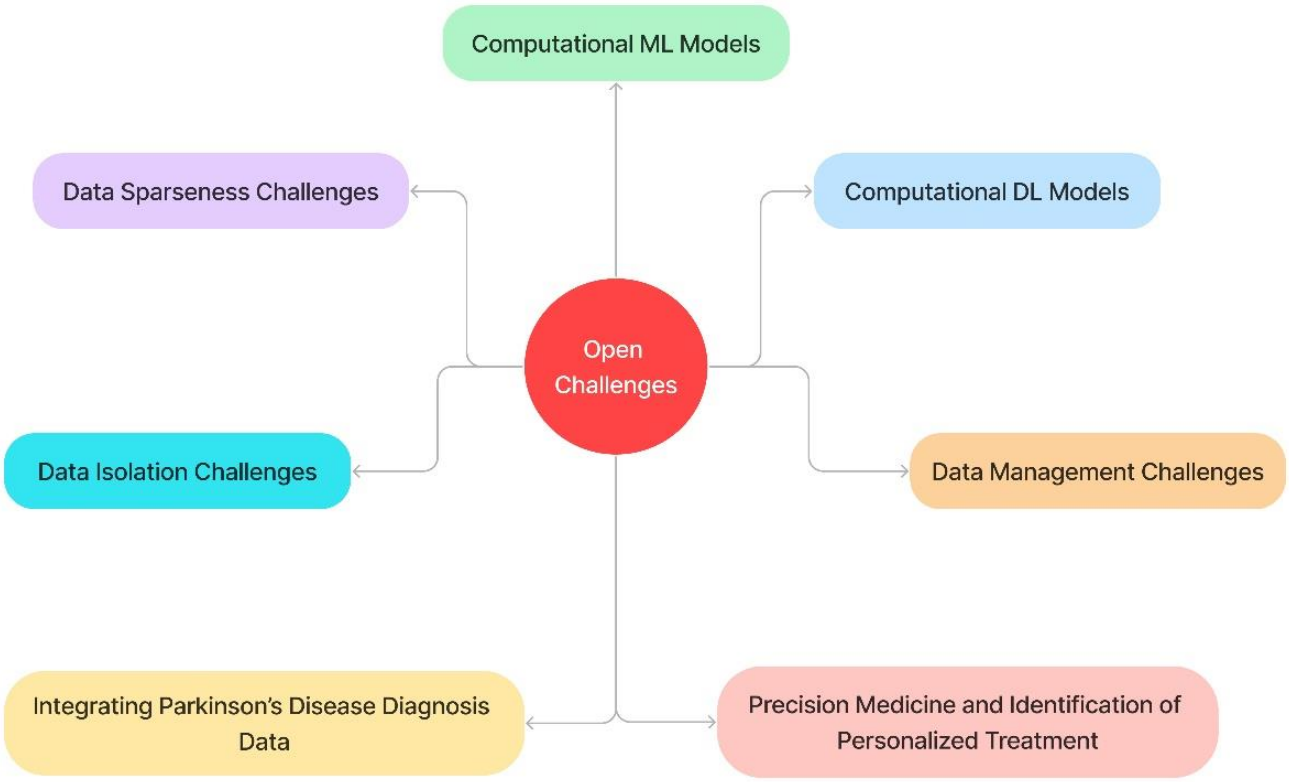

Figure 7. Open challenges for Parkinson's disease diagnosis.

6. Parkinson's Disease Diagnosis using Sensors, Smartphone Devices, and Web Applications

According to Mazilu et al. [36], novel sensor modalities might be used to continually monitor FoG episodes in PD, which could be anticipated using biomedical signals, such as electrocardiography and skin-conductance measurements. Before, during, and immediately after FoG events, they examined the alterations of several specific features retrieved from both ECG and SC. These characteristics were then put up against conventional walking habits. Additionally, the scientists applied an anomaly-based method for anticipating gait-freeze episodes using SC features and multivariate Gaussians. With an average of 4.2 s before the event, they were able to foresee 71.3% of FoG incidents. An overview of various well-known wearable Internet of Things applications for PD was presented by Pasluosta et al. [149]. They discussed wearable technology, its fundamental concepts, and its applications, as well as the most recent advancements in ML and AI, particularly as they relate to diagnosis and treatment. Mobile devices make use of personal computer characteristics that can be expanded to accommodate varying user profiles. Additionally, mobile-focused applications can leverage a variety of sensors included in tablets and smartphones, which can track motions like hand tremors. To enable comparisons with the stepping-in-place condition, the VR environment must be paired with a cognitive, visual two-stimulus-oddball reaction task that should be repeated while seated. The setting was demonstrated to be a highly effective and dependable strategy for inducing FoG-like symptoms in PD individuals with FoG in a controlled manner, offering a platform for more research on the pathology of FOG. Table 8 presents the smart phone applications in Parkinson's disease management.

Table 8. Smart Phone Applications in Parkinson's Disease Management.

S. No.	Name of the Smart Phone Application	Mobile Operating System	Free/Paid	App Description and Features	Users	Utility
1	Neurology Now	Android	Free	Official publication of the American Academy of Neurology	Health care specialists	ideal for PD.
2	Speech Too	iOS	Free	Voice volume training	Patients	ideal for PD.
3	Parkinson's Disease	Android	Free	PD details	Health care specialists	Details about PD
4	Parkinson's Toolkit	iOS/Android	Free	Clinical practice recommendations for treating PD	Health care specialists	Details about PD
5	PD Headline News	iOS	Free	Literature on PD	Health care specialists + patients	Details about PD
6	MDS UPDRS	iOS	5.99	MSD-UPDRS scale	Health care specialists	Evaluation
7	Fox Insight App	Android	Free	Movement, tremor, and sleep tracking	Patients	Evaluation t+ diagnosis
8	Prognosis	Windows Phone	Free	tests to evaluate one's speech, upper limbs, rest, and gait	Health care specialists	Evaluation
9	ListenMee App	Android	121	Using cues to enhance gait	Patients	diagnosis
10	Parkinson Exercises	iOS/Android/Windows Phone	4.22	Videos of exercises for PD patients	Patients	diagnosis

7. Future Research Directions

- Even if rather high accuracies have previously been achieved, the reported results indicate that there is still room for development. For identifying the presence of PD movement disorders in time series data, scientists have suggested using an uncommon combination of algorithms, including the log algorithm. The main goal is to see if these methods can match, if not exceed, the mentioned papers in terms of accuracy. MOSIS, a relevant framework for assessing various techniques, is currently being developed. Future research should focus on this topic, particularly using longitudinal approaches. Dopamine bioavailability, on the other hand, can influence speech results and other communicating abilities. It should also incorporate new processes or at-risk carrier states to see if central mediators can anticipate symptomology more closely linked to PD risks, such as olfaction and sleep disruption, which did not develop much in the established PD cohort.
- There is a need to develop better robust models which will improve PD identification while maintaining the accuracy of the results and developing models' impartial behavior. Feature selection approaches and DL models can be combined to achieve this. A bigger database is needed, and the algorithm will be tweaked and refined for other classification tasks important to PD monitoring (e.g., dyskinesia, tremor). Finally, data collected in the home and community can be used to test these strategies.

7.1. Explainable AI

Assuring that any detection and predicting model concentrates on improving system performance as well as AI ease of understanding, including natural language descriptions to help physicians to comprehend the projections, is a critical potential roadblock [150]. Researchers have suggested a ML-based solution approach to web design for developing a comfortable and practical PD diagnosis service through smartphones. In low-dimensional space, the suggested approach can remap temporal frequency characteristics. A testing mechanism is also being created for testing; telediagnosis of PD using a smartphone is expected to be possible in the future. Che et al. [111] also created a new deep model for learning patient similarities in their study. They built a customized prediction framework based on the learned similarity that is flexible enough to permit different classifiers in

the prediction phase. This research has the potential to be expanded in both directions: similarity learning and tailored prediction. A more comprehensive provision for multitarget prediction should be developed.

7.2. Generative AI

- It is recommended that, in the future, more data augmentation techniques based on various AI paradigms and architectural frameworks be investigated to create a smart model for voice recognition with sparse data. Ref. [151] provided a unique technique for selecting the most exclusionary feature for differential diagnosis of PD and SWEDD, utilizing machine learning methods such as KSOM, LSSVM, and WAT as statistical measurements in the study. Clinically significant ROIs were discovered to be identified by employing MRIs and KSOM-based feature extraction. This technology might be utilized not only to diagnose PD early on, but also for exploratory study into brain regions. This paradigm might hasten the emergence of evidence-based prognosis in this environment. The limited size of the group under research is, of course, the study's fundamental part, making the findings less generalizable. Regrettably, there is currently a void in the scientific community working on this issue in terms of the accessibility of a large benchmark dataset.
- Impedovo et al. [99] findings suggested that a diagnostic assessment based on such technology might appropriately exclude illness in healthy individuals' communities, making it helpful for ruling in disease when a satisfactory reaction is obtained. Even though usage of DL frameworks is on the rise, there are no articles relating to DL in the large and diverse scientific databases. The exploration of this specific field, PD, in conjunction with a well-known, optimized, and robust DL architecture, like Caffe, might be fruitful. In the future, research on new databases only focusing on the DL and DP might be carried out for the recipient to comprehend this difference and, as a result, other research possibilities in the field [134].

7.3. Internet of Everything

The Internet of Things (IoT) has provided a clever method for detecting PD and providing appropriate medicine by evaluating speech samples in this paper. Instead of depending on the IoT's limited storage and processing capabilities, fog computing is being used in intelligent systems to effectively monitor and identify Parkinson's illness. The secure storage of voice records necessitates a huge storage capacity, which the cloud server may supply. Mobility and location awareness are also provided by fog computing. A shortage of dopamine affects bodily equilibrium, motor characteristics, and speech. Medication and therapy are unable to entirely cure it, and it has life-threatening negative impacts. As a result, limiting the disorder's growth early on can be a viable option. The research should be expanded to include the creation of a reliable decision-making system for diagnosis and treatment suggestions. Researchers have also planned to employ expert knowledge to create a rule framework for the better care of Parkinson patients [146].

7.4. Big Data and Augmented Analytics

The feature patterns in the datasets from Michigan and Tel-Aviv noticeably differed. It is unknown whether biological, clinical, physiological, or technical variables contributed to the observed variance. All big data analytic studies that incorporate multisource heterogeneous data have encountered this issue. Features that were completely incompatible between the two data archives were not included in the consolidated database and further analysis. Due to a shortage of data in either data archive, neither the frequency nor the severity of falls were investigated. However, both the incidence and severity of falls need to be investigated further [152]. When just a small quantity of data is available for training, their suggested model, based on data augmentation approaches, demonstrated a considerable improvement in accuracy. It is worth noting that they generated a tiny dataset with a 90% holdout for training data, which has not been utilized before by other scholars. In

future years, the main goal must be to construct an intelligent model for voice recognition that includes limited datasets to investigate additional data augmentation approaches based on other AI methodologies and architectural frameworks [54].

7.5. Cloud, Edge, and Fog Computing

Fog computing is a novel technique to increase the performance of older patients' health conditions while reducing healthcare funds and expenses. Researcher have aimed to discover PD at an early stage so that appropriate drugs might be administered to mitigate the devastating consequences. Although there has been much research on the early diagnosis of PD using speech samples, or dysphonia, the method is effective for patients using a desktop fog workstation. The suggested intelligent systems effectively monitor and recognize Parkinson's disease using fog computing. A cloud server may be able to provide the large storage capacity needed for secure voice record retention. Devarajan et al. [146], incorporated cloud and fog computing for local and central storage, data analysis, market research, privacy, alert methods, and ideal patient-professional communication.

7.6. Robots and Machine Co-Creativity

By using prior knowledge, Ref.[153] was the first comprehensive assessment to assess the possibility of using AI-based technologies and robotic systems to manage the advanced stages of Parkinson's. When considering the work described in the suggested technique, it is noticeable that everything relevant to speech and activity analysis was discussed. The future breadth of this implementation is determined by the types of items used to classify patients with PD. We can use the person's eating habits as a primary criterion, and whether or not the patient has had any accidents in the past is also essential in determining whether or not the patient will develop PD in the future. However, for the time being, the suggested technique recognized PD in fold 3 of 5 folds.

7.7. Quantum Computing

The outcome of the neural network employing quantum computing will provide a process for determining the requirements for implementing cutting-edge technologies in medical care. The fold value will be managed by the network created using quantum computing [118]. Researchers have looked at a person's eating habits as a key factor, and whether or not the patient has a history of accidents is also crucial in determining whether the patient would get PD in the future.

7.8. Transfer Learning

Transfer learning, which also provided a latent space that is more strongly related to clinical indices, produced excellent classification performance. According to the research of [185], a heatmap-integrated image classifier combined with transfer learning may provide a way to classify small sample datasets. The effectiveness of the classifier and research methodology will be further improved. Future suggestions for novel models that make use of transfer learning have a lot of potential. It is also possible to enhance datasets with a variety of qualities that may be important in identifying the condition. In order to analyze the handwriting movement and the number of frames required to complete one set of hand drawings, the long-term objective of this research is to collect a dynamic dataset utilizing samples from an electronic pen-pad. Patients' writing becomes less flowing as their PD deteriorates. Furthermore, this will increase the accuracy and effectiveness of the PD prediction [186]. Future research will assess the [187] model on additional PD databases (PaHaW, HandPD) in order to further validate the findings. We should also look into how PD can be identified through speech and handwriting.

7.9. Federated Learning

The main focus of [188] was the potential of federated transfer learning in healthcare using activity recognition and auxiliary PD diagnosis. FedHealth can be used in more

real-world scenarios for healthcare applications, including elder care, fall identification, cognitive disease diagnosis, etc. The privacy-sensitive issue of patient data must also be addressed by federated learning. As a result, FT-IoMT Health is implemented in hospitals to aid in the diagnosis and treatment of PD [189]. The patient downloads the user model to the biosensor after training it on the user side, then connects to the network to update it before the subsequent access. In order to determine the status of an illness more readily, this enables people to independently detect and receive real-time feedback. The alternative approach in [190] is the challenge of recognizing PD, which allows the findings obtained to use federated learning methodologies, which can be applied to a wide range of real-world circumstances. This study demonstrated how accurate the network designs utilized for federated learning are. These results are not a goal in and of themselves, because while federated learning is significantly more secure than traditional machine learning in terms of protecting privacy, it is not always guaranteed to be so secure. Therefore, a blockchain must be added to address Federated Learning's security concerns.

7.10. Augmented Reality (AR) and Virtual Reality (VR)

7.10.1. Augmented Reality

According to findings, People with Parkinson's and FOG have trouble splitting their focus between physiological and cognitive activities, as well as separating task elements. While choosing a VR model, clinicians must thoroughly weigh the benefits and drawbacks to attain the best training effectiveness. When compared to typical queuing tactics, the HMD that gave visually enhanced signals during locomotion did not lessen the intensity of FOG. Geerse et al. [154] examined the ongoing voice task using data obtained using an internet data collecting system that can be accessible anywhere in the world and only needs a web device with an inbuilt recording device. Furthermore, because the moving language task does not require special directions and is much more akin to the typical discussion, the model might be enhanced to predict PD from a legitimate discussion, which could be a meaningful change in PD diagnosis. In the future, user-approved plug-ins for applications like Alexa, Google Home, and Zoom, which transfer audio between people, could be created.

7.10.2. Virtual Reality

- Virtual reality has been developed as a feasible method for investigating and treating people with PD who have complex deficiencies. In a regulated laboratory or clinical setting, the goal of using VR in stroke recovery is to evoke and/or prepare neurobiological responses that are analogous to the few that happen in real life. The extent to which a user is completely absorbed in a digital environment is known as immersion, which is a major feature of VR.
- Scientists are encouraged to build interactive virtual applications with combined evaluation and training programs that are tailored to the needs of persons with PD and healthcare professionals to maximize the potential of VR rehabilitation and improve rehabilitation results. By immersing persons with PD in an enhanced and highly tailored environment that resembles real-world events, while avoiding risk, VR offers the potential to improve knowledge and treatment of complicated PD impairments. However, its full potential for PD rehabilitation has yet to be realized. When provided in a fully supervised format, both are preferable to no treatment, although there is no indication that VR treatment is better than non-VR therapy in terms of gait and balanced outcomes. Virtual reality enables the secure detection of a person's particular FOG triggers and equilibrium deficits, resulting in specific training targets [147]. Figure 8 illustrates the future research directions for Parkinson's disease diagnosis.

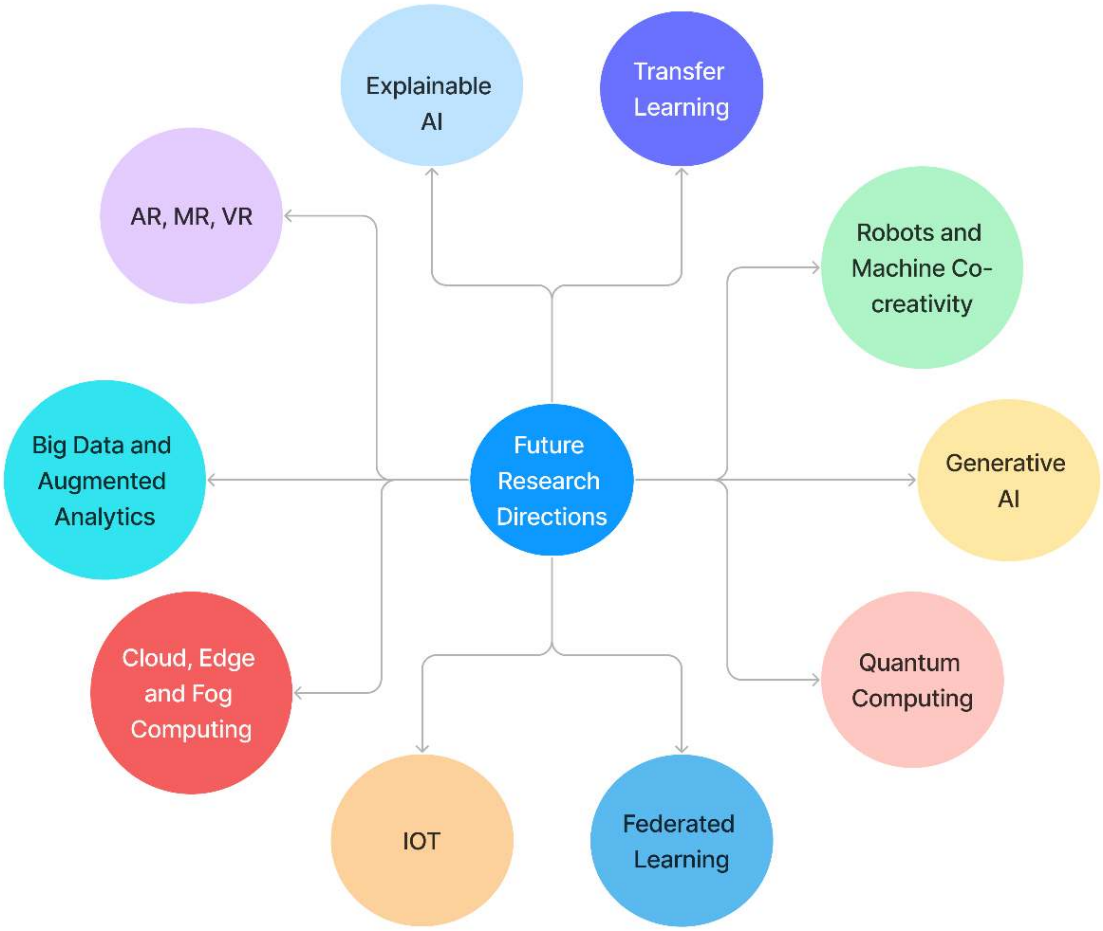

Figure 8. Future research directions—Parkinson's disease diagnosis.

8. Conclusions

As we previously described, the number of Parkinson's patients is increasing at an alarming rate [2]. Therefore, there is a need for increased focus on the diagnosis of this disease. The diagnosis of PD is non-directed, which means that the disease cannot be detected with the currently used test methods, such as a blood test or an ECG. Before performing a comprehensive neurological examination, clinicians typically review the patient's medical records. They determine which subjects exhibit at least two cardinal symptoms before predicting whether they have PD. There is a considerable risk of misinterpretation because there is no reliable test for this, so, in this scenario, an ML model could assist the doctor in reaching an accurate diagnosis. Based on these relevant traits, prediction models are created using ML methods, such as boosted LR, classification trees, Bayes Net, and multilayer perceptron. In the current scenario, the prediction quality of models has been improved. Algorithms, such as Boosted LR, have been shown to generate superior outcomes. These findings motivate us to experiment with additional ensemble learning strategies. Finally, these models can provide nuclear/medical professionals with support in making better and more accurate decisions and clinical diagnoses. The improvement of high-speed computer tools, as well as the creation of advanced DL-based algorithms and models, has created a different opportunity to predict and manage a variety of neurological disorders, such as dementia, PD, and schizophrenia. While there is no treatment for PD, there are some treatments to help a sufferer to live a good and healthy life. Depending on the level and intensity of this disease, many therapies are available. All the strategies utilized in this study might be used for similar disease categorization challenges, requiring databases like the one used in this study. However, considerable work must be done in clustering, noise reduction, and fuzzy rule-based disease diagnostic techniques to fully realize their potential

and value. In the future, more focus should be placed on databases for illness categorization and prognosis using incremental ML techniques. Future studies must look at how the suggested technique may be customized to interact with multiple kinds of medical records. Private sector investment is uncertain to be lucrative in the long term, since this disease evaluation requires a narrow technical usage. Finally, research demands data sharing since it requires ongoing repetition and the verification of new findings. By exchanging datasets, we may improve algorithms and provide more broad and rigorous clinometric verification data, and hence, we will have a better understanding of Parkinson's disease. The development of a practical PD identification app with high precision and specificity is now underway. The problem with identifying Parkinson's is that there is no one quasi-clinical diagnostic test that may identify the disease early on. In certain PD instances, however, it is hard for specialists to conduct a physical evaluation of a patient's language, so they are unable to recognize or misinterpret the symptoms. Moreover, innovative technology that supports the doctor in healing and stopping the illness from propagating to other brain cells is critical. Considering this, the study used a simple-to-use, accurate, and effective deep network system based on domain adaptation for disease diagnosis. It investigated how transfer learning methods with fine-tuning procedures may enhance the detection of PD using a voice sample from a large database. Moreover, by putting the recommended transferable training algorithm into a smart electrical appliance for personal use, future research will be able to consistently and rapidly detect PD without disturbing the client.

Moreover, activities should be available in a range of intensities and durations to assess patient reactions in a variety of fatigue scenarios. Future research should examine the effectiveness of the characteristics used to describe writing motions. On the other hand, these designs should be leveraged to create distinctive and more efficient capabilities. When using restricted datasets to enhance PD identification, the necessity of expanding available data for categorization cannot be stressed. This study was able to successfully handle the problem of class imbalance by using the interpolated approach to augment the original data sample.

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