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A comparative study: prediction of parkinson's disease using machine learning, deep learning and nature inspired algorithm

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Abstract
Parkinson's Disease (PD) is a degenerative and progressive neurological disorder worsens over time. This disease initially affects people over 55 years old. Patients with PD often exhibit a variety of non-motor and motor symptoms and are diagnosed based on those motor and non-motor symptoms as well as numerous clinical indicators. Advancement in medical science has produced medicines for many diseases but till now no significant remedies are discovered for Parkinson disease. It is very necessary to detect PD at early phase to take precautions accordingly to reduce its harmful impact and improve the patient's life style to a considerable level. In this direction Artificial Intelligence (AI) based approaches have recently attracted many researchers to work accordingly as AI can handle vast amounts of data and generate accurate statistical predictions. Addressing this imperative, researchers have turned their focus toward Artificial Intelligence (AI) as a promising avenue. AI's capacity to manage vast datasets and generate precise statistical predictions makes it an invaluable tool for PD detection. This article aims to provide a comprehensive survey and in-depth analysis of various AI-based approaches. Leveraging machine learning (ML), deep learning (DL), and meta-heuristic algorithms, these approaches contribute to the prediction of PD. Additionally, the article delves into current research directions. As the pursuit of advancements continues, the integration of AI holds promise in revolutionizing early detection methods and subsequently improving the lives of individuals grappling with Parkinson's disease.

Keywords Neurodegenerative · Parkinson's disease · Nature inspired algorithm · Deep learning · Machine learning

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1 Introduction

Over the last few years, health informatics systems have been extensively used in identifying and keeping track of crucial diseases. In the monitoring of neurodegenerative diseases, artificial learning-based information systems are used comprehensively these days. Neurodegenerative diseases are hereditary and sporadic conditions that are characterized by debilitation of the progressive nervous system [1]. Among many neurodegenerative diseases like Brain Cancer, Degenerative Nerve Diseases, Alzheimer's Disease and Epilepsy, "Parkinson's Disease" is considered to be the second most common neurodegenerative illness that primarily affects people over the age of 55 [2, 3]. The World Health Organization (WHO) estimates that on average, around 7-10 million people suffer from Parkinson's disease throughout the world in any given year [4–6]. The English physician James Parkinson discovered it for the first time in 1817 [7] and also explained the condition as "Shaking Palsy" [1]. Parkinson's disease (PD) manifests itself by the progressive loss of dopamine neurons in the substantia nigra which is a region of the midbrain and also known as the "movement control centre" of the brain [8]. Dopamine neurons play a crucial role in generating dopamine and regulates human movement [9, 10]. So, due to the lack of production of dopamine neurons, this brain disorder causes inadvertent or unmanageable movements such as stiffness, shaking, unbalancing, etc. Symptoms appear moderately as well as exacerbate along with time. As the condition progresses, individuals may encounter challenges in both speech and mobility. The symptoms of PD are classified into two categories: motor symptoms and non-motor symptoms. Tremor of hands, arms, legs, jaw and face, feebleness of movements, rigidity or stiffness of the muscles belong to the category of motor symptoms whereas depression, loss of smell, tiredness, anxiety, and sleep behaviour disorder are associated with the non-motor symptoms [11]. All the symptomsare demonstrated in Fig. 1.

On the basis of different types of motor and non-motor symptoms, researchers have classified the PD into five different stages [12] that are illustrated in Table 1.

The development of PD can be measured using the Movement Disorder Society-Unified Parkinson's Disease Rating Scale (MDSUPDRS), which vary from 1 to 5. Another frequently used method for assessing the severity of the condition is the Hoehn and Year Scale. The challenge with these metrics lies in the fact that it takes years to observe significant score changes, making it challenging to track the disease's progression in a timely manner [13]. Generally, the primary basis for diagnosing PD in patients is their medical history, especially when doctors examine their signs and symptoms. It is now possible to diagnose Parkinson's disease (PD) by analysing pathophysiological signals such as electromyograms (EMG), speech signal, electroencephalograms (EEG), and neuroimaging methods like magnetic resonance imaging (MRI), functional magnetic resonance imaging (fMRI), transcranial B-mode sonography (TCS), single-photon emission computed tomography (SPECT) and [14]. Recently, research into the potential for early diagnosis of neurodegenerative illnesses using mobile technologies has been conducted. It is therefore intriguing to note that researchers have lately produced encouraging findings by analysing data from cell phones and other personal gadgets [15, 16]. Though PD's diagnosis prospective has increased, 20% of patients with severe illnesses are improperly diagnosed at the primary level [17]. In the United State of America (USA) around 5% of outpatients are misdiagnosed annually. By 2037, it is projected that the entire economic cost of PD would be dollar 79 billion in the USA alone [18]. Due to the significant growth in the number of elderly persons, direct, indirect, and non-medical expenditures have doubled [18]. In India, a patient will spend between 16 and 41.7% of their income on prescription drugs. Even if the cost of therapy is cheaper in India than in other

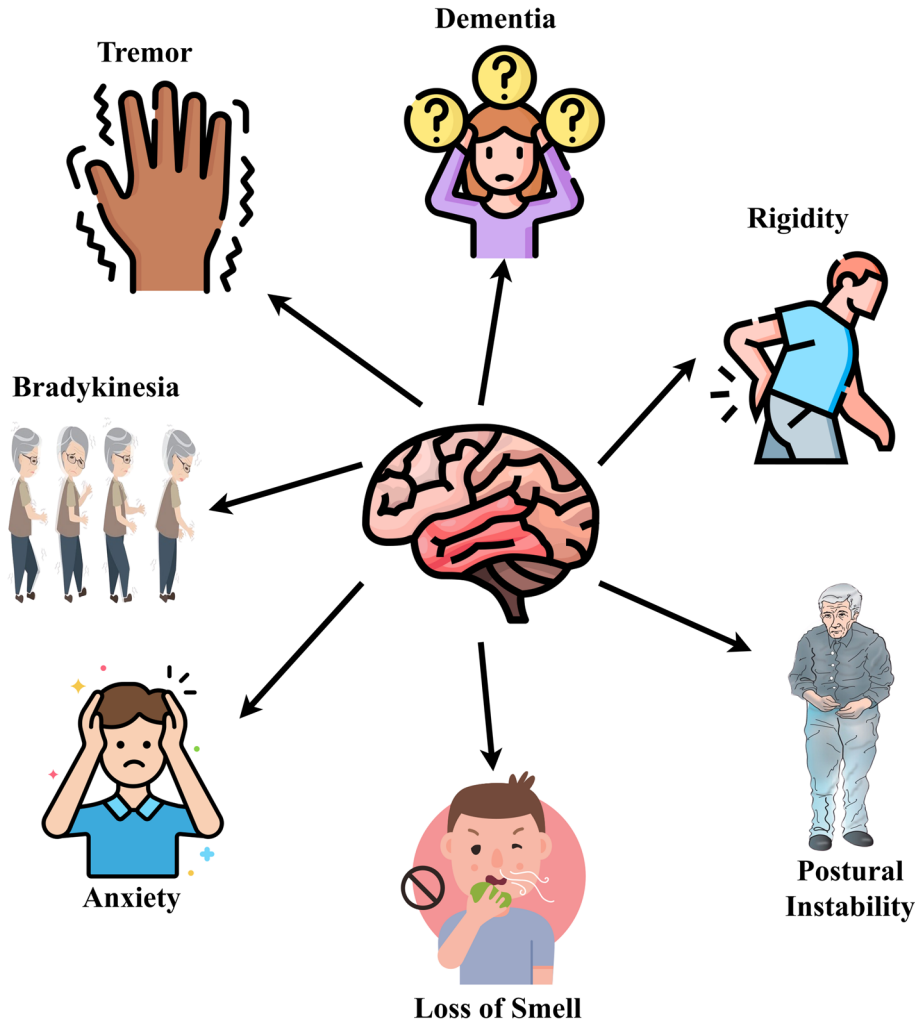

Fig. 1 Symptoms of Parkinson's Disease

nations, those with lower socioeconomic position still cannot afford it [19]. The financial expenditure can be decreased by using AI algorithms to detect PD symptoms in early stage

ML and DL based approaches have advanced significantly recently, particularly in the field of healthcare. Human radiologists typically take longer time to review medical pictures, which slows down decision-making process. Due to the shortage of qualified radiologists, a decision-making delay may have a bigger negative impact on the patients' quality of life. In order to reduce the time taken by the radiologist to diagnose a problem, the medical image processing requires automation and thus accuracy of the diagnosis process is improved [20]. Machine learning and deep learning algorithms must be used to accelerate the diagnostic procedure and get superior outcome than a person since the creation and development of the newest technologies in medical diagnosis are mostly based on the accuracy of the digital procedures [21]. Also using biomarkers to identify different neurodegenerative diseases is

Table 1 Different stages of Parkinson's disease

Stages	Symptoms
Stage-1(Mildest stage)	The people with PD are least hindered from doing daily duties at this stage. One part of human body is affected by shiver and other symptoms.
Stage-2(Moderate stage)	Symptoms such as stiffness, tremors at rest, and shaking become evident at this stage, affecting whole body. Furthermore, there may be changes in facial expressions among individuals with Parkinson's disease.
Stage-3(Mild stage)	In addition to stage II symptoms, significant changes including balance loss and reduced flexibility are observed during this stage .
Stage-4(Progressive stage)	During this phase, the health of the individual with Parkinson's disease will decline, posing difficulties in mobility without the assistance of devices such as a walker.
Stage-5(Advanced stage)	Stage V represents the most critical and progressed phase of Parkinson's disease (PD). Standing with rigid legs may lead to hypothermia, and individuals often struggle to maintain stability, frequently facing challenges in staying still without the risk of falling. Additionally, they may experience intermittent delusions and hallucinations.

one strategy. Biomarkers are classified into four types: clinical, imaging, biochemical, and genetic, and they have been proposed for the early detection of various diseases. These biomarkers help to enhance the efficiency of the disease detection. [22] The major goal of this review is to comprehend numerous machine learning, deep learning (DL) based methods and various nature inspired algorithms for Parkinson's disease diagnosis. This is accomplished by examining the previously written publications by many researchers. These works have been published in IEEE, Science Direct, and others.

1.1 Motivation

From numerous studies it has been noted that there is a steady rise in the number of research in recent years discussing PD diagnosis using ML and DL approaches. In this article, many research findings and studies on the identification of Parkinson's disease utilising ML and DL techniques are presented as well as the new perspectives of future works are also provided.

1.2 Contribution

From the literature review, it is important to highlight that the majority of researchers have only examined the contribution of conventional ML and DL techniques to detect PD. Therefore, the extent of this all encompassing review paper can be outlined as follows:

- This article methodically evaluates the developing AI-based technologies to diagnose Parkinson's disease.
- This document provides examples of the various analogous types and sizes of datasets used by the research community. This specific aspect of the data will enhance ML, DL and NIAs.
- Focuses attention on the various feature extraction and selection methods employed by the researchers, which are essential for increasing the PD diagnostic accuracy.

- This review paper might serve as a precious resource for future research to detect and prevent Parkinson's Disease.
- This article stands out by delving into the utilization of ML, DL and meta-heuristic algorithms not just for predicting Parkinson's Disease (PD) but also by providing a comprehensive survey and in-depth analysis of these AI-based approaches. Unlike some review-type articles that may focus solely on summarizing existing methodologies, our article goes a step further, aiming to discuss the advantages and disadvantages of AI-based approaches. Additionally, we actively address the imperative need for early PD detection, emphasizing the potential impact of AI on improving patient outcomes. By examining the current state of PD diagnosis using data-driven AI technology, our article seeks to contribute a more nuanced and actionable perspective to the existing body of literature on PD prediction.

1.3 Organization of paper

This review paper is coordinated as follows: It begins by simply outlining the significance of Parkinson's disease in the first section. Section 2 presents the idea of various datasets that are utilized to diagnose PD. Section 3 is split into three subsections. The first subsection under Section 3 provides an overview of machine learning techniques and provides an idea about the diagnosis of PD on different datasets such as speech, EEG, EMG, MRI, fMRI, handwritten dataset, gait characteristics, etc. using a machine learning approach. An overview of deep learning techniques and the diagnosis of PD on different datasets using deep learning-based methods are explored in Subsection 3.2. The next subsection discusses the recapitulation of a nature-inspired algorithm and its contribution to the early detection of Parkinson's disease on different datasets. Section 4 gives a brief discussion about the different AI techniques. The scientific assessments of the challenges in this field are covered in Section 5, and Section 6 closes with a conclusion.

2 Dataset description

This subsection provides a detailed overview of various medical datasets used to detect Parkinson's disease using ML and DL techniques. Medical datasets may be divided into a number of categories, such as physiological signals, neuroimaging and other modalities. Based on the different trades in the dataset, PD can be diagnosed. Figure 2 gives an idea of the different categories of health data that are essential to detecting PD.

The following summary gives a quick overview of each piece of medical information that is utilized for the early detection and prediction of Parkinson's disease:

- **Speech:** A one-dimensional function of time (air pressure) describes the speech signal as it leaves the mouth, nose, and cheeks of a speaker. In speech processing, microphones transform the varying air pressure into electrical signals, voltages or currents, which are often used to deal with speech inputs [23]. A speech dataset typically consists of audio recordings of human speech in various contexts, collected for the purpose of training and evaluating speech-related algorithms or models. These datasets encompass a wide range of languages, accents, and speaking styles to ensure diversity and applicability. Researchers use speech datasets to develop algorithms that can automatically identify patterns indicative of Parkinson's disease. These algorithms may leverage features like voice tremors, speech rate, and pauses, extracting information that might not be easily

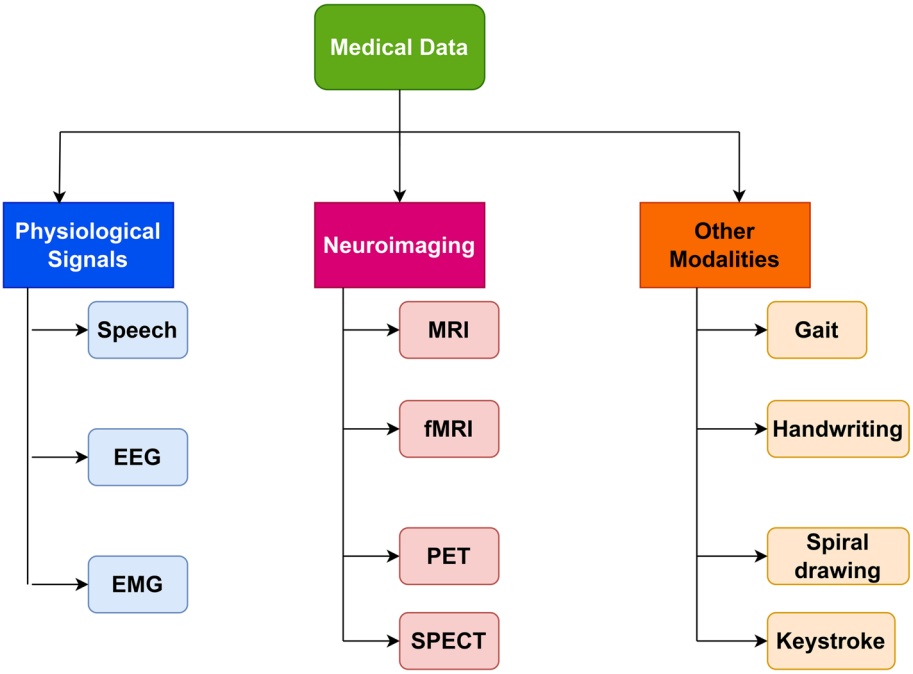

Fig. 2 Classification of dataset used for the diagnosis of PD

perceptible to the human ear. The advantage of using speech datasets lies in their ability to provide a non-invasive and cost-effective means of early detection, potentially enabling timely interventions and improved management of Parkinson's disease.

- **EEG:** The human brain begins to function neurally between the 17th and the 23rd week of fetal development [24]. Electrical impulses produced by the brain are thought to indicate both brain function and the state of the entire body from this early period and throughout life. The electroencephalogram, or EEG, signals represent the electrical activity of the brain [25]. The dataset provide a direct window into brain activity, enabling the identification of specific neural patterns associated with Parkinson's disease. Through detailed frequency analysis, EEG captures subtle changes in neural oscillations, offering a non-invasive and early detection method. This data is instrumental in developing accurate machine learning models for Parkinson's diagnosis and monitoring treatment effectiveness.
- **EMG:** An electrical signal called an EMG, which stands for electromyogram, is a biological signal that analyses electrical currents produced during muscle contractions, or neuro-muscular processes. The neurological system always regulates the contraction and relaxation of muscles [26]. The activities of individual motor unit are superimposed to form electromyographic (EMG) signals [27]. EMG datasets are valuable for Parkinson's disease detection as they capture muscle activity patterns indicative of motor abnormalities. By analyzing EMG signals, researchers can identify subtle changes in muscle response, aiding in early detection of PD. This non-invasive approach provides essential data for developing effective ML and DL models to enhance diagnostic accuracy.

- **MRI:** Magnetic Resonance Imaging (MRI) is an ultra-modern and flexible medical imaging modality [28]. A magnetic field and radio waves produced by a computer are used in the medical imaging procedure known as magnetic resonance imaging (MRI). The MRI scan is used to determine the presence of soft tissue disorders like tumours, including cancer, joint damage or illness, damage to the spine, internal organ damage, including that of the heart, brain, and digestive system, etc. [29]. MRI datasets play a crucial role in Parkinson's disease detection by providing detailed structural insights into the brain. These images enable the identification of specific anatomical changes associated with Parkinson's, aiding in early and accurate diagnosis.
- **fMRI:** While an MRI scan enables medical professionals to study a patient's organs, tissues, or bones, an fMRI focuses on how the brain functions. It is envisaged that successful fMRI analysis and use in neurological disorders may enable the characterization and diagnosis of mental illnesses such as Alzheimer's disease, schizophrenia, bipolar disorder, mild traumatic brain injury, and addiction. Many facets of the illness, including both motor and non-motor symptoms, have been better understood as a result of fMRI research in PD [30]. A poor fMRI signal could not just be a reflection of uneven, global neural activation; it might also be the result of a range of diverse neuronal activity patterns [31]. fMRI datasets are valuable in Parkinson's disease detection by revealing dynamic brain activity patterns associated with the condition. These datasets capture functional changes, offering insights into the neural circuits affected by Parkinson's. Leveraging fMRI data enhances the sensitivity of diagnostic models, providing a nuanced understanding of the neurological aspects crucial for early detection.
- **PET:** A Positron Emission Tomography (PET) scan is an imaging procedure that can assist in determining how the tissues and organs operate metabolically or biochemically. It recognises early indicators of heart disease, cancer, and brain issues. Infected cells are discovered using an injectable radioactive tracer. A PET-CT combo scan generates 3D pictures for a more precise diagnosis. The patients were instructed to fast for at least 6 hours before PET imaging, although they were given unrestricted access to water. An intravenous bolus dose was given 45 minutes before the scan began [32]. PET scan datasets are valuable for detecting Parkinson's disease by highlighting metabolic changes in the brain associated with the condition. The data aids in identifying specific patterns that contribute to accurate and early diagnosis.
- **SPECT:** With the use of a single-photon emission computerised tomography (SPECT) scan, doctors can examine the operation of several internal organs in the human body. The study of neurotransmitter systems in both health and illness may be done using scintigraphic methods such as SPECT [33]. SPECT is used to see the degradation of nigral dopamine neurones, providing a comparable estimate for the length of pre-motor phase of PD [34]. SPECT scan datasets are instrumental in detecting Parkinson's disease by capturing cerebral blood flow patterns, revealing key functional changes in the brain. This information enhances diagnostic precision, contributing to an effective early identification of Parkinson's.
- **Gait:** Gait is a complicated motion made up of a cyclic movement that switches the balance and support from one foot to the other. It is affected by muscle power and function, peripheral neuronal activity and control, but also by central neural directing control [35]. Multiple geriatric disorders like sarcopenia or frailty are detected by the use of the gait speed as a screening criterion [36]. Gait datasets are valuable for detecting Parkinson's disease by analyzing subtle changes in walking patterns, offering insights into motor dysfunction. The data aids in developing precise diagnostic models for early and accurate identification of Parkinson's disease.

- **Handwriting and Spiral Drawing:** Changes in neural systems make it harder for people with PD to regulate their body motions. This may have a detrimental impact on fine motor abilities, including writing and drawing skills [37]. Thus, changes in handwriting and drawing may be a sign of PD before it manifests. Handwriting and spiral drawing datasets are beneficial for detecting Parkinson's disease by capturing fine motor control impairments, revealing distinct tremors and irregularities. Analyzing these datasets provides valuable insights for developing accurate diagnostic tools to identify early signs of Parkinson's disease.
- **Keystroke:** Keystroke dynamics (KSD) are the rhythmic and temporal patterns that are produced when a person types. The amount of time needed to press and release keyboard buttons while typing, which is used to identify PD [38]. Recent advancements in bio-metric research and effective computing based on KSD demonstrate that key stroke variations are a very potent source of input that may reveal important information about a person's psychological and emotional states [39]. Keystroke datasets are valuable for detecting Parkinson's disease by capturing subtle variations in typing behavior, reflecting motor control changes. Analyzing these datasets provides insights for developing sensitive diagnostic tools, aiding in the early identification of Parkinson's disease.

The summary of the dataset utilized in the earlier studies to detect PD is illustrated in Table 2.

3 Technology used

For this research, we have gathered different research papers on different technologies like ML, DL and NIA to discriminate PD patients from normal people and also to enhance a thorough understanding about the severity of the disease. ML and DL are intricately related within the broader field of artificial intelligence. At its core, ML serves as the overarching

Table 2 Summary of Datasets Used in Previous Studies for Parkinson's Disease

Ref.	Dataset Name	Data Characteristics	Description and References
Tsanas et al. [40]	Parkinson Telemonitoring	Time-series data of voice recordings and motor symptom scores.	This dataset contains voice recordings of patients as well as motor symptom scores. It has been used to accurately forecast Parkinson's disease.
Goetz et al. [41]	MDS-UPDRS	Movement Disorder Society Unified Parkinson's Disease Rating Scale. Clinical assessments.	Clinical evaluations based on the Movement Disorder Society's Unified Parkinson's Disease Rating Scale. used to assess the course of a disease.
He et al. [42]	Kaggle Parkinson's PPMI	Comprehensive clinical, imaging, and biological data.	Kaggle's Parkinson's Progression Markers Initiative collection contains a variety of data categories, including clinical, imaging, and biological data.
Robin et al. [43]	Montreal Parkinson Disease	Voice recordings and clinical assessments.	This dataset consists of voice recordings and clinical assessments used to investigate patterns associated to Parkinson's disease.

paradigm, encompassing various algorithms that empower systems to learn from data and make decisions. Deep learning, introduces neural networks with several layers (deep neural networks), allowing for hierarchical and intricate feature representations. In the medical field, ML has been employed for tasks like feature extraction and classification, while DL is remarkably successful to recognize complex pattern, such as medical image analysis and diagnosis. The evolution involves a progression from traditional machine learning methods to the more sophisticated and intricate capabilities offered by deep learning, unlocking new possibilities for accurate disease prediction and diagnosis in the medical domain.This section is subdivided into three subsections and scrutinizes different technologies utilized for diagnosis of PD.

3.1 Overview of ML approach for diagnosis of PD

The scientific community is paying a lot of attention to machine learning, which is regarded as a powerful data-driven AI algorithm and is seen as the solution to many research issues. ML techniques can predict or categorise data more accurately by using computational approaches and learning from experience that is immersed in the data. Machine learning algorithms are effectively employed in medical diagnostics to detect disease based on patients' signs. Simultaneously, the physician's occupation is to support AI's conclusion so that it can determine the condition appropriately and with a decent level of accuracy [17]. Machine learning algorithms can be categorized into four significant types such as: Supervised Learning, Semi-supervised Learning, Unsupervised Learning, and Reinforcement Learning algorithm. Each input value is assigned to a particular target value in the supervised learning that is called labelling of the dataset. Whereas in unsupervised learning, the dataset is unlabelled that's why the desired target value is unknown. Semi-supervised learning first utilises small samples of labelled data to learn, and then it applies the trained model to a huge collection of untagged data to provide the required results. Whereas, reinforcement learning employs a hit-and-trial procedure for producing results. The primary components of machine learning algorithms must be thought of as datasets. The calculation time and complexity of the model will grow if the datasets are too large.

Due to the exponential growth of the digital revolution, the collection of medical datasets is very affordable, and they are shared via extensive information storage systems. By examining secret facts in the data that are not taken into account in a clinical diagnosis for PD, ML approaches can considerably increase diagnostic efficacy in healthcare sector [44]. Pereira et. al. [45] provides a thorough analysis of ML algorithms for identifying PD individuals. Figure 3 illustrates the step wise representation for detecting PD utilising ML approaches. According to the diagram first the relevant data like patient's motor symptoms and medical history are collected and pre-processed accordingly to get better outcome. Then, use feature selection techniques to identify key factors influencing PD. Train the ML model on the prepared dataset, and finally, evaluate the model's performance using testing data, refining it for accurate Parkinson's disease detection. The succeeding subsections narrate the survey of numerous works performed by the research community using the ML approach applied to different medical datasets.

3.1.1 Identifying PD through physiological signals:

This section offers a thorough description of several ML techniques created by scientists to assess the severity of PD using a human physiological signal dataset. In a recent work, Ali

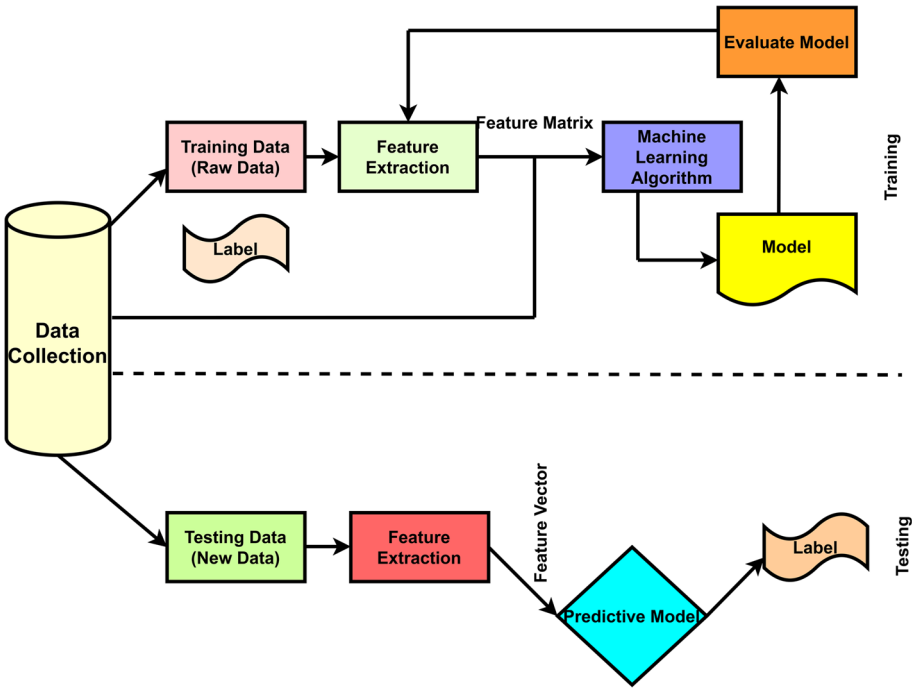

Fig. 3 Diagram depicting ML process for PD diagnosis

et al. [46] employed the two-dimensional data selection method (Selecting Samples, Features, and Hyperparameters or SSFH) to explore relevant attributes. The authors have used AI-based Neural Network (NN) which was applied on speech data and produced impressive results with an accuracy rate of 97.50%. On other hand a PD identification model based on ANN (Artificial Neural Network) was implemented by Sharma et al. [47]. This study employed Principal Component Analysis (PCA) to condense the size of feature set and improve efficiency upto 97% when 754 features are selected from the dataset. Again by reducing dimensionality with linear discriminant analysis (LDA) and optimising the hyperparameters of neural networks (NN) with genetic algorithms (GA), L Ali et al. [48] created an intelligent system. They employed leave one subject out (LOSO) validation to prevent subject overlapping. Using various types of sustained phonation data, the proposed method, LDA-NN-GA, was assessed and it achieved classification efficacy of 95% for training phase and 100% for testing. In same year, Tuncer et al. [49] analysed speech data using the multiple pooling approach. The obtained characteristics were fed into SVM, which was utilised to determine differences between PD patients and healthy people. Singular Valued Decomposition (SVD) and Neighborhood Component Analysis (NCA) are used for feature extraction and feature selection, respectively. Using several ensemble learning techniques, Younisthanoun et al. [50] conducted a comparison research to separate PD patients from healthy individuals. For the purpose of PD prediction in this work, voting classifier and stacking classifier are both are utilised. The accuracy of the stacking classifier is 92.2%, which is better than the voting classifier. In [51] Senturk et al. examined the performance of the speech signals with and without feature selection (FS) and identified PD patients. Authors explored the discrimination of classifier's performance with and without FS and determined that the first one

outperformed. On the other hand, the huge mpower vocal phonation dataset was examined by Wang et al. [52] to identify PD individuals. The study used Bayesian correlated t-test to reach an accuracy of 88.6% in diagnosing Parkinson's disease while examining robust features and introducing novel feature engineering strategies.

A novel method for PD detection called RF-BFO-SVM was introduced by Cai et al. [53]. The PPMI database's Voice dataset, which included 31 participants, was used in this investigation. BFO (Bacterial Foraging Optimization) and RF (Relief Feature) were employed for choosing relevant features and fine-tuning the parameters, and 97.42% of accuracy rate was acquired by SVM. Z Soumaya et al. [54] suggested a model by prosecuting an upgraded method where speech recording from each individual is collected as a dataset. The authors used the optimization method genetic algorithm (GA) to decompose the features of speech data, and the 15 features were selected which in turn fed SVM and achieved 91.18% accuracy. Sakar et al. [55] aimed a thorough examination of the signal processing methods employed in the PD classification from voice recordings. Voice recordings of 252 individuals were gathered, of whom 188 are PD patients and 64 are healthy. Tunable Q-factor Wavelet Transform (TQWT) and Mel-Frequency Cepstral Coefficients (MFCC) were employed for feature extraction and selection purposes, but the first one outperformed. For classification, SVM was used with a radial basis function (RBF) kernel and chieved 86.00% accuracy. In [56], R Prashanth et al. compared the performance of 10 classifiers such as: SVM, AdaBoost, RUSBoost, Random Forest (RF), Linear Regression (LR), k-Nearest Neighbor (k-NN), Probabilistic Graphical Model (PGM), Naive Bayes (NB), NN, Deep Learning (DL) applied on speech dataset of 434 PD patients and 197 non-PD individuals. The AdaBoost classifier fared best, obtaining an accuracy rate of 97.64%. On other hand the objective of the research work presented in [57] was to identify PD individuals from voice recordings. Among 40 features from the whole dataset, only nine were chosen using the Local Learning Based Feature Selection (LLBFS) algorithm and the feature vector was entered through the input layer of various classifiers. Discriminant analysis showed superior performance. M. Hariharan et al. [58] proposed a hybrid intelligent system by accumulating speech signals recorded by 23 PD patients and 8 healthy controls. The authors used Model-based clustering for data pre-processing which in turns was followed by numerous feature selection approaches like principal component analysis (PCA), linear discriminant analysis (LDA), sequential forward selection (SFS) and sequential backward selection (SBS). After that three renowned classifiers least-square support vector machine (LS-SVM), probabilistic neural network (PNN) and the general regression neural network (GRNN) are used for classification and achieved the result with 100% accuracy. The processing of speech signals for Parkinson's disease detection is studied by JS Almeida et al. in [59]. Two microphone channels from an acoustic cardioid microphone and a smartphone were used to capture the audio tasks, allowing for the evaluation of the performance of various microphone types. The method assessed the usage of four machine learning algorithms and 18 feature extraction approaches to categorise data generated from sustained phonation and speech activities. The greatest performance was achieved by the AC channel with 94.55% accuracy by using a KNN classifier. Karabayir I et al. [60] used a voice dataset with 40 PD subjects and 40 healthy subjects to discriminate PD by using the Light Gradient Boosting (LGB) model and achieved 88% accuracy. But the major limitation of this work is the small sample size. Again an innovative technique for classifying PD was proposed by Jebakumari et al. [61] utilising Electro Myography (EMG) data. The diverse classifiers, such as neural networks, logistic regression, and naïve Bayes, receive the extracted features. The naive Bayes classifier outperformed other classifiers with an accuracy of 99%. On the other hand in order to identify Parkinson's disease from background ECG signals, a Support Vector Machine (SVM) and Multilayer Perceptron (MLP) based classifier

was used in the study presented by MPG Bhosale et al. [62]. Signals where preprocessed and fragmented by using discrete wavelet transform (DWT). The achieved accuracy is about 100%. The effectiveness of the SVM (cubic kernel) classifier was examined by Bhurane et al. [63] to recognize PD patients. To achieve the highest accuracy of 99 percent, two important aspects of Electroencephalography (EEG) signals were employed to extract the features from the time-domain data. The characteristics extracted from the EEG and put for experiment by Yuvaraj et al. [64]. The SVM classifier performs better than other classifiers, according to the author's observations. In 2022 Mall et. al. [65] used speech dataset to detect PD instances by using ensemble learning approach based on ML models and achieved 94.87% accuracy. In 2023, Govindu et. al. [66] utilized an RF classifier to identify PD patients form audio data and got accuracy of 91.83% and sensitivity of 0.95. Gupta et. al. [67] provided a concise overview of the significance of early detection of Parkinson's disease using AI and ML algorithms, focusing on analyzing speech recordings, handwriting patterns, gait abnormalities, and neuroimaging techniques.

Table 3 summarizes the work performed by the research communities applied on numerous physiological signal dataset to predict PD using ML techniques. The table represents the dataset types, year of publication (YoP), feature extraction (FE) and feature selection (FS) methods used in the study, classification methods used in the study and the accuracy obtained by the respective models respectively.

3.1.2 Diagnosis of PD based on neuroimages or medical images

Recent developments in computational neuroimaging techniques have effectively validated for diagnosing diseases. This section illustrates numerous ML techniques used by the researchers to predict PD and its severity. To create a model based on the alterations in Grey's cerebellum, Zeng et al. [68] conducted a research where the structural MRI data of 45 likely PD cases and 40 non-PD were taken into consideration. Cerebellar structural alterations are provided by voxel-based morphometry (VBM), and an SVM utilised this information for PD classification with above 95% efficacy. On the other hand the olfactory brain network's neuronal activity and functional connections were investigated by Georgiopoulos et al. [69]. The Generalized Linear Model (GLM) and Independent Component Analysis (ICA) reveal disparities PD and healthy individuals. Authors concluded that ICA showed supremacy in performance. On other hand by using an SVM classifier to analyse the rs-fMRI datasets, Kazeminejad et al. [70] were able to distinguish 19 patients with PD from 18 non-PD subjects and achieved 95% accuracy. In [71], Singh et al. used the fMRI Dataset collected from the PPMI database to develop a prediction model. For the purpose of feature selection and reduction, fisher discriminant ratio and principal component analysis were applied in this work. For the PD discrimination, the least-square SVM was employed which brought about accuracy of 87.89%. Rana et al. [72] looked at how well the SVM classifier performed using the MRI dataset. Voxel Based Morphometry (VBM) and Maximum Relevance Minimum Redundancy (mRMR) were used to extract the features. The accuracy of the results was 88.30% according to the author. Chakraborty et al. [73] employed four distinct machine learning methods in the training of the top-performing features extracted from the gathered 3TT1-MRI data using two level feature extraction method. On other hand utilising the information from Magnetic Resonance Image (MRI) scans, Feis et al. constructed prediction model on the basis of multi-modal method [74]. In this study the authors used multi-kernel SVM as a classifier which produced accuracy rate about 96%. T1-weighted brain MRI were used by Peng B et al. [75] from Parkinson's Progression Markers Initiative (PPMI) dataset. The classification approach employed a multi-kernel (SVM) and a feature selection strategy

Table 3 Overview of PD detection utilizing ML methods with physiological signals:

Ref.	Dataset Types	YoP	FE/FS Method	Classification Method	Hyperparameter	Accuracy (%)
Ali et al. [46]	Speech	2019	SSFH	AI-based NN	LOSO CV	97.50
Sharma et al. [47]	Voice	2019	PCA	ANN	No. of hidden neurons= 25, learning rate= 0.0001	97
Tuncer and Dogan [49]	Voice	2019	SVD, NCA	SVM	No. of selected features=32	99.2
Younis Thanoun and Yaseen [50]	Speech	2020	—	Stacking Classifier	10-fold CV	92.2
Senturk [51]	Voice	2020	Feature Importance and Recursive feature elimination	RT, ANN, SVM	No. of features = 13	93.84
Wang et al. [52]	Speech	2020	—	SVM	10-fold CV	88.6
Cai et al. [53]	Voice	2017	RF,BFO	SVM	10-fold CV, chemotactic step parameter=0.1	97.42
Soumaya et al. [54]	Speech	2021	GA	SVM	3 Shannon entropy, 10-fold CV	91.18
Ali et al. [48]	Voice	2019	LDA,GA	NN	No.of neurons in hidden layer=3	100
Sakar et al. [55]	Voice	2019	TQWT,MFCC	SVM (RBF)	Q-value=2, reducdancy=4, no. of level=35	86.0

Table 3 continued

Ref.	Dataset Types	YoP	FE/FS Method	Classification Method	Hyperparameter	Accuracy (%)
Prashanth and Roy [56]	Speech	2018	—	AdaBoost	Mean=0.137156	97.64
Benmalek et al. [57]	Voice	2017	LLBFS	KNN,SVM,DA	2nd and 11th MFCC coefficients	67.20, 90.10, 96.50
Hariharan et al. [58]	Speech	2014	PCA, LDA, SFS, SBS	LS-SVM	—-	100
Almeida et al. [59]	Voice	2019	—	KNN	k-value =1	94.55
Karabayir et al. [60]	Voice	2020	—	LGB	4-fold CV	88
Jebakumari et al. [61]	EMG	2017	Statistical Features	NN	—-	99
Bhosale and Patil [62]	ECG	2012	DWI	SVM-MLP	—-	100
Bhurane et al. [63]	EEG	2019	—	SVM	—-	99
Yuvaraj et al. [64]	EEG	2018	PDDI	SVM	—-	99.62
Mall et al. [65]	Speech	2022	—	ML based ensemble learning	—–	94.87%
Govindu and Palwe [66]	Speech	2022	—	RF	—-	91.83%

based on filters and wrappers method were suggested by the authors in this study and the proposed model showed a promising performance. Wabnegger et al. [76] carried out a research on functional magnetic resonance imaging-based facial emotion identification (fMRI). The authors of this study used fMRI to measure brain activity, identify and separate PD patients and healthy controls by capturing various facial expressions by using meta-cognitive radial basis function network (McRBFN) classifier with Recursive Feature Elimination (RFE).

Like MRI imaging, PET and SPECT images becomes popular and hugely used by the researchers to detect PD accurately. In their work, Hsu et al. [77] presented the distribution of all brain activity as well as an analysis of the characteristics of striatal activity volume. The SPECT pictures obtained from the subjects are then subjected to a three-dimensional feature extraction approach. In order to evaluate the effectiveness of the best classifier, logistic regression and SVM with RBF kernel were employed as classifiers. It was discovered that SVM provided greater accuracy than logistic regression, with an accuracy rate of 83.2%. Again, in a previous study proposed by Segovia et al. [78] in 2015 by collecting PET imaging data to distinguish PD subjects from non-PD subjects by using SVM classifier with leave-one-out cross validation did not show a good performance. In this works the obtained accuracy is about 78.16%. Again the same authors suggested almost the a same work with an increased data size by gathering SPECT images as dataset and applying the SVM for distinguishing PD participants from the healthy controls and they achieved a better result than the previous experiment with 94.25% accuracy [79]. Similarly, the goal of the study initiated by Huertas-Fernández et al. [80] was to create diagnostic prediction models utilising information from two widely utilised FP-CIT SPECT evaluation techniques. The authors enrolled 164 individuals with Parkinson's disease and 80 patients with vascular parkinsonism in this study. VP and PD may be distinguished with high accuracy using the prediction models created using ROI and SPM data. Logistic Regression, LDA, SVM were employed as the classifiers and SVM performed the best with 90.4% accuracy. But the model suggested by Illan et al. in [81] used SVM, KNN, NN with 3-fold cross validation on the SPECT imaging data accumulated from 100 PD individuals and 108 healthy controls. According to the authors' statements SVM classifier outperformed with 89.02% sensitivity and 93.21% specificity. Similarly, Nicastro et al. [82] accomplished a classification of different phase of PD from SPECT imaging dataset collected from 578 participants. SVM generated a good classification outcome which is about 92.9%. Again in [83] Oliveira F et al. assembled SPECT imaging data from PPMI database for discriminating PD patients from HC using numerous classifiers like SVM, KNN, Logistic Regression. But after the assessment of all the classifiers' performance the authors concluded that SVM showed the supremacy in the accuracy with 97.9%. Tagare et al. [84] developed a PD prediction model by employing Logistic Lasso approach. Features extracted from the SPECT images were fed to the input of the classifier and the model obtained false positive (FP) rate of 2.83%, false negative (FN) rate of 3.78% and ner error rate was about 3.47%. In 2019, Wu et al. [85] proposed study that distinguished between Parkinson's disease patients and healthy individuals based on brain PET images. The authors employed an SVM model with variety of kernels and obtained 91.26% accuracy. In [86], Sateesh et al. developed a PBL-mcRBFN-RFE approach for evaluating the effectiveness of SVM with mcRBFN classifier in their study. Recursive Feature Elimination (RFE) method made it possible to pinpoint the crucial area of the brain that causes Parkinson's disease (PD). A classification model based on SPECT images was examined by Rojas et al. [87]. Empirical mode decomposition was used to analyse the collected characteristics and separate PD patients from healthy controls. Again, using SPECT scans, Mabrouk et al. [88] focused on distinguishing between PD patients and scans without evidence of dopaminergic deficit (SWEDD). Because of this, the features were chosen using PCA from the SPECT pictures. The chosen characteristics are

fed into multiple machine learning classifiers, and for motor features, the highest classification accuracy was 75.4%, and for non-motor features, it was 82.2%. Table 4 summarizes the work performed by the research communities on various medical image datasets to predict PD using ML techniques.

3.1.3 Diagnosis of PD based on other modalities

It is worth mentioning that researchers have utilized various modalities to predict PD, even though the PD diagnostic study largely relies on the use of physiological signals and neuroimaging approaches. Gait characteristics, motion of the body, keystroke, handwritten character, spiral drawing belong to the part of the other modalities those are employed to predict PD. In order to predict PD, Mazilu et al. [89] collected DAPHNet dataset [90] and discovered freezing of gait (FOG) by examining the accelerometer readings collected from a smartphone. The gait impairment can be used to determine the severity of PD. Later Wahid et al. [91] looked at the spatial-temporal gait data. They used a random forest classifier to categorise the patients, and their accuracy was 92.6%. Similarly, in a different study, Kour et al. suggest that utilizing human gait data can enhance the efficiency of computer-aided technologies for diagnosing Parkinson's Disease [92]. In the same year Ahmadi et al. [93] classified Parkinson's disease (PD), acute unilateral vestibulopathy (AVS), phobic postural vertigo (PPV), distal sensory polyneuropathy (PNP), anterior lobe cerebellar atrophy (CA), downbeat nystagmus syndrome (DN), primary orthostatic tremor (OT), and healthy controls (HC) from the dataset of 293 individuals. The ensemble method of seven models such as: logistic regression, KNN, ANN, random forest, SVM, extra randomized trees were employed by the author for classification purpose and according to the authors' statement the obtained accuracy of this multi class classification is 82.7%. Comparably, a classification model implemented by Buongiorno et al. [94] for discriminating PD patients from HC based on extracted postural and kinematic features from motion disorder datasset achieved better accuracy rate than the previous model, which is of about 89.4%. But previously in 2018, Caramia et al. [95] investigated IMU-based gait parameters to differentiate PD patients and healthy subjects by employing a numerous classifiers like: LDA, Naive Bayes, KNN, decision tree, SVM-RBF, SVM-linear and they acquired the outcome with 96% accuracy. Again the primary purpose of a work aimed by Butt et al. [96] in 2017 was to examine the Leap Motion Controller's (LMC) capability for the evaluation of motor impairment in PD patients. Hence, in order to detect PD patients from HC, the authors utilized Naive Bayes, logistic regression and SVM classifiers. Among these classifiers Naive Bayes performed the best with 81.45% accuracy rate, 76% sensitivity rate and 86.5% specificity rate. In that particular year, Adams et al. [97] introduced a distinctive procedure for predicting PD, relying on the motion of fingers observed during computer keyboard typing. They used a variety of keystroke characteristics in their study and used ensemble classifiers to analyse them. Finally, with specificity of 97%, AUC of 0.98 and 96% sensitivity, the author has produced encouraging findings. On the other hand, the method proposed by Cavallo et al. [98] segregated PD subjects from healthy individuals from the collected motion data by using a a wearable inertial device, named SensHand V1. In this experiment the motion from the upper limbs during the performance of six tasks were selected from three categories' people such as: 30 healthy subjects, 30 Idiopathic hyposmia (IH) people, and 30 PD patients. On three separate datasets, several analyses were conducted to compare the performance of three supervised learning algorithms: Support Vector Machine (SVM), Random Forest (RF), and Naive Bayes. For the categorization of patients vs the healthy, excellent results were attained with accuracy of 95%, F-measure of 94.7%. Farashi et al. [99] investigated eye movements through vertical electrooculography

Table 4 Overview of PD detection utilizing ML methods with neuroimaging

Ref.	Dataset Used	YoP	FE/FS Method	Classification Method	Hyperparameter	Result
[68]	MRI	2017	VBM	SVM	Mean=9.50	Accuracy=95%
[70]	rs-fMRI	2017	Floating Forward Automatic Feature	SVM	—-	Accuracy=95%
[71]	fMRI	2019	PCA	SVM	—-	Accuracy=87.89%
[72]	MRI	2015	VBM and mRMR	SVM	—-	Accuracy=88.3%
[73]	3TT1-MRI	2020	Two level feature extraction	ANN	p-value< 0.0001	Accuracy= 95.3%
[74]	MRI	2015	—	Multi Kernel SVM	MNI coordinate: x=-6,y=-84,z=-3, cluster size=661	Accuracy= 96%
[75]	T1-weighted brain MRI	2017	Filters and wrapper methods	SVM	p=0.05	Accuracy=85.78%
[77]	SPECT	2019	3D-feature extraction	SVM(RBF)	p<0.001, 10-fold CV	Accuracy= 83.2%
[78]	PET	2015	—	SVM with leave one out cross	—	Accuracy= 78.16%
[79]	SPECT	2019	—	SVM with 10-fold CV	Size of voxel cluster= 5×10^5	Accuracy= 94.25%
[80]	FP-CIT-SPECT	2015	—	SVM	p<0.001	Accuracy= 90.4%

Table 4 continued

Ref.	Dataset Used	YoP	FE/FS Method	Classification Method	Hyperparameter	Result
[81]	SPECT	2012	—	SVM	10-fold CV	Sensitivity= 89.02% Specificity= 93.25%
[82]	SPECT	2019	—	SVM	voxel size=2mm X 2mm, p=0.05, 10-fold CV	Accuracy= 92.9%
[83]	SPECT	2015	Voxel analysis	SVM, KNN, Logistic Regression	X=-14,Y=18,Z=-22	97.9%
[84]	SPECT	2017	Voxel analysis	Logistic Lasso with 10-fold CV	—-	FN= 3.78%, FP= 2.83%,
[85]	PET	2019	Auto correlation fisher score algorithm	SVM-RBF	—-	Accuracy= 91.26%
[86]	MRI	2014	VBM	McRBFN with Recursive Feature Elimination	—-	Accuracy= 83.32%
[88]	SPECT	2018	PCA	ML classifier	—-	Accuracy= 82.2%

(VEOG) during the resting situation for detecting Parkinson's disease. A variety of time- and frequency-domain characteristics were recovered from the filtered VEOG time-series and extracted eyes-open/eyes-closed segments. An SVM classifier in error-correcting output code (ECOC-SVM) mode was utilised for classification.

Aghanavesi et al. [100] examined drawing tests conducted on both PD patients and individuals without the condition. Time series analysis was employed in this work to extract and choose the features and then fed to several classifiers to gauge the intensity of symptoms associated with PD. Klein et al. [101] obtained 89% of accuracy to segregate PD patients from HC individuals using SVM classifier applied on the collected multi-touch gestures dataset. In [102] the authors created two wearable inertial sensors, SensHand V1 and SensFoot V2, for collect motion data. 15 PD patients, 15 HC people and 15 IH people joined in this study. 71 features per side were calculated by using spatiotemporal and frequency data analysis and the selected rich features were fed to SVM-polynomial and random forest classifiers. For binary classification of two classes HC and PD the accuracy rate is 100% whereas for multiclass classification the accuracy rate is declined and it was about 91.1%. Ricci et al. [103] used Naive Bayes, KNN and SVM classifiers to differentiate PD patients from healthy subject of controls. But SVM classifiers showed supremacy in accuracy rate which is about 95%. The proposed model also obtained precision value of 0.951 and area under curve (AUC) of 0.950. Where as the model proposed by Félix et al. [104] had achieved 96.8% accuracy in classification od PD and HC by using SVM, KNN and decision tree classifiers among numerous classifiers used by the authors.

Rosenblum S et al. [105] accumulated the handwriting data 20 PD patients and 20 healthy controls. Each participant in this project was required to write their name and address on a sheet of paper using the writing from a digital tablet. For the whole task, the mean pressure, mean velocity and the the spatial and temporal properties of each stroke of handwriting were assessed. The results were obtained with a 97.5% accuracy, a 100% specificity, and a 95% sensitivity. Later in 2014 Drotar et al. [106] proposed a model by employing spatiotemporal handwriting measures to detect PD. For automated diagnosis, the chosen features were loaded into a SVM classifier using a Radial Gaussian Kernel. The maximum values of sensitivity and specificity were 89.47% and 91.89%, respectively, with a classification accuracy of PD of up to 88.13%. Again, after some years, Ali et al. [48], investigated the random under-sampling approach. Based on a handwritten sketch, the authors created a cascaded learning system that combines the Chi2 model with adaptive boosting. For the purpose of identifying the differences between PD patients and healthy people, Pereira et al. [107] suggested a detection model applied on the Hand PD dataset, and they used structural co-occurrence matrix for selecting relevant features, which were then fed to the Naïve Bayesian classifier for classification of PD patients. In [108] to distinguish PD patients from healthy people, Akyol et al. separately designed three tests on three different datasets, such as the static spiral test (SST), the dynamic spiral test (DST), and the stability test on a certain point (STCP). They then fed the input to random forest (RF), ANN, and logistic regression models. According to the authors observations, ANN showed superior performance to RF and Logistic Regression, with an accuracy value 100% for all three datasets individually. Very recently, Sandhiya et. al. [109] performed an experiment to detect PD patients from wave and spiral-like drawing dataset by using ANN and RF classifiers, and the authors also employed the histogram of oriented gradients feature extraction method. Table 5 summarizes the details of the work performed by the research communities in a tabular format using numerous modalities to identify PD patients using ML techniques. The study was explored by Trabassi et al. [110] to identify the most accurate supervised machine learning algorithm for classifying individuals with Parkinson's disease from healthy subjects based on a minimal set of gait features derived

from inertial measurement units (IMUs). After a rigorous feature selection process, SVM, DT, RF demonstrated superior classification performance, achieving over 80% accuracy on the test set. The proposed machine learning approach emphasized mitigating the risk of overfitting by strategically selecting gait features, enhancing both model interpretability and predictive accuracy.

From the summary of Tables 3, 4 and 5 it is clear that most of the researchers used SVM as the classification method while using physiological signals and neuroimaging as the dataset for PD detection.Support Vector Machines (SVM) offer a robust advantage in Parkinson's disease prediction through physiological signals and neuroimaging datasets. Firstly, SVM's ability to handle high-dimensional data makes it particularly adept at capturing intricate patterns within complex neuroimaging information, enhancing accuracy in diagnosis. Secondly, SVM's versatility allows it to efficiently classify diverse physiological signals, providing a comprehensive approach to Parkinson's detection that spans multiple data modalities. Moreover, SVM's inherent capacity for non-linear classification accommodates the intricate relationships present in neuroimaging, ensuring nuanced detection of Parkinson's markers. Additionally, SVM's proficiency in managing small sample sizes, often a challenge in medical datasets, contributes to reliable predictions even with limited data points, crucial for effective early diagnosis of Parkinson's disease. But some of the researchers have also used KNN, ANN models which offer distinctive advantages in Parkinson's disease prediction using physiological signals and neuroimaging datasets. KNN excels in capturing local patterns within data, making it well-suited for discerning subtle variations in physiological signals, contributing to nuanced and accurate classification. On the other hand, ANN's capacity for complex feature learning allows it to extract hierarchical representations from neuroimaging data, enabling a deeper understanding of the intricate patterns associated with Parkinson's disease. Both methods showcase adaptability by accommodating various data types, ensuring a comprehensive analysis that leverages the strengths of physiological signals and neuroimaging. But, maximally the researchers got the better result while using SVM model for PD prediction. Again, when other modalities like gait data, movement disorder data are used the researchers selected various ML methods like RF, SVM, KNN Logistic Regression, ANN etc. But mostly they have chosen RF due to its capability of leveraging ensemble learning, combining multiple decision trees for robust accuracy. Its capability to deal with a vast number of attributes and capture complex relationships within the data makes RF particularly effective in identifying subtle patterns indicative of Parkinson's, enhancing diagnostic precision.

3.2 Overview of DL approach for diagnosis of PD

In recent years, researchers have increasingly adopted deep learning algorithms. The utilization of deep learning has expanded into a number of disciplines like industries including image identification, computer vision, healthcare, voice and audio processing, and natural language processing etc [116]. Additionally, deep learning techniques may be used to improve the online learning environment so that teachers could more easily evaluate the learning process. One of the most important thing is that large and diverse datasets are compatible with deep learning. Over the last ten years, PD researchers have made a concerted effort to find a machine learning algorithm that can properly predict the disease's early start. However, it was extremely difficult for these ML systems to increase forecast accuracy for untested test data [117]. But, deep learning algorithms have also been given the task of accurately identifying a variety of diseases from a large dataset in the realm of healthcare. Deep learning is a type

Table 5 Overview of PD detection utilizing ML methods with other modalities:

Ref.	Dataset Used	YoP	Classification Method	Hyperparameter	Result
[91]	Spatial temporal gait data	2015	Random Forest, SVM, Kernel Fisher Discriminant	—-	Accuracy=92.6% for Random Forest
[89]	DAPHNet dataset (FOG in daily life)	2012	Randon tree, random forest, c4.5, Naive Bayes, KNN-1, KNN-2, MLP, AdaBoost with C4.5, Bagging with C4.5	p=0.015, 50-fold CV	Average of sensitivity and specificity is 95%
[93]	Movement disorder data	2019	Ensemble methods of models (KNN,shallow and deep ANN,SVM, random forest,logistic regression,extra randomized tree)	p<0.0001	Accuracy = 82.7%
[94]	Motion disorder dataset	2019	SVM-linear, SVM- cubic, SVM- Gaussian klernel, ANN	—	For ANN: Accuracy= 89.4%, Sensitivity =87.0%, Specificity=91.8%
[95]	IMU-based gait dataset	2018	Naive Bayes, LDA, KNN, decision tree, SM-linear, SVM-RBF	—	Accuracy=96%
[96]	Movement disorder dataset	2018	Logistic Regression, Naive Bayes, SVM	10-fold cross validation	Accuracy, Sensitivity and Specificity for Naive Bayes classifier are 81.45%, 76% and 86.5% respectively.
[98]	Movement disorder data	2019	SVM, random forest, Naive bayes	—	For random forest Accuracy= 95% in binary classification
[97]	Keystroke characteristics	2017	Ensemble classifiers	—	Sensitivity=96%, Specificity=97%, AUC= 0.98
[100]	Spiral drawing dataset	2017	ML models	—-	—
[101]	Multi-touch gesture	2017	SVM	—	Accuracy=89%
[102]	Motion control dataset	2019	SVM-polynomial, random forest	—	For binary classification acciuracy=100%, for multiclass classification accuracy= 91.1%

Table 5 continued

Ref.	Dataset Used	YoP	Classification Method	Hyperparameter	Result
[103]	Motion control dataset	2019	Naive Bayes,KNN,SVM	Leave-one-out-cross validation	SVM: Accuracy= 95%, Precision = 0.951, AUC= 0.950
[104]	Motion control dataset	2019	—	SVM-linear, KNN,Naive Bayes, LDA, decision tree	Accuracy= 96.8%
[106]	Handwriting dataset	2014	SVM with Radial Gaussian Kernel	—	Sensitivity= 89.47%, Specificity = 91.89% , Accuracy =88.13%
[105]	Handwriting dataset	2013	Discriminant analysis	—	Accuracy =97.7%, Specificity= 100%, Sensitivity = 95%
[107]	Hand PD dataset	2018	Naive Bayes	—	Accuracy =95%
[108]	Spiral drawing dataset	2017	Logistic Regression, ANN, RF	—	Accuracy (ANN)= 100%
[111]	Movement disorder dataset	2018	Logistic regression, Naive Bayes, Random forest	10-fold cross validation	Random Forest: Accuracy =82%, FNR= 23%, FPR= 12%
[112]	Gait characters	2019	SVM-Gaussian	—	Accuracy=100%
[113]	Motion disorder dataset	2018	Neuro-fuzzy inference system	—	—
[114]	Motion disorder dataset	2018	LS-SVM	Leave-one-out,2-fold,5-fold, 10-fold cross validation	Accuracy =100%, Sensitivity= 100%, Specificity=100%, AUC=1
[115]	Motion disorder dataset	2019	KNN, CART, SVM, Decision tree, random forest, Naive Bayes, SVM-polynomial, SVM-linear, K-means clustering, GMM	Leave-one-out-cross validation	SVM: Accuracy=90.32%, Precision=90.55%, Recall=90.21%, F-measure=90.38%
[109]	Spiral Drawing	2022	RF,ANN	—	Above 90% accuracy
[110]	Gait	2022	SVM,RF,DT	—	Accuracy=86%, F1-Score= 85%

of machine learning technique, also called a special form of representation-based learning which involves the construction of intrinsic properties by the network from each subsequent hidden layer of neurons [118]. The term "deep" in Deep Neural Networks (DNN) refers to the presence of numerous hidden layers within the structure of the Artificial Neural Network (ANN). Recently, it has been acknowledged that deep learning approaches perform extremely favourably and in many cases, outperform traditional ML techniques when analysing medical pictures for the diagnosis of Parkinson's disease. It is noteworthy to note that data representation differs in DL approaches. The main benefit of DL is its ability to automatically extract data from a raw, unstructured, and unlabeled dataset without the need for human interaction. As a result, as the datasets grow much more significantly, DL might become a crucial tool for analysing that large dataset. Many researchers are working harder right now to enhance DL models with cutting-edge structures for resolving challenging issues. Convolutional Neural Networks (CNNs), Long Short Term Memory Networks (LSTMs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), Radial Basis Function Networks (RBFNs), Multilayer Perceptrons (MLPs), Deep Belief Networks (DBNs) are different types of deep learning models.

CNN are a popular DL model that are commonly applied to the analysis of medical images. This model can automatically recover features, in contrast to standard machine learning systems where it is necessary to construct manually created features [119]. The ability of CNN is to harness spatial or temporal association in data is its main advantage. CNN has also been utilised for feature extraction and classifications in the domain of healthcare. CNN comprises three essential layers: convolutional layers, pooling layers, and fully-connected layers. Along with these layers, there are two more crucial parameters: the dropout layer and the activation function. Convolution 2D layers, pooling 2D layers, and completely connected layers were initially investigated for image processing. Another DL model recurrent neural network (RNN) constitutes self-feedback connection weights, activation functions, interconnection weights, amplification, functions, and delays [120]. There are typically two approaches that may be used to construct effective stability requirements of RNN. One approach is to effectively employ recurrent neural network information under various assumptions. A recurrent neural network with a state memory and multilayer cell structure is known as a long short-term memory (LSTM) [121]. In contrast to feedforward neural networks, RNN can handle input sequences of any length in between nodes and layers. Researchers are also employed another deep learning algorithm called deep belief network (DBN) in the field of healthcare. It is a useful approach for resolving issues from deep neural networks [122]. In addition to these, there are many other deep learning models that are quite helpful for disease identification. Gautam et al. [123] investigated the deep learning methods used to diagnose different neurological imbalances. Authors reviewed most of the DL models already in use, but there is still need to examine how other advanced DL architectures perform in medical field. The next subsections provide an overview of multiple research projects carried out by the research community that used the DL methodology mentioned above when applied to various datasets.

3.2.1 PD detection through DL algorithms to physiological signals:

The categorization of PD utilising physiological signal data and cutting-edge artificial deep learning techniques is the main emphasis of this section. In 2016 Convolutional neural networks (CNN) was used to automatically extract characteristics from voice datasets in order to distinguish PD patients from healthy participants, as stated by Frid et al. [124]. Later in 2017 the pronunciation of words, phrases, and read text from the Spanish dataset was investigated by Naranjo et al. [125]. On other hand, in the same year Caliskan et al. [126] et al. employed

a model and applied it on Parkinson's speech dataset of Oxford. Numerous tests were run on two separate datasets to justify the performance of the proposed model. To decrease the dimensionality of the data and increase classification model accuracy, stacked auto-encoders (SAE) were used in conjunction with a deep neural network (DNN) classifier and achieved 93.79% accuracy. In order to discriminate between PD and normal people, the investigation collected characteristics using CNN model. Again, in order to separate between people with Parkinson's disease (PD) and healthy people, Gunduz et al. [127] experimented with the notion of employing two CNN frameworks. A CNN model with 9 layers received the combined features from the combined datasets. The author connected convolution networks to receive the deep features. On the same year Wodzinski et al. [128] demonstrated that speech signals might be used as picture input for ResNet model. The results are encouraging, as the prediction accuracy was above 90%. Later in 2020 for the purpose of PD prediction, Oh et al. [129] constructed a 13-layer CNN model. EEG data from 20 PD patients and 20 healthy participants were used in this investigation. The accuracy, sensitivity, and specificity of the classification model used by the authors were 88.25%, 84.71%, and 91.7% respectively. Again in 2020 PC-GITA database were used by Zahid et al. [130] and applied on Alex net model. Using a RF, MLP and transfer learning the researchers acquired 99.7% of accuracy on vowel 'o' and 99.1% of accuracy on vowel 'i' by using deep random forest technique. On the same year a prediction model was created by Xiong et al. [131] to separate PD patients from healthy individuals. To increase the prediction rate, the collected features were selected using sparse autoencoders and the relevant features were fed into a number of classification models, but according to the authors' statements LDA gained 91% accuracy rate, 94% sensitivity rate, and 92% specificity rate. Again the research conducted by Khojasteh et al. [132] examined 81 people in order to define the multivariate characteristics of PD patients. Their strategy yielded findings with a 75.7% accuracy rate. Al-Fatlawi et al. [133], on the other hand, introduced a novel method employing Deep Belief Networks (DBN) to examine speech data and separate PD and normal individuals. Again built upon speech data, Sadek et al. [134] suggested ANN model using a backpropagation technique to identify PD. They were able to help the doctors to diagnose PD with a 93% accuracy rate. In [135] Quan et al. developed an innovative end-to-end deep learning model for recognizing PD by utilizing speech data. The suggested approach first uses time-distributed two-dimensional convolutional neural networks (2D-CNNs) to extract time series dynamic features, and then uses a one-dimensional CNN (1D-CNN) to encapsulate the relationships between these time series. Two datasets were used to confirm the suggested model's performance. Using the speech signals, a maximum accuracy of 92% was attained for the second dataset, whereas the first dataset attained 81.6% of accuracy. Hireš et al. [136] proposed an ensemble of convolutional neural networks (CNNs) for identifying PD from the voice recordings of 50 PD patients and 50 healthy individuals collected from PC-GITA, a publicly available database. The authors used 10-fold cross validation method to test the model and achieved an accuracy rate of 99%, sensitivity rate of 86.2% and specificity rate of 93.3% and 89.6% AUC. Wroge et al. [137] gathered digital biomarkers and voice recordings of people with and without Parkinson's disease via a mobile application. To extract the feature sets from the preprocessed speech signal, the authors employed an open-source tool, named OpenSmile in this study. After feature extraction, Minimum Redundancy Maximum Relevance (mRMR) was applied to select the rich and important features which in turns fed into the input of the 3-layered deep neural network (DNN) for classification and obtained the accuracy rate of 85%. In [138] the authors utilized hybrid DL and neuro-fuzzy techniques to detect PD.

The researchers also showd their interest to detect PD using other physiological signals such as EEG, EMG etc. Shu Lih Oh et al. [139] suggested a model by accumulating EEG

signals from PD and non-PD participants on which they applied CNN to classify the individuals. According to the authors' statement the model had achieved the accuracy of 88.25%. On the same year Shah et al. [140] constructed a new model of deep neural network called Dynamical system Generated Hybrid Network. The authors used 12 EEG channels for classification of On state and Off state of medication of PD patients and reported that the proposed model had shown supremacy in performance with 99.2% accuracy. Similarly, for the purpose of PD prediction, Oh et al. [129] constructed a thirteen-layer CNN model. EEG data from 20 PD patients and 20 healthy participants were used in this investigation. The accuracy, sensitivity, and specificity of the classification model used by the authors were 88.25%, 84.71%, and 91.7%, respectively. Later in 2021 Khare et al. [141] invented a automated PD detection model called Parkinson's disease CNN (PDCNNet). The data used in this study included EEG signals from which time-frequency representation (TFR) was obtained by using smoothed pseudo-Wigner Ville distribution (SPWVD). Then these TFR plots were fed to an CNN for classification of PD patients from healthy persons and achieved a promising performance with 100% of accuracy rate. A recent study done by Zhang et al. [142] combined time-frequency analysis with deep learning, tunable Q-factor wavelet transform with deep residual shrinkage network (TQWT-DRSN) and the wavelet packet transform with deep residual shrinkage network (WPT-DRSN) to classifiy four types of EEG data taken clinically for identifying PD. For binary class classification the model acquired 99.92% accuracy. Whereas, for 3-class and 4-class classification, the accuracy rate was 97.81% and 92.59% respectively for the WPT-DRSN combination and 95.20% and 90.46% respectively for the TQWT-DRSN combination. Khoshnevis et al. [143] introduced new feature sets based on higher order statistics. The authors utilized EEG signals derived from the alpha and beta rhythms for discriminating PD patients. Using the Bagged trees ensemble classifier,the proposed method provided an average sensitivity of 99.28% and a specificity of 99.10%.

Table 6 gives an outline of the work performed by the science community for detecting Parkinson's disease using physiological signals:

3.2.2 Identification of PD using medical imaging through DL algorithms

The primary goal of this part is to present multiple evaluations for the diagnosis of PD utilising various medical images applied to a DL model. In order to improve the imaging diagnosis of Parkinson's disease, Choi et al. [144] created a deep learning-based FP-CIT SPECT interpretation system by using PPMI database in their work. The database consists of 431 patients with PD, 193 with non-PD and 77 patients with dopaminergic deficit (SWEDD). Later in 2018 Zhang et al. [145] provided a DL method based on graph convolutional networks (GCN) for combining several brain imaging modalities in relationship prediction, which is beneficial for differentiating PD patients from normal controls and also exhibited a strong potential on graph neural network. The proposed Multi-view graph convolution network outperformed with an AUC of 95.37%. On other hand in 2019, Wenzel et al. [146] collected SPECT imaging data for classifying PD patients from Healthy comtrols (HC). CNN was employed for classification. The proposed model achieved accuracy rate of 0.972, sensitivity of 0.983 and specificity of 0.962. Mohammed et al. [147] provided a CNN-based method to correctly identify PD using a large database of SPECT pictures. Later in 2021 the same authors (Mohammed et al.) [148] suggested to use CNN for diagnosing PD using SPECT images. This work uses image normalisation to extract features from SPECT images, and then the features were fed to the CNN model for classification. The model shows a supremacy in the performance with a classification accuracy of 99.34%. Similarly, in order to distinguish early-stage PD patients from healthy people, Pahuja et al. [149] used SPECT images. With

Table 6 Overview of PD detection utilizing DL methods with physiological signal:

Ref.	Dataset Used	YoP	Classification Method	Hyperparameter	Result
[130]	pc-GITA	2020	Random forest, MLP, Transfer learning	—-	Accuracy= 99.7% for vowel 'o' and Accuracy=99.1% for vowel 'i'
[131]	Speech dataset	2020	LDA	Filter size= 96,16 for MaxPool layer, 32 and 16 for dropout layer, 8 for dense layer	Accuracy= 91%, Sensitivity = 94%, Specificity =92%
[125]	Voice dataset	2017	CNN	—-	Accuracy=86.2%, Sensitivity=82.5%, Specificity=90.0%
[124]	Voice dataset	2016	CNN	—-	Average classification accuracy= 85.47%
[127]	Voice dataset	2019	Nine-layered CNN	—-	Accuracy=86.9%, F-Measure= 0.917, Matthews correlation coefficient (MCC)= 0.632
[128]	Speech signal	2019	Residual Neural Network (ResNet)	Learning rate= 0.9 Epoch=100, Batch=128	Accuracy is above 90%
[126]	Speech dataset	2017	SAE-DNN	Learning rate=0.3, Epoch=7, Batch size= 10	Accuracy= 93.79%
[132]	Speech signal	2018	Deep Convolutional Neural Network (DCNN)	—-	Accuracy= 75.7%
[133]	Speech dataset	2016	DBN	—-	Accuracy=94%
[134]	Speech dataset	2019	ANN with backpropagation	—-	Accuracy=93%
[135]	Speech signal	2022	1D-CNN,2D-CNN,	Accuracy= 92%	

Table 6 continued

Ref.	Dataset Used	YoP	Classification Method	Hyperparameter	Result
[136]	PC-GITA	2022	CNN	—-	Accuracy=99%, Sensitivity= 86.2%, Specificity= 93.3%, AUC= 89.6%
[137]	Voice recordings	2018	DNN	Accuracy= 85%	
[139]	EEG signal	2020	CNN	—-	88.25%
[141]	EEG signal	2021	CNN	—-	Accuracy=100%
[140]	EEG signal	2020	Dynamical system Generated Hybrid Network	—-	Accuracy=99.2%
[129]	EEG data	2020	Thirteen layer CNN	Learning rate=0.001, No. of neurons in hidden layer=32	Accuracy= 88.25%, Sensitivity= 84.71%, Specificity= 91.7%
[142]	EEG signal	2022	Deep Residual Shrinkage Network	—-	Accuracy=99.92% for binary classification
[143]	EEG signal	2022	Bagged trees ensemble classifier	—-	Average sensitivity of 99.28% and a specificity of 99.10%
[138]	Speech signal	2023	DL with neuro-fuzzy technique	—-	Higher accuracy

the use of multivariate logistic regression and deep learning, the researchers investigated nonlinear relationship between SPECT and several biomarkers

Sivaranjini et al. [150] used CNN model for PD categorization from MRI dataset and achieved an encouraging outcome of 88.9% accuracy. Again a unique model 3D-CNN was used on MR images by Soheil et al. [151] for identifying PD. In the recent study PD prediction model was created by Kaur et al. [152] utilising deep transfer learning methods. In this work, pre-trained AlexNet architecture was employed with MR-Images and data augmentation approach was used to improve the performance of the classification, and it revealed a classification accuracy of 89.23%. Shinde et al. [153] proposed a technique based on neuromelanin-sensitive magnetic resonance imaging (NMS-MRI) to distinguish PD patients from healthy people. The authors proposed a model by using CNN which had produced prognostic and diagnostic biomarkers of PD from NMS-MRI and also achieved 85.7% of test accuracy. Banerjee et al. [154] investigated diffusion MRI (dMRI) signals to differentiate PD patients from healthy subjects. The signal is captured in each voxel of the dMRI scan as a real number in each direction of the diffusion sensitising magnetic field throughout a hemisphere of directions in three dimensions. The whole dataset are divided into 85 training subjects and 9 testing subjects. The obtained training accuracy is 95.24% and testing accuracy is 88.88%. On the same year, the work implemented by Kiryu et al. [155] is to detect Parkinson's disorder from MRI imaging of human brain. In this study CNN was used as a classifier for multi-class classification of PD, PSP, MSA-P and HC. The accuracy rate of these four classes are 96.8%, 93.7%, 95.2%, 98.4% respectively. Similarly in [156], Yagis et al. made use of two different architectures of CNN models. The first one is VGG16, which consists of 16 layers and built by Oxfords Visual Geometry Group (VGG). VGG16 ranked first the ImageNet competition in ILSVRC-2014 with the accuracy rate of 92.7%. Similarly the second model used in this study is Resnet50 which also won ILSVRC 2015 classification competition with top-5 error rate of 3.57%. The authors collected the MRI slices of individuals and separated them into training and testing datasets. The Restnet model showed the supremacy in classification accuracy with 88.6%.

PET images are also used vastly in medical image processing are and fordetecting disease. Zhao et al. [157] used 18 F-FDG PET scans in their study to train a 3D deep convolutional neural network with 6-fold cross validation for autonomous prior determination of PD. A multi-class classification of Parkinson's Disease (PD), Multiple System Atrophy (MSA) and Progressive Supranuclear Palsy (PSP) was accomplished by the author in this work. The PD-related pattern (PDRP), MSA-related pattern (MSARP), and PSP-related pattern (PSPRP) were extracted using principal component analysis (PCA). For the class PD the sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV) are 97.7%, 94.1%, 95.5% and 97.0% respectively. Again, for class MSA and PSP the sensitivity are 96.8% and 83.3% respectively. Shen et al. [158] introduced a model to classify PD and normal control (NC) by utilizing Group Lasso Sparse Deep Belief Network (GLS-DBN) on PET imaging. 225 NC and 125 PD cohorts from Huashan and Wuxi 904 hospitals were chosen for this study. The whole dataset was separated into a training and validation dataset and two test datasets. For test dataset 1, the authors acquired 90% accuracy. The research community's endeavor to differentiate Parkinson's disease patients from healthy participants using deep learning methods on neuro-images is elaborated in the Table 7.

3.2.3 Identification of PD grounded in other modalities using DL algorithms

The main objective of this section is to offer a variety of evaluations for the diagnosis of PD using DL algorithms those are applied on miscellaneous datasets like gait characteristics,

Table 7 Overview of PD detection utilizing DL methods with neuroimaging:

Ref.	Dataset Used	YoP	Classification Method	Hyperparameter	Result
[147]	SPECT image	2021	CNN	Momentum parameter=0.9, Learning rate= 0.0001	Accuracy: With augmentation (method-1)=95.34%, without augmentation(method-1)= 97.47%, with augmentation(method-2)=99.34%, without augmentation=99.18%, Specificity: with augmentation (method-1), without augmentation(method-1)= 92.38%, with augmentation(method-2)= 99.63%, without augmentation=99.71%, Sensitivity: method-1=98.75%, method-2=99.04%
[149]	SPECT images	2020	Multi variate logistic regression and deep learning	—-	Accuracy=100%
[148]	SPECT images	2021	CNN	Learning rate=0.001, Batch size=20	Accuracy=99.34%
[150]	MRI images	2020	CNN (AlexNet)	Learning rate= 0.1, Epoch=94	Accuracy=88.9%
[151]	MRI images	2018	3D-CNN	Batch size=32, Epoch=117	High accuracy
[152]	MRI images	2021	Deep transfer learning	Batch size=40, Epoch=50	Accuracy= 89.23%
[153]	NMS-MRI image	2019	CNN	—-	Accuracy=85.7%

Table 7 continued

Ref.	Dataset Used	YoP	Classification Method	Hyperparameter	Result
[144]	FP-CIT SPECT	2017	Deep neural network	—-	96.2%, 82.6% and 92.0% for sensitivity, specificity and accuracy, respectively
[157]	18 F-FDG PET scan	2019	CNN	—-	Accuracy: PDRP=97.7%, MSARP=94.1%, PSPRP= 95.5%, NPV=97.0%
[146]	SPECT imaging data	2019	CNN	—-	Accuracy=0.972, sensitivity=0.983, specificity=0.962
[158]	PET images	2019	GLS-DBN	Learning rate= 0.001, Epoch=1000	Dataset-1: Accurcay=90%, sensitivity= 0.96, specificity=0.84, AUC=0.9120 Dataset-2: Accuracy=86%, sensitivity=0.92, specificity= 0.80 and AUC=0.8992
[154]	dMRI	2019	Deep neural network	Learning rate=0.0001	Training accuracy=95.24%, testing accuracy=88.88%
[155]	MRI images	2019	CNN	—-	Accuracy rate: PD=96.8%, PSP=93.7%, MSA-P=95.2%, MSA-P=98.4%
[156]	MRI images	2019	VGG-16, Resnet50	Batch size=100, Epoch=25	Accuracy for VGG-16 model=92.7%, Accuracy for Resnet50 model=88.6%
[145]	Brain images	2018	GCN	Learning rate=0.01	AUC=95.37%

keystroke movement, body movement, handwriting, drawing etc. In 2018 Zhao et al. [159] suggested a hybrid prediction model that merged LSTM and CNN models for detecting the advancement of Parkinson's Disease based on gait data. The model used publicly available datasets of vertical ground reaction force for training and testing. As per the recommendation by the author, the proposed hybrid model outperformed in comparison with other standalone ML and DL models with 98.80% of accuracy rate. In the next year Gil-Martin et al. [160] sought for creating an architecture for identifying PD patients using CNN. The authors used Parkinson Disease Spiral dataset from which important features are extracted using the convolutional layers of the CNN model. The extracted features were fed to the fully connected layers of the classifier for classification. The top outcomes from this effort included accuracy rates of 96.5%, AUC of 99.2% and F1 scores of 97.7%. In same year a deep learning approaches were suggested by Alharthi et al. [161] to analyse and integrate raw spatiotemporal ground reaction forces (GRF) to effectively identify gait patterns and suggested LSTM-CNN-2D model showed a promising performance with 96.00% accuracy. In [162] Papadopoulos et al. offer a technique for automatically recognising PD-related tremorous episodes using IMU data collected via smartphone. The whole dataset contained a total of 45 subjects which was again divided into 14 HC and 31 PD people. The authors implemented a Multiple-Instance Learning (MIL) approach that was amalgamated with deep feature learning approach with a learnable pooling stage. With the LOSO trial, the model provided better performance with a precision, sensitivity, specificity and F1-score of 0.987, 0.9, 0.993 and 0.943 respectively. On the other hand, Vidya et al. [163] suggested a PD stage detection model using CNN-LSTM network which classified PD based on gait datasets. The author used the publicly accessible Physionet gait dataset for assessment, which comprises vertical ground reaction force (VGRF) signals from walking steps. The signals were broken down using the empirical mode decomposition (EMD) approach which helped to obtain intrinsic mode functions (IMFs) that comprised of rich gait charactyeristics. Proposed hybrid CNN-LSTM network acquired 98.32% of accuracy for multi-class classification. Similarly, Papavasileiou et al. [164] collected moving disorder data from participants which were comprised of three classes, such as: 3 HC subjects, 5 PD subjects and 3 post-stroke individuals. Multi-task feature learning (MTFL) was employed by the authors, which classified the different classes with AUC= 0.96. Again the model developed by Xia et al. [165] is a dual-modal deep-learning-based model composed of convolutional neural network (CNN) and attention-enhanced long short-term memory (LSTM) or DCALSTM network. An analysis using a 5-fold cross-validation approach was done on three datasets (Ga dataset, Ju dataset, Si dataset) to see how successful the suggested model was. The Ga dataset provided the greatest accuracy for the challenge of distinguishing PD patients from normal individuals, with accuracy, sensitivity and specificity values of 99.31%, 99.35% and 99.23% respectively. In [166] Balaji et al. suggested a novel deep learning model established on LSTM network. The LSTM network was trained using three separate gait datasets, each of which was comprised of recordings of vertical ground reaction force (VGRF) for various walking conditions. The suggested method made use of dropout and L2 regularisation techniques to prevent data overfitting. In terms of binary classifications, the LSTM classifier has an average classifier accuracy of 98.6% and 96.6%. Similarly, in the study introduced by Reyes et al. [167] the dataset was prepared by taking the recordings of three samples of gait where 88 PD patients and 94 healthy control people are involved. To accomplish the experiment the authors employed three classifiers such as: Long-Short Term Memory (LSTM) model, one-dimensional convolution model (Conv1D) and the combination of both known as Conv LSTM. The last one achieved 83.1% of accuracy, 83.5% of precision, 83.4% of recall and 81% of f1-score. Liu et al. [168] applied a combination of LSTM and CNN for predicting PD

symptoms based on gait. The accuracy, sensitivity, and specificity of the proposed model are 99.22%, 100%, and 98.04%, respectively. In order to discover the variations in gait between PD and HC as well as between PD with various severity levels, Yang et al. [169] created a novel model based on residual network (ResNet) architecture called PD-ResNet. The input gait characteristics are enlarged using a polynomial elevated dimensions approach and the resultant processed data is then entered into the PD–ResNet model as a 3D-image. The suggested model performs exceptionally well, according to the trials on the clinical gait dataset, with accuracy of 95.51%, specificity of 94.44%, F1-score of 95.50%, precision of 94.44% and recall of 96.59%. On other hand Oğul et al. [170] implemented an innovative approach to analyse the gait signals derived from the foot-worn sensors. The model achieved 82% accuracy rate and AUROC of 0.89.

Prince et al. [171] accumulated data from mPower database which consists of 866 HC and 949 PD individuals. They combined LR, RF, DNN, CNN with and achieved 82.0% of accuracy which is promising than other standalone classifiers. Similarly Baby et al. [172] applied ANN, SVM and Naive Bayes classifiers on gait data collected from PhysioNet database with 73 healthy people and 93 PD patients. Among all these classifiers ANN produced 86.75% of accuracy. Wan et al. [173] creatively predicted the course of Parkinson's Disease (PD) using accelerometer signals collected utilising cellphones at various periods of the same day. Based on information from the University of California, Irvine, this study assessed their speech and movement habits. The gathered datasets are categorised using a variety of machine learning (ML) approaches such as logistic regression, KNN, M5P, random forests and ultimately, they used a deep multi-layer perceptron (DMLP) to produce meaningful results with 80% accuracy, 73% specificity, 72.5% sensitivity and 0.40 MCC. In a tabular format, Table 8 describes the work done by the scientific community to distinguish PD patients and Non-PD persons using DL techniques applied on miscellaneous modalities like gait characteristics, handwriting etc.

The data summaries from Tables 5, 6, and 7 reveal a predominant preference among researchers for employing CNN as the primary classifier model when utilizing physiological signals and neuroimaging datasets for Parkinson's disease detection. CNN's inherent ability to automatically learn hierarchical features from physiological signals and neuroimaging datasets facilitates the extraction of intricate patterns crucial for accurate diagnosis. Its convolutional layers enable spatial hierarchies in neuroimaging data, capturing fine-grained details indicative of Parkinson's-related changes. Additionally, CNN's adaptability to varying data types ensures a versatile approach that enhances the classification of diverse physiological signals, contributing to a comprehensive understanding of the disease. Furthermore, the deep learning architecture of CNN allows it to discern complex relationships within the data, providing a nuanced and effective tool for precise Parkinson's disease prediction. In addition to CNN, researchers have explored the application of various models like ANN, ResNet, VGG-16, Deep Residual Shrinkage Network, among others, for Parkinson's disease prediction. However, the prevalent preference for CNN arises from its superior advantages, leading to its predominant use in the majority of studies. In instances where alternative modalities such as gait data and movement disorder data are employed, researchers have opted for a diverse range of DL methods, including CNN, LSTM, combine LSTM-CNN and others but among them hybrid LSTM-CNN models are mostly utilised. The hybrid LSTM-CNN model offers distinct advantages in Parkinson's disease detection when utilizing movement disorder and gait datasets. LSTM networks excel in capturing temporal dependencies within sequential data, making them well-suited for analyzing movement disorder data, which inherently involves dynamic patterns over time. The combination with CNN enhances the model's ability to extract spatial features from gait data, providing a comprehensive understanding of both

Table 8 Overview of PD detection utilizing DL methods with other modalities:

Ref.	Dataset Used	YoP	Classification Method	Hyperparameter	Result
[160]	Spiral drawing	2019	CNN	—	Accuracy= 96.5%, F1-score= 97.7%, AUC= 99.2%
[159]	Gait	2018	LSTM-CNN	—	Accuracy= 98.80%
[163]	Gait	2022	LSTM-CNN	Learning rate=0.001, Dropout=0.2 to 0.3	Accuracy=98.32%
[161]	Gait	2019	LSTM-CNN-2D	Batch size= 128, Learning rate=0.01, Epoch=15000	Accuracy=96.00%
[162]	IMU data	2019	Learning rate=0.001, Epoch=60	MIL with deep feature learning	Specificity= 0.993, Precision 0.987, F1-score= 0.943, Sensitivity= 0.9
[171]	mPower dataset	2018	Combined LR, RF, DNN, CNN	—	Accuracy= 82.0%
[172]	Gait	2017	ANN,SVM,Naive Bayes	—	Accuracy for ANN = 82.0%
[164]	Gait	2017	MTFL	Batch size=128, Learning rate=0.001, Epoch=100	AUC= 0.96
[165]	Gait	2019	DCALSTM	—	Accuracy= 99.31%, Sensitivity= 99.35%, Specificity= 99.23%

Table 8 continued

Ref.	Dataset Used	YoP	Classification Method	Hyperparameter	Result
[173]	Movement and speech	2018	DMLP	—	Accuracy= 80%, Specificity= 73%, Sensitivity= 72.5%, MCC= 0.40
[166]	Movement	2021	LSTM	—	Accuracy= 98.6%
[167]	Gait	2019	Conv LSTM	—	Accuracy= 83.1%, Precision= 83.5%, Recall= 83.4%, F1-score= 81%
[168]	Gait	2021	LSTM-CNN	Epoch=10403	Accuracy= 99.92%, Sensitivity= 100%, Specificity= 98.04%
[169]	Gait	2022	PD-ResNet	—	Accuracy= 95.51%, Specificity= 94.44%, F1-score=95.50%, Precision=94.44%, Recall=96.59%
[170]	Gait	2021	Ranking by Siamese Recurrent Network with Attention	—	Accuracy= 82% and AUROC=0.89

the temporal and spatial aspects crucial for Parkinson's detection. This integration allows the model to effectively process movement disorder data by capturing nuanced patterns and relationships, contributing to improved accuracy in identifying Parkinson's disease markers.

3.3 Works based on NIAs and meta-heuristic approaches as a feature optimizer for detecting PD

A group of unique problem-solving techniques and approaches that are obtained by natural processes are known as "nature-inspired algorithms." Several nature-inspired metaheuristics have been put out in the literature and used in numerous real-world applications during the past two decades [174]. The major usage of NIA is to extract optimized feature vector from a vast dataset. NIAs have shown to be more effective and efficient in some cases than other traditional optimization techniques. This section represents an overview of the research works done by the researchers to detect PD using optimized set of features obtained by using nature inspired metaheuristics approaches. Shrivastava et al. [175] compared and contrasted many nature-inspired algorithms to identify the best traits and factors for distinguishing the PD affected patients from the healthy individuals. The authors accumulated the real life records of gait and speech signal from 166 people containing PD patients as well as HC. According to the authors' observation, the Binary Bat Algorithm beat conventional methods like Particle Swarm Optimization (PSO), Genetic Algorithm, and Modified Cuckoo Search Algorithm with a superior recognition rate. On the other hand Gupta et al. [176] used HandPD and NewHandPD dataset for early detection of Parkinson's disease by employing an innovative natural inspired optimization algorithm called optimized crow search algorithm (OCSA) to select rich features from the dataset so that the classification accuracy increased. Again a conjugated version of chaos-mapped bat algorithm (CMBA) with the support vector machine (SVM) known as CMBA-SVM was developed by Sahu et al. [177] in their study. Data were gathered from UCI repository and Istanbul collected data set. CMBA was responsible for extracting vital features from the dataset and the extracted feature vector was fed to the input of the SVM for classification and the model provided a promising outcome. Masud et al. [178] developed a model by amalgamating CROW Search and Deep learning (CROWD) stack sparse autoencoder neural network for detecting Parkinson's disease. ACSA algorithm was employed to choose rich feature subset and to create the compressed feature vector, a stack spare autoencoder with seven hidden layers was used in this study. According to the author this experiment enhanced the classification accuracy with 96% accuracy rate. On the same year Raihan et al. [179] suggested a study by considering TQWTs, MFCCs, and other common features of speech signals. They used BRB-based adaptive differential evolution (BRBaDE) algorithm for selecting optimized feature vector. In the next year Rajammal et al. [180] suggested a a wrapper-based Binary Improved Grey Wolf Optimizer (BIGWO) method for discriminating PD patients by obtaining an optimal feature subset from the datasets. The authors also optimized the number of neighbors in KNN by applying the Adaptive kNN (AkNN) approach while calculating the fitness value to enhace the classification accuracy. On the other side, Olivares et al. [181] had achieved 96.74% of accuracy for PD classification by employing Bat algorithm in the training phase of the ML models. In this study the authors accumulated voice data from UCI Machine Learning Repository. Again Sehgal et al. [182] detected PD in their study by modifying Grasshopper Optimization Algorithm to select optimal features from handwriting, voice and speech datasets. They utilized Decision Tree, Random Forest and k-Nearest Neighbour classifier to manipulate the selected feature vector for classification and provided 95.37% accuracy rate. In [183], Dash et al. proposed

a novel hybrid model by namely (CFA-KNB) merging the characteristics of chaotic firefly algorithm(CFA) and Kernel-based Naïve Bayes (KNB) algorithm. The chaotic firefly algorithms were created by using six distinct chaotic mappings and then these were integrated with a nonparametric kernel density estimated Naïve Bayes classifier for choosing most features due to which a reliable and generalized PD diagnostic model could be formed. The proposed logistic CFA-KNB model achieved 89% of accuracy. Pasha et al. [184] collected PD dataset of 252 PD patients with 756 number of rows and 755 number of columns which were normalized using MaxAbsolute feature scaling method. They also used BPSO (Binary Particle Swarm Optimization) and GA (Genetic Algorithm) and on eleven ML classifiers to calculate the optimal feature vector from the dataset among which GA-inspired AB provided supremacy in classification accuracy with 90.7% and GA-inspired MLP delivered maximum dimensionality reduction by choosing only 359 features. On other hand, on the basis of Internet Protocol addresses (IPA), a novel coding strategy is created by Chen et al. [185] to diagnose Parkinson's disease. The authors obtained the optimal structure of deep convolutional neural networks (DCNNs) by utilizing chimp optimization algorithm (ChOA) and the optimized DCNN was used to identify disruption in speech. In order to identify aberrant speech signals from individuals with Parkinson's disease and cleft lip and palate, big datasets are divided into smaller ones and tested at random. Initially the authors developed an IPA-based encoding technique for DCNN layers using chimp vectors. Then, for variable-length DCNNs, an Enfeebled layer with predetermined chimp vector dimensions was shown. The implemented model achieved 96.37% of accuracy to discriminate normal and disordered speech signal. Sharma et al. [186] collected four publicly available PD datasets from UCI repository on which they applied binary versions of Rao algorithms for evaluating an optimal feature subset as well as for optimizin the k-value of kNN algorithm. The method achieved 99.25% of accuracy. Cai et al. [187] proposed a model by implementing an enhanced fuzzy k-nearest neighbor (FKNN) approach along with chaotic bacterial fore-aging optimization (CBFO) feature optimization method and provided supremacy in performance. Again in order to analyse datasets including Speech, Voice, Handwriting, and Spiral Drawing while maintaining the model's efficiency, Gupta et al. [188] used an optimised cuttlefish method. For the PD classification, reduced features were fed into KNN and DT Classifiers. The efficacy was compared to that of the conventional cuttlefish algorithm, and it was shown that, with an accuracy of 92.19 percent, the optimised cuttlefish algorithm outperformed the conventional one. On the same way modified grey wolf optimisation approach was suggested by Sharma et al. [189] for feature selection from the different data sets, including handwriting, voice, and speech. It is crucial to notice that compared to speech, the handwritten data set's accuracy level is rather low; this may be further examined.

4 Discussions

The primary objective of this survey is to investigate and estimate the upcoming research path in the area of AI-based PD diagnostic approaches. A thorough analysis of conventional ML and DL based PD identification methods is also provided in this paper along with the optimal feature set creation strategies using nature inspired metaheuristics techniques. In order to identify Parkinson's disease, ML and DL approaches can be explored to handle physiological signal dataset (EEG,EMG,Speech signal etc.), neuroimaging (MRI,CT,SPECT,DaTSCAN etc.), and other other modalities (handwritten character,gait characteristics,spiral drawing etc.). In this study, we discovered that the majority of researchers employed physical sig-

nals for detecting PD. Limited number of research papers are accessible for detecting PD on the basis of EMG and EEG signals. But for better diagnosis and classification numerous researchers worked on medical images and gait characteristics using ML tools. Additionally, numerous research have supported the use of deep learning approaches for diagnosing PD in order to speed up computation times and enhance the performance of prediction models during training. Similar to this, cellphones will be crucial in the subsequent research to investigate mobile health technologies to frequently monitor patient behaviours at home. Recent technology developments enable anybody, regardless of prior knowledge of the sickness, to properly anticipate the disease using deep learning-based algorithms without the need for human participation. This thorough evaluation presents the information on Parkinson's disease (PD) diagnosis to aid physicians in their decision-making. Again, this survey provides the idea about various nature inspired metaheuristics approaches which select optimal features to enhance the classification accuracy of PD detection. So, this survey clears that nowadays several ML,DL and NIA approaches provide an excellent effect in the field of health care as well as detection in neurodegenerative disorders like Parkinson's Disease.

While acknowledging the imperative need for early detection of Parkinson's Disease (PD), we recognize the importance of providing concrete examples of how AI-based approaches, employing ML and DL, have been successfully utilized in real-world scenarios. Through a meticulous examination of relevant case studies and experimental outcomes, we intend to offer a more detailed and empirical understanding of the effectiveness of these techniques in predicting PD. By incorporating tangible evidence, our goal is to bridge the gap between theoretical discussions and practical applications in future by simulating a more robust comprehension of the role of AI in improving PD diagnosis and patient outcomes. To enhance the practicality and substantiate the application of ML and DL in the field of healthcare specific case studies and experimental results. will be investigated in future.

Different kinds of comparative analyses are also made based on this survey. So, the central argument of the article is based on a comparative analysis of predicting PD using artificial intelligence. It investigates the suitability of deep learning, machine learning, and algorithms inspired by nature in this situation. The main objective is to assess and compare various approaches in order to facilitate the development of more precise and effective early diagnosis

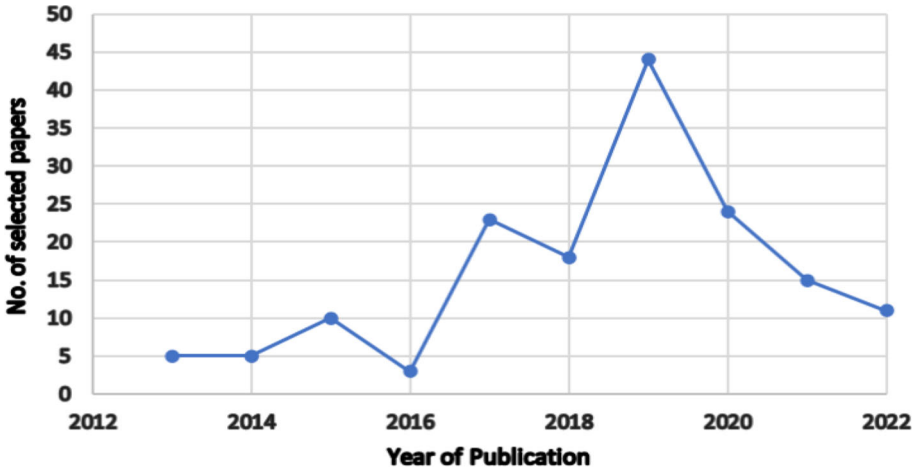

Fig. 4 YoP-wise Distribution of surveyed Papers

of Parkinson's disease, which will ultimately lead to better patient outcomes. The articles were categorised based on the year they were published. Figure 4 portrays the distribution of surveyed paper based year of publication. The diagram makes it evident that the most articles from the years 2019, 2020 and 2021 are being analysed in this survey.

Numerous dataset are used in this survey and according to different dataset types a statistical comparison is illustrated in Fig. 5. It is clear from the figure that most of the studies in the publications that are chosen are dealing with speech and voice signal, gait characteristics, medical imaging etc.

Figure 6 represents the graphical analysis of number of selected papers in different publishers. The visual representation makes it apparent and understandable that the article form Elsevier and IEEE publishers are mostly selected.

5 Challenges

This survey provides a thorough analysis that emphasizes relevant information for diagnosing PD, aiding physicians in their decision-making process. Healthcare professionals keen on adjusting ML and DL models or implementing diagnostic systems with new biomarkers are advised to exercise caution in the interpretation of published findings. In this perspective, we would want to emphasise the importance of employing consistent reporting standards in ML, DL and NIA investigations. Despite these schemes we also suffer from various shortcomings or challenges those are enlisted below:

1. Recognizing that collecting real-world data from patients poses a greater challenge in the healthcare sector compared to other research areas.
2. Neurodegenerative medical datasets are frequently characterized by imbalance, presenting a challenge in the current scenario as addressing this imbalance proves to be challenging due to its potential impact on biased results.

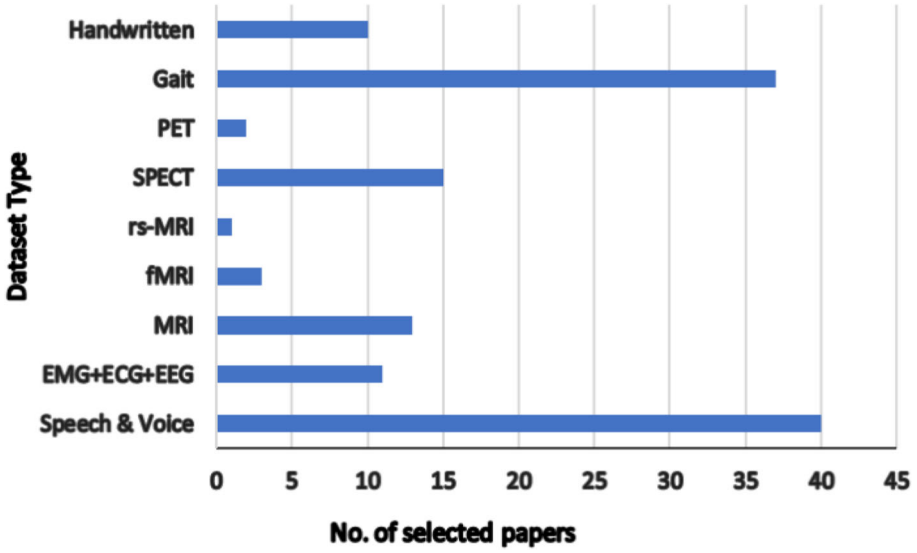

Fig. 5 Classification of selected papers according to dataset type

Fig. 6 Existing research scheme in different publishers

3. It was difficult to directly compare the outcomes associated with each type of model across studies due to the high variation of data sources.
4. Furthermore, certain studies omitted details regarding whether the evaluation of model performance involved a test set or relied on results generated by the models.
5. The latent potential to enhance prediction accuracy exists through the utilization of multimodal datasets, leveraging advancements in deep learning techniques alongside nature-inspired methodologies.
6. Some drawbacks may arise for using physiological signals. For example, because of the surrounding environment and motion disturbances, voice signal quality suffers and EEG signals have limited spatial resolution and are contaminated with numerous artifacts.
7. Furthermore, there is a huge scope to apply metaheuristics approach to select optimize feature vector from neuroimaging dataset.
8. While it is crucial to employ appropriate criteria for evaluating the performance of ML and DL models in Parkinson's disease classification, there remains significant room for enhancement.

6 Conclusion and future work

This study has evaluated a number of publications on ML, DL and NIA based methods for detecting Parkinson's disease. The accuracy of various implemented models have been improved by several experiments on speech signals using ML and DL approaches to identify Parkinson's disease. Similarly, many studies have been done on medical imaging, gait characteristics and other modalities using ML, DL and NIA approaches to detect Parkinson's disease as well as enhance the efficiency of the model. This study has shown that a number of ML, DL and NIA approaches can be enhanced, and there is still need for more study to increase accuracy and speed up decision-making.

The future scope of PD detection utilizing ML, DL and meta-heuristic approaches is composed for exciting developments and advancements. The integration of these sophisticated technologies holds immense potential for refining and revolutionizing early detection methodologies, thereby contributing significantly to the field of neurology and healthcare. The incorporation of multi-modal data fusion could be a crucial direction for future research. Integrating information from diverse sources such as speech recordings, handwriting patterns, gait abnormalities, and neuroimaging techniques into a unified predictive model could provide a more comprehensive and holistic understanding of PD. Ethical considerations and the responsible deployment of AI in healthcare also constitute an essential aspect of the future scope. Ensuring transparency, interpretability, and fairness in AI models for PD detection is crucial to gaining trust from both healthcare professionals and patients. Collaborative efforts between researchers, clinicians, and industry stakeholders will play a pivotal role in advancing the field. Establishing interdisciplinary partnerships could facilitate the development of robust, real-world applications, bringing AI-based PD detection approaches from the laboratory to clinical practice. In conclusion, the future of PD detection using ML, DL, and meta-heuristic approaches holds great promise. As research progresses, it is anticipated that these technologies will continue to evolve, contributing to earlier and more accurate diagnoses, ultimately improving the quality of life for individuals affected by Parkinson's disease.

Summary points

- A structured survey of ml, dl and nia approaches are presented to detect and diagnose parkinson's disease.
- Every existing review is being examined along with its merits and demerits.
- Challenges and potential future applications of the parkinson's disease domain are also discussed in this survey.

Data Availability Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Conflicts of interest There is no 'conflict of interest' in the publication of this manuscript "A Comparative Study: Prediction of Parkinson's Disease using Machine Learning, Deep Learning and Nature Inspired Algorithm".

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