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Classification, Prediction, and Monitoring of Parkinson's disease using Computer Assisted Technologies: A Comparative Analysis ☆

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ABSTRACT

Parkinson's disease is a neurogenerative disorder that occurs due to the loss of dopamine-producing cells. Till now, there is no cure for this disease but correct medications can slow down the progression. Therefore, early diagnosis of this disease is very important to improve the quality of life of Parkinson patients. This paper provides a comparative analysis of computer-assisted technologies for classification, prediction, and monitoring of Parkinson patients. The articles are selected based on the type, source of data, and symptoms to diagnose Parkinson's disease. Our contribution in this paper includes the study of recent articles from the year 2017, 2018, and 2019 and some other articles to consolidate some of the previous work as well. Research articles are chosen based on symptoms, type, and source of data to cover each aspect of Parkinson's disease. There is a great potential for early diagnosis as well as improving the quality of life with the help of computer-assisted rehabilitation techniques. We have divided our analysis into six sub-categories. A detailed analysis has been done on each sub-category. Information about some tools, software, and libraries are provided for the use of researchers. A comparison has also been done on different feature extraction and classification techniques so that researchers can further explore these techniques. Research gaps and future directions are also discussed along with challenges related to each gap for researchers to work on.

1. Introduction

Parkinson's Disease (PD) is a progressive neurological disorder that affects the nerve cells in the brain which are responsible for producing dopamine. It is the second most common neurological condition (Leroy et al., 1998). Dopamine producing cells (in Substantia Nigra part of the brain) start to die which otherwise acts as a messenger to control body movements. When dopamine-producing cells become prominently low, then there is a problem in controlling the body movements and symptoms start to appear. There is no known cause as to what causes the death of these cells. Many scientists think that genes and the environment play an important role in the degradation of these cells. Factors that increase the risk of Parkinson's disease include people with the age of 60 or above (Prusiner, 2001), family history, type of job environment, serious head injury. Symptoms of Parkinson's disease are not visible abruptly. It starts with mild early symptoms and progresses slowly. Common symptoms of Parkinson's disease include:

- Stiff muscles: It becomes hard to move parts of the body as muscles are not able to relax normally.
- Tremor: There is uncontrolled shaking in hands and arms. It may start on one side of the body and may spread to both sides.
- Bradykinesia: Slowness occurs while walking, getting out of the bed, talking, etc.
- Gait: There starts trouble while walking. Steps might become short and freezing may also occur.
- Other symptoms may include non-motor symptoms like loss of sense of smell, hallucinations, sleep disorders, dementia.

The above-listed symptoms may vary from person to person, one person might have tremors but no other symptoms, other might not have tremors at all. This disease progresses with time. Symptoms may get worse and new symptoms may occur with time. There are five stages of Parkinson's disease which are measured using Hoehn and Yahr Scale (HY) (Jankovic, 2008).

- **Stage 1:** This is the mildest stage where there may even be a case that the symptoms may go unnoticed.
- **Stage 2:** The progression to this stage can take several months, there are symptoms such as muscle stiffness, tremors, change in facial expressions, etc. Changes in gait and posture also become noticeable.
- **Stage 3:** Symptoms start to interfere with your daily activities.

☆ Survey Article.

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- **Stage 4:** Assistance is needed in this stage to perform daily activities.
- **Stage 5:** Patients become totally bedridden in this stage.

HY rating is solely based on current observation of Parkinson's patient, so, another way to measure Parkinson's disease is Movement Disorder Society-Unified Parkinson's Disease Rating Scale (MDS-UPDRS) (Goetz et al., 2007, 2008). It consists of a detailed analysis of PD symptoms divided into four sections consisting of sixty-five items. This rating scale provides the Unified Parkinson's Disease Rating Scale (UPDRS) scores and each sub-scale has ratings from 0–4 (0 means normal and 4 means severe).

The PD patients are treated with medicines such that they stimulate remaining dopamine-producing cells to produce more dopamine. This treatment is based on individual and goes lifelong. The major medications include Levodopa, Syndopa, Dopamine Agonists like Bromocriptive to play the role of chemical messengers. For many patients, medications improve quality of life but for some patients, motor fluctuations become more prominent. In these cases, surgery is suggested by doctors considering risks involved.

As the cause of Parkinson's disease is unknown, prevention is not possible but early diagnosis of Parkinson's disease can slow down the progression with the help of the right quantity of medication. Therefore, Parkinson's disease must be diagnosed at an early stage so that the quality of life can be improved. As symptoms are analyzed based on individual judgment, UPDRS scores suffer from a problem of inter-rater inconsistency. Moreover, UPDRS scores are calculated whenever patients visit health care centers but symptoms vary with time of the day. A short visit to the clinic is not sufficient for monitoring the symptoms and effects of medications accurately. So, there is a need for remote monitoring of Parkinson's patients to check symptoms consistently to analyze the patient's condition more efficiently. A lot of research is going on in this field with computer-assisted technologies to assist the doctors in diagnosing the PD, provide individualized treatments to each patient, and supports remote monitoring.

This paper provides a comparative analysis of work done in classification, prediction, and monitoring of Parkinson's disease using the machine and deep learning techniques. The common machine learning and deep learning techniques include algorithms like Logistic Regression (LR), Decision Trees (DT), Naive Bayes (NB), Random Forest (RF), Support Vector Regression (SVR), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), Extreme Learning Machine (ELM), Optimum Path Forest (OPF), Mahalanobis Distance Classifier (MDC), Neural Networks (NN), Deep Neural Networks (DNN), Single Layer Neural Network (SLNN), MultiLayer Perceptron (MLP), Convolution Neural Network (CNN), Recurrent Neural Network (RNN), Long Short Term Memory (LSTM), GRU (Gaited Recurrent Unit), Probabilistic Neural Networks (PNN), Probabilistic Generative Model (PGM), Stacked AutoEncoders (SAE), Restricted Boltzmann Machine (RBM), Gaussian Mixture Model (GMM)-Universal Background Model (UBM) and others. The related articles have been chosen from IEEE, ACM, Elsevier, Springer, Hindawi, Science Direct, Nature, MDPI, and other important publications from the year 2017, 2018, and 2019.

The rest of the paper is organized as follows. Section 2 presents review methodology, Section 3 presents the review of already reviewed articles before the year 2017 to cover previous years' articles as well. Section 4 provides classification, prediction, and monitoring technologies, and this section is further divided into subcategories based on the symptoms, source, and type of data. Section 5 presents the work done in the rehabilitation of Parkinson patients. Section 6 provides information on some Tools, Softwares, libraries to use. Section 7 presents a comparative analysis of subcategories as well as the comparison of feature extraction and the classification techniques. Section 8 provides research gaps and future directions for the researchers to work upon. Finally, Section 9 concludes the paper.

2. Review Methodology

The symptoms of Parkinson's disease can be majorly divided into motor and non-motor symptoms. The motor symptoms include tremor, gait, Freezing of Gait (FoG), dysphonia (also known as voice disorder), micrographia (also known as handwriting disorder), bradykinesia, and others. The non-motor symptoms are cognitive parameters which can be measured using ElectroEncephaloGram (EEG), Magnetic Resonance Imaging (MRI), Dopamine Transporter SCAN (DATSCAN), functional MRI (f-MRI), Single Photon Emission Computerized Tomography (SPECT) images or signals. Parkinson patients also have blank facial expressions, a lot less blinking. Other symptoms include memory disorders, olfactory disorder, sleep disorder, and many more. The data of these symptoms is collected either in the form of signals, images, videos, or clinical measures.

Based on the above-mentioned symptoms, type, and source of data, we have divided our analysis into six subcategories which are most researched by researchers. These subcategories include voice-based symptoms that contain data of voice patterns from Parkinson patients. The second and third sub-category includes data from wearable and non-wearable devices which further contains tremor, Gait, FoG, Fear of Falling (FoF), facial expressions, and other motor data. The fourth sub-category includes handwriting data to analyze the exam templates for classification purposes. The fifth sub-category collects data in the form of EEG signals. The final sub-category includes clinical data which further includes olfactory scores, sleep scores, MRI images, DATSCAN images, UPDRS scores, and many other forms of data. The above-mentioned methodology is shown in Fig. 1.

To find articles based on each symptom, different keywords were searched in Google Scholar like Parkinson's disease, Parkinson's disease + voice, Parkinson's disease + machine learning, Parkinson's disease + tremor, Parkinson's disease + accelerometer, and many more.

The inclusion criteria of research papers are as follows:

- The articles should be from the year 2017, 2018, and 2019.
- The research articles belonged to journals and conferences from ACM, IEEE, Springer, Elsevier, Hindawi, Nature, MDPI, and other important publications.
- First, the research articles were scanned by reading title, then included articles' abstracts were read, and finally articles were selected after reading the full text.

3. Review Articles

Some review papers related to Parkinson's disease have also been considered in this analysis so as to include previous literature as well. The authors in De Lima et al. (2017) have reviewed 27 articles until the year 2016 based on FoG and fall detection in Parkinson patients using wearable technology. The authors found that shin is the most efficient position to detect FoG with a single accelerometer sensor. According to the authors, less work has been done in fall detection as it may be difficult to monitor falls in real scenarios and this process cannot be simulated accurately.

The authors in Pereira et al. (2019) have surveyed 84 articles from the year 2015–2016 and categorized the diagnosis of Parkinson's disease based on the type of processing done i.e. web applications, sensors, virtual and augmented reality, smart-phone devices, signal analysis, image processing, and machine learning. The authors concluded that almost all the articles used machine learning technology for diagnosis and maximum work has been done in signal processing using sensors.

Authors in Son et al. (2018) have reviewed 31 articles from the year 2010–2016, which did research on remote monitoring of Parkinson patients using wearable sensors, smartphones, web-based technologies, and ambient sensors. The authors concluded that there has been less work in remote monitoring in a real-life environment. Most of the current work has been performed in controlled conditions. There is

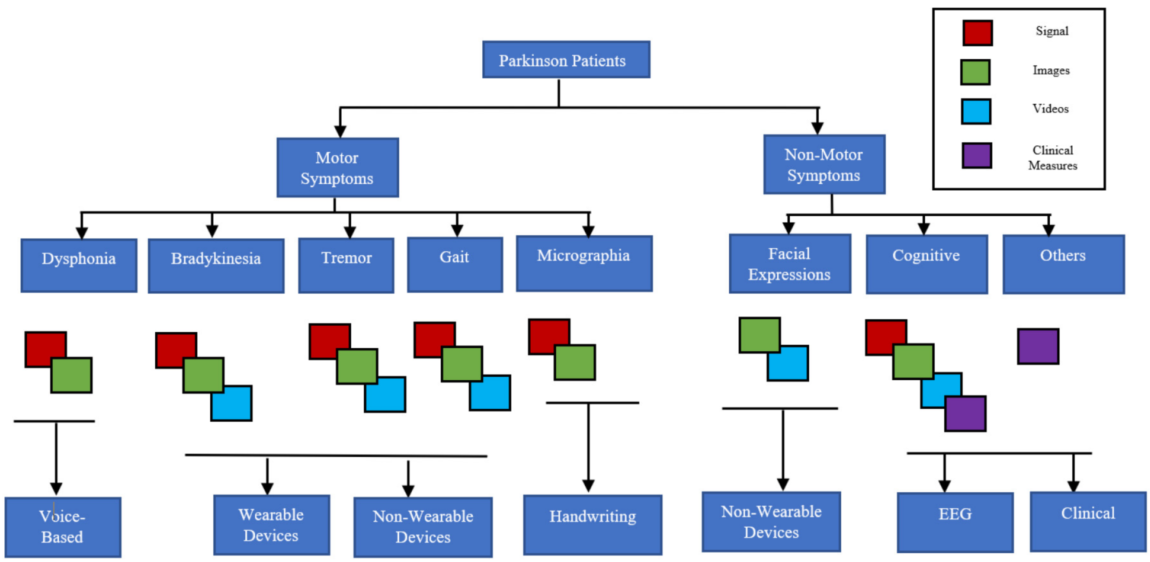

Fig. 1. Review Methodology.

a lot of potential to check for system validity, maintenance cost, and feasibility in a free-living environment.

Authors in Ramdhani et al. (2018) have reviewed the articles based on the type of sensors and devices used with respect to symptoms like gait, tremor, dyskinesia, and bradykinesia. The authors also categorized articles based on machine learning algorithms like DT, RF, NB, SVM, LR, NN, and unsupervised learning. They concluded that a lot of work has been done in this area but there is a need for standardization so as to apply the proposed techniques in real-life scenarios.

There was another kind of survey called the methodological review in which authors surveyed different nature-inspired feature selection techniques on two different public datasets to identify Parkinson's disease (Shrivastava et al., 2017). The first dataset is the Telemonitoring dataset, the details of which are mentioned in Table 1. The second one is the gait dataset, the details of which are mentioned in Table 3. The different nature-inspired feature selection techniques include Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Modified Cuckoo Search (MCS), and Binary Bat Algorithm (BBA). These feature selection techniques were able to reduce the dimensionality of the dataset considerably and BBA outperforms all other nature-inspired feature selection techniques using NN.

4. Classification, Prediction, and Monitoring of Parkinson's disease

4.1. Voice-based Classification, Prediction, and Monitoring

Dysphonia or voice disorder is one of the first symptoms to appear in Parkinson patients. Approximately 70%–90% of people are believed to have dysphonia in Parkinson's disease (Rusz et al., 2011). A person with PD has a low-volume voice with expressionless quality. It becomes difficult to understand due to tremous voice, a sudden burst, long pauses, and many more problems (Schulz and Grant, 2000).

Machine learning classification techniques based on voice patterns can help in early diagnosis of Parkinson's disease as it is one of the first symptoms to appear in PD patients. Moreover, it provides a low-cost, non-invasive solution of diagnosis as data can be easily collected using a microphone (smartphone-based/headset-based). Therefore, a lot of work has been done based on voice patterns.

Many datasets are available for researchers to work upon. Some of them are public, some are private. The details of the voice-based datasets are given in Table 1. It contains information like dataset description which provides details of the dataset. It also contains a device description which includes the name of the device used and sampling rate. The last column of the table contains information on extracted features and number of features (mentioned in braces). The most common voice features that are extracted by researchers include Jitter, Shimmer, Harmonicity, Pitch, Mel-Frequency Cepstral Coefficients (MFCC), Recurrence Period Density Entropy (RPDE), Detrended Fluctuation Analysis (DFA), Pitch Period Entropy (PPE), Glottal to Noise Excitation (GNE), Vocal Fold Excitation Ratio (VFER), and Empirical Mode Decomposition (EMD).

The methodology for voice-based classification, prediction, and monitoring followed by different researchers are provided in Table 2. The table includes work done in a particular study, signal processing techniques, classification techniques, and performance of the system. The signal processing techniques further consist of Pre-Processing (Pre-P), Feature Extraction (FE), Feature Selection (FS), and Post-Processing (PP) techniques. Feature Selection is very important to reduce the dimensionality of the dataset as well as improve the performance of the system. Some of the most common FS techniques include Principal Component Analysis (PCA), minimum Redundancy Maximum Relevance (mRMR), Correlation-based FS (CFS), Information Gain (IG), Gain Ratio (GR), Genetic Algorithm (GA), Fuzzy Mutual Information (FMI), Recursive Feature Elimination (RFE) with Correlation Bias Reduction (CBR), Chi-Square (CS), ANalysis Of VAriance (ANOVA) test, and others. The most common classification techniques used for voice-based diagnosis of PD include DT, RF, SVM, LSVM (Linear SVM), RSVM (Radial Basis Function (RBF) SVM), KNN, MLP, NB, LR, and NN. The performance of the system is measured mostly in terms of Accuracy (Acc), Sensitivity (Se), Specificity (Sp), F1-Score (F1), Precision (P), G-Mean (G), Receiver Operating Characteristic curve (ROC), Area Under ROC Curve (AUC), Matthew's Correlation Coefficient (MCC), Detection Rate (DR) (Sharma et al., 2019), False Alarm Rate (FAR) (Sharma et al., 2019), Equal Error Rate (EER) (Almeida et al., 2019) and Mean Absolute Error (MAE) (Nilashi et al., 2018).

4.2. Wearable Devices based Classification, Prediction, and Monitoring

Parkinson patients suffer from various motor symptoms like tremors (in different body parts), bradykinesia, dyskinesia, Stooped Posture (SP), imbalanced gait, FoG, Fear of Falling (FoF), stiffness, and many more (Salarian et al., 2007). Doctors\Clinicians measure these symptoms subjectively with the help of HY Scale and UPDRS scale. HY scale performs staging of PD patients whereas the UPDRS scale gives ratings

Table 1
Voice-based datasets for Classification, Prediction, and Monitoring of PD.

Reference	Dataset description	Device description (Sampling Rate)	Features (Size)
Braga et al. (2019)	(Proença et al., 2014) 22 PD (12 F + 10 M), Age: 44–79, 1002 speech lines/88.8 min	Plantronics table Microphone, EMU4040, Olympud WS memo Recorder (44.1 KHz)	Formant, Vocal Space Area (VSA), Vowel Articulatory Index (VAI), MFCC, GMM supervector (2652)
Braga et al. (2019)	30 Healthy Control (HC) (21 F + 9 M), Age: 20–71, 785 speech lines/28.2 min	Steel Series Siberia V3 Prism Device (44.1 KHz)	Jitter, Shimmer, Harmonicity, Pitch, Gender (19)
Braga et al. (2019), Parisi et al. (2018), Sharma et al. (2019), Cai et al. (2018), Zhang (2017)	20 PD (6 F + 14 M), 20 HC (10 F + 10 M), Age: 43–77, 116 Sustained vowels (/o/, /a/) (Dua and Graff, 2017; Sakar et al., 0000a)	Trust MC-1500 Microphone (Sakar et al., 2013)	Jitter, Shimmer, Pulse, Voicing, Pitch, Harmonicity (26)
Sakar et al. (2019), Tuncer and Dogan (2019)	188 PD (107 M + 81 F) + 64 HC (23 M + 41 F), Age: 33–87, sustained phonation /a/ (Sakar et al., 0000b)	Microphone (44.1 KHz)	Jitter, Shimmer, Fundamental frequency, Harmonicity, RPDE, DFA, PPE, Intensity, Formant, Bandwidth,MFCC, wavelet, Glottis Quotient (GQ), GNE, VFER, EMD, TQWT (754)
Lahmiri et al. (2018), Avci and Dogantekin (2016), Lahmiri and Shmuel (2019), Sharma et al. (2019), Kadam and Jadhav (2019), Yoon and Li (2018), Mostafa et al. (2019), Rajagopal et al. (2019), Cai et al. (2018), Haq et al. (2018), Zhang (2017), Nilashi et al. (2018), Li et al. (2017a), Haq et al. (2019), Shrivastava et al. (2017)	42 PD (28 M + 14 F), Age: 36–85, 5875 recordings (Tsanas and Little, 0000; Little, 0000; Little et al., 2008; Tsanas et al., 2009; Little et al., 2007)	Head mounted microphone (AKGC420)	Jitter, Relative Amplitude Perturbation (RAP), Period Perturbation Quotient (PPQ), Shimmer, APQ, Harmonicity, DFA, PPE, Correlation Dimension, motor_UPDRS, total_UPDRS (26)
Shukla et al. (2019)	14 PD (8 M + 6 F), Age: 51–69, (Tsanas, 0000; Tsanas et al., 2013)	Head mounted microphone	Jitter, Shimmer, vocal-fold, RPDE, PPE, GQ, Harmonicity, DFA, GNE, VFER, EMD-Excitation Ratio, EMD, MFCC (309)
Oung et al. (2018b)	65 subjects (31 M + 34 F), 15, 20, 20, 15 – rated 0, 1, 2, 3 based on HY scale	Sennheiser DW Pro2 headset	Wavelet Energy, Wavelet Entropy (Shannon, Renyi, Tsallis, Permutation, Fuzzy) (214)
Zhang (2017)	HC speech signal sent over browser/server system	Smartphone's Microphone	not given
Tuncer et al. (2019)	756 signals from 252 subjects, /a/ three times	Microphone (44.1 KHz)	Maximum singular value from each block (122)
Almeida et al. (2019)	99 subjects with Phonation and speech recordings (Vaiciukynas et al., 2017)	Acoustic cardioid (AKG Perception 220, frequency range 20–20,000 Hz), Smartphone (44.1 KHz)	avec2011 (1941), avec2013 (2268), emo_large (6552), emobase (988), emobase2010 (1582), IS09_emotion (384), IS10_paraling (1582), IS10_paraling_compat (1582), IS11_speaker_state (4368), IS12_speaker_trait (5757), IS12_speaker_trait_compat (6125), IS13_ComParE (6373), Essentia descriptors (1915), MPEG7 descriptors (527), KTU features (1267), jAudio features (1794), YAAFE features (1885), Tsanas features (339)
Moro-Velázquez et al. (2018)	The Albayzin database: Phonetically balanced dataset utterances in Spanish (Moreno Bilbao et al., 1993)	(16 KHz quantized with 16 bits)	not mentioned
	GITA database: 50 PD patients, 50 HC (Orozco-Arroyave et al., 2014)	DDK, Sentences, Sustained vowel /a/ (44.1 KHz)	MFCC (20), Perception Linear Predictive coefficient (PLP) (20), Linear Prediction Coefficient (LPC) (20)

APQ-Amplitude Perturbation Quotient; DDK-DiaDchoKinetic rate; TQWT-Tunable-Q factor Wavelet Transform.

of pertinent features. But both these scales are based on the "rate as you see" basis, which suffers from the problem of inter-rater inconsistency.

These symptoms can be measured accurately with the help of some wearable devices embedded with different sensors like Accelerometer (Accl) (Weiss et al., 2010), Gyroscope (Gyro) (Salarian et al., 2009), Magnetometer (Mag) (Casamassima et al., 2014), Goniometer (Li et al., 2017b), Telemeters (Saad et al., 2017) and many more. The measurement based on these sensors is more precise as compared to subjective clinical based evaluation with UPDRS scores.

Therefore, a lot of work has been done by researchers in estimating tremor severity, estimating three different types of tremors including Rest Tremor (RT), Postural Tremor (PT), and Kinetic Tremor (KT). Work has also been done to estimate bradykinesia, dyskinesia, FoG, FoF using gait patterns. Work has also been done to estimate Stooped Posture which is considered a major problem in PD patients. The authors in Dang et al. (2019) have proposed a method to estimate stooped posture in Parkinson patients using accelerometer data and comparing it with C7-SAR distance as ground truth. It has been found that a single sensor on the back is sufficient to measure stooped posture in PD patients. These devices can also provide remote monitoring of Parkinson patients which can assist doctors in providing personalized treatment.

The details of the dataset based on wearable devices based classification, prediction, and monitoring of PD is given in Table 3 which includes information of the dataset used, device description i.e. type of sensor, description of the sensor, and its sampling rate. It also shows different activities understudy to estimate motor symptoms and their recording time. It can be observed from the table that most of the work has been done on Accelerometers, Gyroscopes, and Magnetometers. These sensors are embedded in the Inertial Measurement Unit (IMU) of different configurations. Very little work is done on other sensors like Telemeters and Goniometers. The potential of these sensors is still

Table 2
Classification, Prediction, and Monitoring of PD using Voice features.

Study	Proposed work	Signal Processing	Classification	Performance
Braga et al. (2019)	Early detection of PD with optimized ML algorithms	(Pre-P) Standardization,(FE) Pratt Script,(PP) PCA and LR for Pattern Analysis, Kruskal's, Levene's	RF, SVM, NN	Acc- 99.94%
Sakar et al. (2019)	Effectiveness of TQWT features compared with state of art features	(Pre-P) Standardization, (FE) MFCC, TQWT, EMD, WT, RPDE, DFA, Basic, (FS) mRMR, (PP) Mc Nemar's	LSVM, RSVM, MLP, NB, LR, RF, KNN, Ensemble	Acc-85%, F1–84%, MCC-57%
Lahmiri et al. (2018)	Comparison of ML classifiers	(PP) t-test	LDA, KNN, NB, RT, RBF-NN, MDC	SVM, Acc-92%, Se-95%, Sp-91%, F1–90%, P-77% G-87%, AUC-89%
Avci and Dogantekin (2016)	Proposed GA-WK-ELM based diagnosis system	publicly available features	GA-WK-ELM, Single Layer Neural Network	Acc-96.81%
Lahmiri and Shmuel (2019)	Access the performance of FS techniques	(FS) t-test, entropy, Bhattacharyya statistic, ROC, Wilcoxon Statistic, FMI, GA, RFE-CBR	RSVM	Acc-Wilcoxon based (92.21%), Se-ROC based (99.63%), Sp-ROC based (82.79%)
Parisi et al. (2018)	Hybrid artificial intelligence based classifier (MLP-LSVM)	(Pre-P) Normalization, Standardization, (FS) MLP, (PP) t-test — statistical significance of gender	LSVM	Acc, Se, Sp of 100% with faster convergence
Sharma et al. (2019)	Modified Gray Wolf Optimization (MGWO) as a search strategy for FS	(FS) MGWO	KNN, RF, DT	outperformed OCFA with Acc-94.83%, DR-98.28%, FAR-16.03%
Kadam and Jadhav (2019)	Proposed feature ensemble based SAE	(FE) SAE	DNN (SoftMax Regression)	outperforms DNN with Acc-92.19%, Se-97.28%, Sp-90%
Yoon and Li (2018)	Proposed PTL approach using AHTD measurements to predict UPDRS scores	publicly available features	Positive Transfer Learning (PTL)	PTL outperforms Transfer Learning (TL) with lower negative transfer
Shukla et al. (2019)	Proposed Multiple Pre-Processing technique for early detection of PD	(Pre-P) Discretization, (FS) CFS, ReliefF, IG, CS, PCA	J48, NB, SVM, RF, KNN, MLP, DT, NB Tree	Best-RF, Acc-94.98%, Se-93.18%, F1-94.7%, P-94.96%
Mostafa et al. (2019)	Proposed multiple feature evaluation - a multiagent approach	autocorrelation, CFS, GR, IG, SVM evaluator	ZeroR, DT, NB, NN, RF, SVM (RBF, SMO)	Increase in Acc by 10.51%, 15.22%, 9.19%, 12.75%, 9.13% in DT, NB, NN, RF, SVM
Cai et al. (2018)	Chaotic Bacterial Foraging Optimization (CBFO) for tuning of Fuzzy KNN	CBFO to optimize number of neighbors (K) and Fuzzy Strength (m)	Fuzzy KNN	Gender does not affect much the diagnosis process, Acc-96.97% (Oxford dataset), 83.63% (Istanbul dataset)
Oung et al. (2018b)	Multiclass classification with integration of voice and motion data	(Pre-P) Segmentation, (FE) EWT, EWPT, Hilbert, (PP) ANOVA	KNN, PNN, ELM	Acc-90% (Single data), 95% (Integrated data)
Zhang (2017)	Potential of smartphones in low-cost PD diagnosis	(FE) SAE	KELM, SVM (MultiLayer, Linear, RBF), CART, KNN, LDA, NB	Acc-94%–98%
Li et al. (2017a)	Improved Gray Wolf Optimization (IGWO) to find optimal feature sub-set	(Pre-P) Normalization, (FS) IGWO	IGWO-KELM, GWO-KELM, GA-KELM	Acc-96.97%, Se-98.16%, Sp-94.99%, P-97.99%, G-96.57%, F1-98.08%
Tuncer et al. (2019)	Find most distinctive features from 3 vowels	(Pre-P) 3 level-MAMa tree, (FE) SVD, (FS) ReliefF, (PP) 2 vowels are PD then resultant is PD	LDA, SVM (Linear, RBF, Cubic), LR, KNN, BT	KNN-Acc-92.46%, 96.83% (with PP)
Tuncer and Dogan (2019)	Eight-pooling Octopus based FE network	(Pre-P) Octopus method-minimum, maximum, range, average, variance, median, kurtosis and skewness, (FE) SVD, (FS) NCA, (PP) Mode based	SVM (Linear, RBF, Cubic), KNN, LR, DT	Acc-99.21% (Gender), 98.4% (PD), 97.62% (PD & Gender)
Almeida et al. (2019)	Evaluation of various feature extractors and classifiers	(Pre-P) Separate voiced and unvoiced parts, (FE) 18 different feature sets, (FS) t-SNE, (PP) N-way ANOVA, Friedman/Kruskal–Wallis, Nemeyi	KNN, MLP, OPF, SVM	AC channel-Acc-94.55%, AUC-0.87, EER-19.01%, SP channel-Acc-92.94%, AUC-0.92, EER-14.15%
Haq et al. (2019)	ML based prediction system to fill the gap between FS and classification	(Pre-P) Removing missing values, Standardization, Normalization, (FS) L1-Norm SVM	SVM	Acc-99%, Se-100%, Sp-99%
Nilashi et al. (2018)	Incremental update of data to predict UPDRS scores	(Pre-P) Self Organizing Maps for clusters (9), (FS) Non-linear Iterative Partial Least Squares	Incremental SVR, NN, ANFIS, MLR, SVR	reduces computational time, MAE-0.4656 (Total UPDRS), 0.4967 (Motor UPDRS)
Moro-Velázquez et al. (2018)	Influence of kinetic changes for automatic PD diagnosis	(Pre-P) Filtering, Downsampling (16 KHz), Normalization, Hamming windowing (10-40 ms), (FE) PLP, MFCC, LPC, (PP) RASTA for PLP	GMM-UBM (Reynolds et al., 2000), i-vector-GPLDA (Dehak et al., 2010)	Acc-87%, AUC-0.93

AHTD-At-Home Testing Device ANFIS—Adaptive Neuro-Fuzzy Inference System BT—Bagged Tree CART—Classification And Regression Tree EWPT—Empirical Wavelet Packet Transform EWT—Empirical Wavelet Transform i-vector GPLDA-Gaussian Probability Linear Discriminant Analysis KELM—Kernel Extreme Learning Machine MAMa-Minimum Average Maximum MLR—Multiple Linear Regression NCA—Neighborhood Component Analysis OCFA—Optimized Cuttlefish Algorithm RASTA—RelAtive SpecTral Analysis RT—Regression Trees SMO—Sequential Minimal Optimization SVD—Singular Value Decomposition t-SNE—t-distributed Stochastic Neighbor Embedding WK—Wavelet Kernel WT—Wavelet Transform

Table 3
Datasets based on Wearable devices for Classification, Prediction, and Monitoring of PD.

Study	Dataset	Device description (Sampling Rate)	Sensor placement (Number)	Activities (Recording time)
Abdulhay et al. (2018), Shrivastava et al. (2017)	Goldberger et al. (2000), (2008)	Force Sensor measures Vertical Ground Reaction force (100 Hz)	8 underneath each foot (16)	Walking (2 min)
Abdulhay et al. (2018), Pedrosa et al. (2018)	Goldberger et al. (2000), (2001)	Low-intensity velocity-transducing laser measures Velocity (100 Hz)	Index Finger tip (1)	RT (60 s)
Kim et al. (2018)	Kim et al. (2018)	Custom wearable device, SNUMAP, Accl- LIS3DSH, Gyro- L3G4200D, ST microelectronics, Switzerland (125 Hz), FHD video camera	1 Accl + 1 Gyro each for wrist and finger (4)	RT (60 s)
McKay et al. (2019)	McKay et al. (2019)	ADXL335BCPZ-analog devices, Norwood, MA, Tri-axial Accl mounted on three-axis Accl evaluation board, video recoder	Upper Extremities — each index finger, each wrist joint, Lower Extremities — each big toe, leg above ankle joint (4)	RT (3 min), PT (10 s), FT (10 times), HM (10 times), PSH (10 times), Arising from chair, RT while counting backwards (30 counts), TT (10 times), Leg agility (10 times)
Camps et al. (2018)	Camps et al. (2018)	IMU, $99 \times 53 \times 19$ mm^3, 3-axis Accl, Gyro, Mag, video recorder (200 Hz)	Left side of the waist (1)	Moving and showing around the house, walking outside the house, standing up, walking 6 m straight, turning 180 degree, walking 6 m back, sitting down, cleaning a cup, carrying a glass of water, typing in a computer, brushing one's teeth, drawing, erasing (18.64 h)
Rovini et al. (2018)	Rovini et al. (2018)	IMU based SensFootV2, iNEMO-MI board, based on MEMS contains 3-axis Gyro L344200D, six-axis geomagnetic module LSM303DLHC and arm based 32-bit microcontroller STM32F103RE (100 Hz)	Each foot (1)	TT with heel pin (10 s), Heel Tapping (10 s), GAIT (15 m), Rotation (360°)
Stack et al. (2018)	Stack et al. (2018)	Tripod mounted video camera, Battery powered, non-commercial, tri-axial Accl and Gyro	Waist, Each Ankle, Each wrist (5)	Sit-to stand (3 times), Stand-to-sit (3 times), 180° turn (1 time), Walk (3 m), Tandem walk (3 m), Rising to walk (3 times), Reaching high & low (3 times)
Pham et al. (2017), Oung et al. (2018a)	Dua and Graff (2017), Roggen et al. (0000), Bachlin et al. (2009)	Tri-axial Accl, video camera (64 Hz)	Shank, Thigh, Lower Back (3)	Walking in straight line, Walking with numerous turns, Fetching coffee, Opening doors (10–15 min each)
Pham et al. (2017)	Shine et al. (2012), Moore et al. (2013)	Accl, IMU-XSensMTx $38 \times 53 \times 21$ mm, 30 g, video camera (50 Hz)	Back (1), Foot (2), Thigh (2), Knee (2)	TUG Test (5 m)
Zhang et al. (2018)	Zhang et al. (2018)	Accl, video camera	Wrist (1)	Daily living activities
Daneault et al. (2017)	Daneault et al. (2017)	Accl	Upper arm, Forearm, Thigh, Shank (8)	HM, Heel Tapping (4 times each)
Tahavori et al. (2017)	Tahavori et al. (2017)	Accl, Gyro, video camera (50 Hz)	Lumber Spine (near Center of Mass (COM) of the body) (1)	Tandem Walk, Stand to sit, sit to stand, standing, backwards walking, 3 m- walk (3 times each
Oung et al. (2018b)	Oung et al. (2018b)	Motion Node Bus, IMU ($35 \times 35 \times 15$), 10 g, having tri-axial Accl, Gyro, Mag (100 Hz)	each wrist, each limb (4)	Arising from chair, PSH, HM, FT, TT, LM
Zhang et al. (2017)	Zhang et al. (2017)	Axivity AX3 Accl, video camera (100 Hz)	Wrist (2)	Sit and Walk (5 min), RT (3 min), PT (6 min), KT (2 min), FT (1 min), OCH (1 min), Writing (4 min), Typing (4 min), Playing chess (10 min), Playing cards (10 min), Making a sandwich (5 min), Eating a sandwich (10 min), Drinking from a cup (1 min), Walking (2 min), PSH (1 min)
Samà et al. (2018)	Samà et al. (2018)	IMU, 9×2 and 78 g, small, light ($77 \times 37 \times 21$ mm^3), Accl, video recorder (40 Hz)	Left side of Waist (1)	Part 1: before medication-Showing patient's home, go through a narrow space, turning back, going outdoors for short walk, reading something while carrying an object, Part 2-Brushing teeth, painting, erasing (20 min each part)
Chomiak et al. (2018)	Chomiak et al. (2018)	Ambulosono Sensor system, Accl, Gyro	(1)	Using sensors-Walking Test,Clinical Data-Alternating trail making, visuoconstructional cube, clock, attention processing, short term memory retrieval (delayed word recall), FES-1 scale with 16 items, UPDRS-III activities

(continued on next page)

to be explored by researchers. It can also be observed that the common activities to measure motor symptoms include Finger Tapping (FT), Opening and Closing of Hands (OCH), Pronation and Supination of Hands (PSH), Toe Tapping (TT), Leg Movements (LM), and Timed Up and Go (TUG) test.

Table 3 (*continued*).

Study	Dataset	Device description (Sampling Rate)	Sensor placement (Number)	Activities (Recording time)
Hssayeni et al. (2018)	Hssayeni et al. (2018)	Tri-axial Gyro sensor (128 Hz)	Back of most affected Ankle (1)	OFF and ON state: Ambulation, sitting, drinking, dressing, unpacking groceries, cutting food, hair brushing (15-60 s each)
Hssayeni et al. (2018)	Pulliam et al. (2017)	Tri-axial Gyro sensor (64 Hz)	Most affected Ankle (1)	OFF and ON state: Cycle through six stations: Hygiene, laundry, entertainment, snack, desk work
di Biase et al. (2018)	di Biase et al. (2018)	Magneto-inertial units containing Accl, Gyro, Mag, camera GoPro Hero4	Index finger, Thumb, Wrist, Arm, Metacarpus (5)	OFF and ON state: Rigidity, FT, PSH (15 times each)
Prateek et al. (2017)	Prateek et al. (2017)	MEMS-based IMU consists of 3-axis Accl, Gyro, video camera (1000 Hz)	Heel of left foot (1)	Walk backwards and turn (3 m), Walk again (3 m), Walk along a narrow path (3 m), Walk between cones over the block (3 m), Walk by following eight figure trajectory, 180° turn
Lonini et al. (2018)	Lonini et al. (2018)	MC10 BioStampRC (soft wearable sensor that adhere to skin) consists of 3-axis Accl, Gyro (62.5 Hz)	Hands, Arms, Thigh (6)	Walking, Walking while counting, Finger to nose, Alternating hand movements, Sit to stand, Sitting, Standing, Drawing on paper, Typing on computer keyboard, Nuts and bolts, Pouring water from a bottle and drinking, Organizing set of folders, Folding towels
Nguyen et al. (2017)	Nguyen et al. (2017)	IGS-180 motion capture suit consists of 17 IMU's, each having Accl, Gyro, Mag (60 Hz)	Full body 3D movements (17)	Two TUG test (3 trial of 10 & 5 m each)
Dang et al. (2019)	Dang et al. (2019)	OptiTrack camera system contains Infrared Cameras (100 FPS), XSensM1 sensors with Accl (100 Hz)	Neck, Upper back (2,6)	Slow gait with SP & tremor, Fast gait with SP & tremor, Slow gait with changing SP & tremor, Fast gait with changing SP & tremor (4 m each)
Saad et al. (2017)	Saad et al. (2017)	NIDAQ PCI-6259 with 3 sensors, ADXL330 3-axis Accl (28.3×18.5 mm), Telemeters infrared proximity sensors GP2Y0A21K, Goniometer (360° Smart Sensor Model 601 HE), Video recorder (100 Hz)	Shin (1), Foot (1), Far from foot (1), Near foot (1), Thigh (1), Shin (1)	Simulation-Walking with normal steps (15 s), Walking with short steps (15 s), Walking with FoG (15 s), Walking normal + FoG + normal (10+5+5 s),Testing-Straight walk with turns (6 m), Straight walks above cones with turns (6 m), Clinical tour
Delrobaei et al. (2018)	Delrobaei et al. (2018)	17 IMU-based Wearable Motion Capture System (IGS-180) consists of Accl, Gyro, Mag (60 Hz)	Head, Trunk, each arm, each Leg (17×3)	ON and OFF State-RT (20 s), PT (20 s)

FES-I-Falls Efficacy Scale-International MEMS-Micro Electro Mechanical System

The methodology used for classification, prediction, and monitoring of PD is provided in Table 4. It includes proposed work by different authors, signal processing techniques, classification methods, and features. Signal Processing further contains information about different Pre-Processing techniques (Pre-P), Feature Extraction methods (FE), Feature Selection methods (FS), Post-Processing techniques (PP). It can be observed from the table that most of the work has been done on tremor and FoG symptoms. Other symptoms like bradykinesia, rigidity, dyskinesia are yet to be explored properly. The most common pre-processing techniques include data filtering. This can be done with the help of High Pass Filter (HPF), Low Pass Filter (LPF), Band Pass Filter (BPF), and Butterworth Filter (BF). Windowing of the data is mostly done using Hanning Window (HW) and Spectral Window Stacking (SWS). The feature extraction plays a very important role in estimating the robustness of the system. It can be observed that most common FE techniques include Fast Fourier Transform (FFT), and PCA. The Post Processing is done to find the statistical significance of the data and features. The common methods include ANOVA, Kolmogorov–Smirnov (KS), t-test, Shapiro–Wilk, Mann–Whitney Wilcoxon (MWW) and others. Features directly influence the system's performance. The most common features related to gait include stance time, swing time, stride time, tapping frequency, Freeze Index (FI), Integrated FoG (IFoG). There are some important statistical features which include Mean (M), Standard Deviation (SD), Variance (V), Correlation Coefficient (CC), Root Mean Square (RMS), Mean Absolute Value (MAV). The time–frequency based features are also considered which include Power Spectral Density (PSD), Power Index (PI), ENTropy (ENT), and Energy.

It can be observed that the combination of sensors like Accelerometer and Gyroscope can produce better results as compared to a single sensor. It also came to the knowledge that the location and number of sensors plays an utmost important role in diagnosing the symptoms correctly and more accurately. One sensor per limb is sufficient to estimate a symptom correctly, therefore accuracy can be improved with minimum invasion. Moreover, the wearable devices which have been used are lightweight, low-cost, and do not require a technological expert to collect data.

4.3. Non-Wearable devices based Classification, Prediction, and Monitoring

There has been a lot of technological advancement in the medical field. Initially, 3D depth infrared cameras were used for video analysis, force plates were used for gait and freezing analysis. But these devices were large, invasive, and costly. With the new techniques, wearable technologies came into being which were small, low-cost and easy to handle. Despite the many advantages offered by wearable devices, there was a drawback of the invasive nature of these devices. To solve this problem, low-cost non-wearable devices offer potential solutions to diagnose PD patients with little or no invasion. These devices include video cameras, smartphones, Kinect Sensors, Leap Motion Controller (LMC), and others. Video recordings can capture motor movements like FT, PSH, HM without any extra burden. Cameras can capture facial expressions such as blank expression with less blinking and smiling. Smartphones can capture data from inbuilt sensors like accelerometer, gyroscope, and others. Kinect Sensor has also shown great potential in 3D data capturing. These devices can help PD patients to improve their physical and cognitive capabilities. Remote monitoring is also possible with the help of these non-invasive non-wearable devices. The process of calculation of UPDRS-III scores can be automated with the help of these devices.

The detailed information about the datasets related to non-wearable devices based classification, prediction and monitoring of PD are shown

Table 4
Classification, Prediction, and Monitoring of PD using Wearable Devices.

Study	Proposed work	Signal Processing	Classification	Features
Abdulhay et al. (2018)	PD severity using gait and tremor analysis	(Pre-P) Chebyshev type 2 HPF,BF of order 2, HW, (FE) FFT	Medium Gaussian SVM, LSVM	Stance time, Swing time, Stride time, Foot Strike profile, PSD
Kim et al. (2018)	Assessment of tremor severity based on CNN	(Pre-P) HPF (1 Hz), FFT signals under 20 Hz, middle 50 s, (FE) CNN, FFT	CNN, RF, MLP, DT, RSVM, NB, Linear Regression	weights of CNN as features, time–frequency features
Camps et al. (2018)	Deep learning method to access FoG	(Pre-P) Removing missing values, downsampling (50 Hz), 8th order LPF (20 Hz), Normalization, windowing, data augmentation, shifting, rotating, (FE) FFT, SWS (window size=2.56 s), labeled FoG if at least 50% data is FoG	Covnet, tree bagging, AdaBoost, LogitBoost, RUSBoost, RobustBoost, RSVM	Automatically extracted features from Covnet, FI (Bächlin et al., 2009), PI (Bächlin et al., 2009), M (Mazilu et al., 2012; Samà et al., 2018), SD (Mazilu et al., 2012; Samà et al., 2018), V (Mazilu et al., 2012), ENT (Tripoliti et al., 2013), skewness (Samà et al., 2018), frequency (Samà et al., 2018), CC (Samà et al., 2018)
Rovini et al. (2018)	Differentiate between PD and Idiopathic Hyposmia (IH) to investigate early onset of PD	(Pre-P) Fourth order LPF with digital BF (5 Hz cutoff, 3 Hz for gait), (FE) M and SD of features, (FS) p-values, (PP) KS, Kruskal–Wallis, Wilcoxon, spearman's correlation coefficients	SVM (Linear, quadratic, RBF, Polynomial), RF, NB	Gait time & frequency, No. of strides, stride, swing & stance time, relative stance, Dorsiflexion angular excursion of the foot, Rotation time & frequency, tapping frequency, no. of taps, toe angle, Coefficient of variation of tapping frequency & toe angle, Energy, M power, fundamental frequency, Max peak
Pham et al. (2017)	Subject-independent automated FoG detector	(FS) Saliency (Mutual Information), separability calculated using Euclidean Distance, Variance Ratio of clusters, Robustness, accuracy	Anomaly Score Detector	Max Peak, number of peaks in spectral coherence, FI (koopman operator, multiple channels), M, SD, V, median, ENT, energy, power
Zhang et al. (2018)	Several feature sets for tremor detection	(FE) MFCC, CNN	RF, MLP	MFCC, CNN (tremor/Activity Spectra), baseline
Daneault et al. (2017)	Minimum no. of sensors required to estimate full body bradykinesia	(Pre-P) Data filtering (0.5–12 Hz), Data segmentation (30 overlapping epochs of 5 s), (FS) ReliefF, Davies–Boulden Index, (PP) ANOVA	SVM (Pearson Universal Kernel)	RMS, peak frequency, energy in peak frequency:total energy, range of auto-covariance, correlation between upper and lower limbs, ENT, range, variability, Min, sum:length.
Oung et al. (2018a)	Robust FE to improve FoG detection	(FE) Spectral analysis (117 — time and 126 — frequency), (FS) t-test	SVM, PNN	M, V, SD, IFoG, MAV, SSI, RMS, v-order 2 & 3, WL, AAC, DASDV, MFL, FI, ENT, power, frequency, FR, PSR, 1st, 2nd, 3rd spectral moments
Tahavori et al. (2017)	Activity recognition of PD patients using wearable sensor data	(Pre-P) Sliding window (2 s), Activity segmentation with ELAN annotation software, (FE) Spectral analysis, (FS) CFS, forward, backward & wrapper	RF, NB, LogitBoost, SVM	M, autocorrelation, PSD, spectral power, ENT, Sum Power Determinant Coefficient, spectral variance, Inter Quartile range, frequency, intensity, Zero Crossing Rate (ZCR), skewness, CC
Zhang et al. (2017)	Stratified weakly supervised algorithms to know approximate amount of tremor	Windowing, Consecutive windows are combined to form segments (30 s-10 min), (FE) Sensor data and video are labeled for tremor events, (PP) Segments are labeled as standard, stratified	Multiple Instance SVM & NN, ID-APR, EM-DD	not extracted
Samà et al. (2018)	New set of features to detect FoG in real environment	Second order LPF, BF,window size-64 samples, (FE) FFT (CETpD features), PCA, (FS) Directed graph for sub set along with Leave One Patient Out, (PP) t-test	KNN, RF, LR, NB, MLP, SVM (Linear, Poly, RBF)	M, Difference among M values, SD, frequency, highest harmonics and center of mass, skewness, kurtosis, Integrals, auto-regression coefficients, principal components, correlation
Chomiak et al. (2018)	Cognitive, motor boundaries of self-efficacy & FoF	(Pre-P) Linear Regression, (FE) PCA, (PP)- LR, t-test	SVM	principal components as features
Hssayeni et al. (2018)	LSTM to identify motor fluctuations	(Pre-P) BFS (FIR) (3 dB, 0.5-15 Hz), (FE) automatic FE from LSTM	LSTM	(Hssayeni et al., 2016; Pulliam et al., 2017)
di Biase et al. (2018)	Locate sensor placement to monitor bradykinesia and rigidity	(Pre-P) HPF (1 Hz), BPF (tremor — 4-8 Hz, bradykinesia — 1-4 Hz), (FE) FFT, (PP) Shapiro–Wilk, ANOVA, Bonferroni correction, p-values, Post hoc	preliminary analysis	Movement time, Peak-to-Peak Velocity, Fatigability, Total power, Smoothness
Prateek et al. (2017)	Automatic detection of onset & duration of FoG in real-time	(Pre-P) Downsampling, Gaussian autoregressive model, (FE) GLRT framework, Dead reckoning, Conditional intensity function	preliminary analysis	Zero Velocity Event Intervals, Trembling Event Intervals, Position, Velocity, Orientation, Probability of FoG

(*continued on next page*)

Table 4 (*continued*).

Study	Proposed work	Signal Processing	Classification	Features
Lonini et al. (2018)	No. of sensors, amount of labeled data to estimate bradykinesia, tremor	(Pre-P) Segmentation (5 s clips with 50% overlap, total 41802 clips), 4th order BF, HPF (0.5 Hz), LPF (3 Hz)	RF, CNN	Range, Skew, Kurtosis, Cross-correlation peak, Cross-correlation lag, Dominant frequency, Relative magnitude, PSD, Movements of jerk magnitude, ENT
Pedrosa et al. (2018)	Differentiate low and high frequency RT	(Pre-P) Normalization, (FE) FFT	KNN, LSVM	Signal peak, PSD, SD of power spectrum
Nguyen et al. (2017)	Detection and segmentation of TUG test activities	(Pre-P) Detrented, Normalization, BPF (Nguyen et al., 2015)	preliminary analysis	Trunk acceleration, Thigh acceleration, Angle of hip, Shin acceleration
Saad et al. (2017)	Detect FoG with multisensor device and GNN	(Pre-P) 2 s window (step size-0.2 s), (FE) time–frequency analysis, (FS) PCA	Gaussian Neural Network (GNN) (Barakat et al., 2011)	M, SD, PSD, Power, frequency, FI
Delrobaei et al. (2018)	Estimate full body tremor and differentiate tremor and non-tremor dominant PD patients	(Pre-P) BPF (2-20 Hz), (PP) Shapiro–Wilks, Pearson Product Moment, Spearman Rank-order Correlation	preliminary analysis	RMS

AAC—Average Amplitude Change DASDV—Difference Absolute Standard Deviation Value EM-DD—Expectation Maximization-Diverse Density FIR—Finite Impulse Response FR—Frequency Ratio GLRT—Generalized Likelihood Ratio Test ID-APR—Iterative Discriminative-Axis Parallel Rectangle MFL—Maximum Fractal Length PSR—Power Spectral Ratio SSI—Simple Square Interval WL—Waveform Length

Table 5
Datasets based on Non-Wearable devices for Classification, Prediction, and Monitoring of PD.

Study	Description	Device description	Activities
Li et al. (2018)	24 PD with Deep Brain Simulation (DBS), 4-6 TUG test before and after surgery (127 videos)	2-D Video Camera with 25 frames per second	5 m TUG Test with 6 sub-task: Sit, Sit-to-Stand, Walk, Turn, Walk-back, Sit-back
Khan et al. (2014)	13 PD (387 videos) + 6 HC (84 videos), Labeled 0-3 based on severity level (Nyholm et al., 2005)	Pivoted camera with 25 frames per second and frame resolution 352×288 pixels	Rapid Finger Tapping for 10 s
Bandini et al. (2017)	RaFD database (for pretraining): 57 adults + 10 children (Langner et al., 2010)	Camera: Each expression was shown with eyes directed straight ahead, averted to the left, and averted to the right	8 facial expressions (neutral, anger, sadness, fear, disgust, surprise, happiness and contempt)
Bandini et al. (2017)	CK+ Database (for pretraining): 210 adults (327 image sequences) (Lucey et al., 2010)	Panasonic AG-7500 cameras	8 facial expressions (neutral, anger, sadness, fear, disgust, surprise, happiness and contempt)
Bandini et al. (2017)	17 PD + 17 HC, 1 neutral + 8 expressive video (4 posed, 4 imitated)	Microsoft Kinect (at distance between 0.5-0.7 m from mouth), 640×480 pixels at 30 frames per second	Neutral expression (10 s), Basic expressions like happiness, anger, disgust, sadness, Basic expressions by imitating emotive faces shown on the screen
Butt et al. (2018)	16 PD + 12 HC	LMC:motion & position of hand in 3D. 3 infrared transmitters, 2 infrared depth data capture cameras (at 20 mm), 35 Hz	PSH, OCH, FT, PT (3 times each)
Joshi et al. (2018)	117 PD (772 video samples) (Tickle-Degnen et al., 2010)	Camera (audio and video) (frontal face view)	Patient speaking about positive or negative experience (20 s clips)
Eltoukhy et al. (2017)	9 PD	2 floor embedded force plates (Type 9286AA, Kristler instrument AG, Winterhur, Switzerland), 1000 Hz, Kinect V2, 30 Hz	Stance phase of gait cycle when foot was in contact with the force plate
Tan et al. (2019)	62 PD	Kinect V2 / Kinect Xbox One: Video and depth sensing, infrared cameras	Habitual Gait Speed (HGS): Walk at comfortable speed to other end without stopping & talking (4 m), Modified TUG (MTUG): TUG test with turn at 2 m

in Table 5 which includes a description of the dataset, devices, and different activities that were performed to measure various symptoms. It can be observed that the most commonly used non-wearable device includes Kinect V2. It is easily available, low cost, and does not require any expert to collect data. It can also be observed that the TUG test is the most common activity to consider FoG and bradykinesia symptoms.

The detailed methodology followed by researchers is shown in Table 6. It includes proposed work, signal processing techniques, classification techniques, and extracted features. The signal processing techniques further contain information about Pre-Processing (Pre-P), Feature Extraction (FE), Feature Selection (FS), and Post Processing (PP) techniques. It can be observed from the table that non-wearable devices provide a non-invasive diagnosis process with low-cost instruments like a camera, video recorders, Kinect, and LMC. The data from these instruments can be collected by common individuals and does not require technical experts. Some of these devices can also help in remote monitoring of PD patients which would help them to get personalized treatment without going to clinicians frequently.

4.4. Handwriting based Classification, Prediction, and Monitoring

Apart from motor symptoms, there is another problem of handwriting abnormality commonly known as Micrographia (McLennan et al., 1972) i.e. small, cramped handwriting, progressing to smaller handwriting with time. Handwriting also becomes crooked due to tremors in hands. So, tremors can also be estimated from handwriting templates. Diagnosis based on Handwriting Exam (HE) is one of the easy and non-invasive ways for early diagnosis of PD patients.

The details of the dataset for classification, prediction, and monitoring of PD with handwriting template are mentioned in Table 7. The Table contains details of the dataset, activities performed, and device used for various handwriting templates. It can be observed from the table that most common handwriting templates include Archimedes

Table 6
Classification, Prediction, and Monitoring of PD using Non-Wearable devices.

Study	Proposed work	Signal Processing	Classification	Features
Li et al. (2018)	Automatic sub-task segmentation from video recordings	(Pre-P) Sliding window,ground truth- 2 experts (0.99 Intra-Class Correlation coefficient), (FE) Human Pose Estimator (IEF & OpenPose (OP)), (FS) Faster Regions with CNN, (PP) DTW	IEF+(SVM/LSTM), OP+(SVM/LSTM)	6 Sub-task
Khan et al. (2014)	PD severity based on Rapid Finger Tapping (RFT) features from video recordings	(Pre-P) OpenCV & Haar Cascade classifier for face detection, frame is divided into ROIs, moving average, filtered using 3-SD rule, (FE) Peak finder Algorithm, (FS) Jackknifing estimates precision of guttman monotonicity coefficient, CS, (PP) Spearman pair-wise correlation, guttman correlation model	SVM	no., acceleration, diff of FT, M & V coefficient of FT speed and diff between max amplitude of FT, M open and close velocity of index finger, average ZCR, T_E, Avg_{CCNP}, Avg_{CCNV}, SFT
Bandini et al. (2017)	Automatic method to study facial bradykinesia	(Pre-P) Facial landmark aligned to template (rotations, translations, scaling, and skewing) Euclidean distance for each video frame, (FE) Intraface tracking algorithm, (PP) Two-tailed t -test, Procrustes analysis	Multi-class RSVM	49 facial landmarks, 20 geometric features (4 eyebrows, 10 eye, 6 mouth), Mean, SD, Max, Min, range
Butt et al. (2018)	Potential of LMC to assess motor dysfunction	(Pre-P) Signals were reconstructed using Linear interpolation method (50 Hz), LPF, BF (14 Hz), (FE) LMC-SDK (Palm Angle, Fingertip distance, Thumb forefinger distance, Fingertip velocity index), Burg's Method, Peak finder Algorithm, (FS) PCA, SVM, Consistency, J48, Filtered subset evaluation, IG, GR, CS, attribute evaluation, (PP) Spearman's correlation,MWW, ANOVA	SVM (SMO, Poly), LR, NB	Number of rotational movement, OCH movement, FT, PSH speed, OCH speed, Variability of frequency, amplitude, Signal strength of movements, PSD
Joshi et al. (2018)	Predict facial expressivity score	(FE) Video: Open Face, Audio: MFCC (Librosa Library), (PP) F1-scores before and after randomly permuting the values of the features while training	HBNN(C/R), RF (Regression)	Video: 18 Action Units (AU) presence, 17 AU intensity values, Audio: M, SD, Min, Max
Eltoukhy et al. (2017)	Potential of kinect to predict 3D Ground Reaction Forces (GRF)	(Pre-P) GRFs were normalized w.r.t subject's body weight, (FE) GRFs (Vertical and Horizontal), (PP) t-test	preliminary analysis	2 features from each GRFs i.e. braking and propulsive peak points
Tan et al. (2019)	Potential of kinect to provide incremental value by evaluating MDS-UPDRS and PIGD sub-scales	(PP) Association between Kinect V2 and MDS-UPDRS and Postural Instability and Gait Difficulty (PIGD) scale	Linear & proportional odds regression	HGS: Gait speed, Gait speed variability, Step length, Step time, Vertical pelvic displacement, MTUG: MTUG time, First step length, Time to turn

Avg_{CCNP}—Mean of Cross-Correlation between the Normalized Peaks Avg_{CCNV}—Mean of Cross-Correlation between the Normalized Valleys DTW—Dynamic Time Wrapping HBNN(C/R)—Hierarchical Bayesian Neural Network (Classification/Regression) IEF—Iterative Error Feedback SFT—Standard deviation of Face-rectangle centroid during Tapping ROI—Regions of Interest SDK—Software Development Kit T_E-Signal Energy

spiral, meanders, and alphabets. Data can also be taken in the form of signals from the smartpen. Most of the work that has been done is on images. Two datasets MNSIT (LeCun et al., 0000) and ImageNet (0000b) can be used for pre-training models to overcome the problem of overfitting and underfitting. The fine-tuned models perform better as compared to traditional classification models.

The details of the methodology followed by researchers is explained in Table 8. It contains information about proposed work, Signal processing, classification, and extracted features. It can be observed from the table that most of the handwriting related work is done on images. Very few researchers have done work based on signals. There is still a lot of potential in analyzing signals for classification purposes based on handwriting templates. New handwriting templates are also being analyzed to find new discriminative properties. It is found that drawing spirals gave the best results which maybe because of the coordination required to perform this activity. Deep learning models have also been explored to extract distinctive features to improve the accuracy of the classification of PD.

4.5. EEG based Classification, Prediction, and Monitoring

Apart from motor and non-motor symptoms, PD patients also suffer from cognitive impairments. These cognitive impairments can provide a great deal of information as to how the disease develops, how medications are affecting patients. EEG signals can serve as an essential biomarker to distinguish PD patients from HC. It has been observed that PD patients show different EEG patterns as compared to HC. Moreover, EEG signals can also serve as objective biomarkers to predict the onset of PD, years before the actual development of PD. This can be done by analyzing Rapid eye movement Behavior Disorder (RBD) and IH patients. RBD is known as an early stage of PD. Analyzing EEG signals of RBD may have the potential in preventing this disease. So. it is important to study EEG signals. The details of the device used to capture data and the description of the datasets are discussed in Table 9. It can be observed from the table that EEG data can be collected using headsets with different number of channels. Data is mostly collected in the resting state for a time ranging from 5 min to 30 min. Work can be done on channel optimization to find the optimal number of channels for the diagnosis of PD.

The details of the methodology followed by researchers is discussed in Table 10. It can be observed from the table that there is a lot of potential in analyzing EEG signals for Parkinson's disease diagnosis. It provides the cognitive biomarkers to study and analyze the PD symptoms. RBD analysis using EEG signals has great potential in slowing down the progression or may even prevent the development of PD. Though limited studies have been found on EEG, most of the feature extraction is done with FFT. Other feature extraction techniques need to be explored to further enhance the system's performance.

4.6. Clinical data based Classification, Prediction, and Monitoring

Clinical measures of Parkinson's disease include demographics data, MRI, f-MRI, SPECT, DATSCAN, Positron Emission Tomography (PET),

Table 7
Handwriting-based datasets for Classification, Prediction, and Monitoring of PD.

Reference	Dataset description	Activities	Device description (Sampling Rate)
de Souza et al. (2018), Sharma et al. (2019), Passos et al. (2018), Pereira et al. (2017), Ali et al. (2019)	(0000a): 18 HC + 74 PD a total of (144+592=736 images) (368 spirals + 368 meanders) (Pereira et al., 2016a)	Drawing of: 2 Spirals, 2 Meanders	pen-paper
Afonso et al. (2019), Pereira et al. (2018)	(0000a): 35 HC + 31 PD a total of 9 images and 12 signals from each subject (Pereira et al., 2016b)	4 spirals, 4 meanders, 1 circle on paper, 1 circle in air, Left and Right DDK	Biometric Smart Pen with 6 sensors-tilt, acceleration, refill, grip, writing pressure
Kotsavasiloglou et al. (2017)	59 subjects (20 HC + 24 PD + 15 young HC)	10 lines left to right, 10 lines right to left with each hand, A total of 40 drawings from each patient	Wacom pen-tablet device, model Bamboo CTE-450, Active surface of 147.6×92.3 mm having resolution of 100 dots per mm (60 Hz)
Naseer et al. (2019)	(LeCun et al., 0000): Public database for handwritten digits with 60,000 training and 10,000 testing examples. Used for pre-training	✗	✗
Naseer et al. (2019)	(0000b): Contains 10,000 images divided into synonym set or synset, Used for pre-training	✗	✗
Naseer et al. (2019), Moetesum et al. (2019), Impedovo et al. (2018)	(Drotar et al., 2014) PaHaW Dataset: 37 PD + 38 HC	Archimedes Spiral, Repeated cursive letter *l*, The bigram *le*, The trigram *les*, Cursive words *lektorka*, *porovnat*, *nepopadnout*, Cursive sentence *Tramvaj dnes uz nepojede*	Intuos 4M digitizing tablet (Wacom), Features extracted from (x, y) coordinates of pen trajectory and pen status (whether in air or touching the writing surface) (200 Hz)
Rios-Urrego et al. (2019)	39 PD + 39 elderly HC, 40 young HC, Different and separate Validation set: 6 HC + 6 PD	Draw spiral between the lines of the template and avoiding to cross them, Wrote sentence *El abecedario es a,b,c,. . . ,z*	Wacom Clintiq 13 HD tablet with visual feedback,Captures six signals—horizontal & vertical position, azimuth & altitude angle, distance to the tablet surface & pressure of the pen (180 Hz)
Bernardo et al. (2019)	10 PD + 10 HC	Three different drawing patterns i.e. triangle, cube and Archimedean spiral	Desktop software: loads the image and collect the drawings. Computer monitor was attached to the notebook responsible for taking data, Mindwave EEG with two channels

Local Field Potential (LFP) images, UPDRS scale, HY scale, Mini-Mental State Examination, sleep scores from Epworth Sleepiness Scale (ESS), olfactory scores from the University of Pennsylvania Smell Identification Test (UPSIT) and many more. Different types of images like MRI, f-MRI, SPECT can serve as biomarkers to find cognitive impairments in Parkinson patients. Clinical measures combined with different scales can serve as a method to predict UPDRS scores, remote monitoring of PD patients, and finding the severity of the motor and non-motor symptoms. It contains multivariate and multimodal data that can help to slow down the progression. Parkinson's Progression Markers Initiative (PPMI) database serves as a standard database which contains multivariate data which can be used to find the relationship among symptoms for robust classification of Parkinson's disease.

The details of the datasets and collected multivariate data are discussed in Table 11. It can be observed from the table that PPMI is the main database that contains clinical data which includes data from PD with and without Mild Cognitive Impairment (MCI), HC, SCANs without Evidence of Dopamine Deficit (SWEDD) subjects. It contains MRI, f-MRI, SPECT, Fluid Attenuation Inversion Recovery (FLAIR) images in Digital Imaging and COmmunications in Medicine (DICOM) format. It contains multivariate data that can help the researchers in a wide range of symptoms. It can also serve as a measure to find relationship of the symptoms with various types of clinical scores.

The details of the methodology followed by the researchers is discussed in Table 12. It can be observed from the table that clinical measures have a lot of potential in the diagnosis of Parkinson's disease. Different types of brain images can provide important cognitive biomarkers. It can also be observed that pre-processing of the clinical data is a very important process that includes resampling, reorientation, filtering, binarization, data correction, and others. The clinical measures can be combined with UPDRS, sleep, olfactory scores, and help to estimate the severity of the disease. The UPDRS can be combined with the HY scale to combine the scoring and staging process.

5. Rehabilitation of Parkinson patients

Till now, there is no cure for this disease to the best of our knowledge. Medicines can only help to slow down the progression. There is another non-invasive way to help Parkinson patients by providing them rehabilitation facilities to perform the daily routine tasks efficiently like walking, cooking, taking groceries, cleaning, shopping, etc. The rehabilitation tasks include physical therapy that can help improve coordination, stooped posture, balance, and strength. The same daily exercise routine becomes boring for the patients and they are least motivated to perform these exercises. So, researchers are using computer-assisted technologies to help Parkinson's patients in different ways.

The authors in Pachoulakis et al. (2018) proposed Kinect sensor based 3-D games (The Balloon Goon, The slope Creep Game) to improve decision making, cognitive reactions, postural stability, reflexes, and mobility of PD patients.

There can be another form of rehabilitation to help Parkinson's patients by providing some external aid to perform daily tasks. Authors in Punin et al. (2019) provide external stimuli to decrease the FoG time with the help of wearable and non-wearable external stimuli devices. The devices used for this purpose include the Arduino Pro Mini Module with an Accelerometer, ATmega328 microcontroller, Bluetooth Module, Radio Frequency emitter, On–off switch, LED Indicator, and Vibratory Module. The authors collected real-time data of walking, turning, and climbing steps through a mobile app. The important features are extracted with Discrete Wavelet Transform (DWT) in real-time. The signals are analyzed and checked for freezing. If there is any freezing, vibration stimuli is given to the left leg sufficient enough to help the patients walk again.

Therefore, wearable and non-wearable devices can help the PD patients to perform the daily activities more efficiently in an interesting and non-invasive way.

Table 8
Classification, Prediction, and Monitoring of PD using Handwriting features.

Study	Proposed work	Signal Processing	Classification	Features
de Souza et al. (2018)	Measures the similarity between Exam Template (ET) & Handwriting Trace (HT) with SCM	(Pre-P) Median filter (5×5), Erosion (9×9 ellipse structure), Otsu threshold, (FE) Structural Co-occurrence Matrix (SCM)-3 divisions: Handwriting Exam (HE) & HT, HE & ET, HT & ET	RSVM, OPF (Euclidian Distance), NB	correlation, Inverse Difference Moment, ENT, CS distance, CS distance ratio, Mean absolute difference ratio, Divergence of Kullback Leibler, Complimentary absolute difference
Afonso et al. (2019)	Application of Recurrence plots to map signal into images	(Pre-P) Recurrence Plots, Normalization, (FE) 6 channel data	3 architectures of CNN: CIFAR10_quick, ImageNet, LeNet, OPF	Images(64×64, 128×128)
Kotsavasiloglou et al. (2017)	Potential of simple and objective metric of drawing horizontal lines	(FE) Pen's Horizontal velocity, (FS) Correlation, Consistency, J48, Wrapper, Variation, clustering, GR, IG, One-R, Relief, SVM, Symmetrical, Uncertainty, (PP) Jarque–Berra, Liliefors, Levene, Brown Forsythe, t-test, MWW, Pearson product-moment correlation coefficient	NB, AdaBoost, LR, SVM, RF, J48	Mean, Normalized Velocity Variability, SD, ENT_X, ENT_Y, mean over lowest & highest scoring hand & movement Direction
Passos et al. (2018)	ResNet-50 to learn patterns	(FE) ResNet-50, (FS) 100 dimensional –PCA	RSVM, OPF, NB, ResNet50	weights of ResNet50 as features
Naseer et al. (2019)	Early detection of PD with transfer learning	(Pre-P) Signals to images, Removal of in-air movements, Median filter, Gray scale transformation, Data Augmentation, (FE) AlexNet on MNIST & ImageNet with freeze & fine tuning	SVM on PaHaW dataset	weights of AlexNet as features
Pereira et al. (2017)	RBM for unsupervised feature learning	(Pre-P) Otsu threshold, (FE) RBM, (PP) Mean Square Error (MSE) during learning process	OPF, NB, RSVM	weights of RBM as features
Moetesum et al. (2019)	Visual attributes to extract discriminating features	(Pre-P) Early fusion Technique: Raw data, median filter residual data, Edge Data, (FE) CNN (AlexNet), (FS) Late fusion Technique, (PP) Friedman, post-hoc Nemenyi test	SVM	weights of CNN as features
Impedovo et al. (2018)	Early detection of PD with dynamic features	(FE) EMD, (FS) Filter Method	KNN, LSVM, RSVM, NB, LDA, RF, AdaBoost, Ensemble	M, median, SD, 1st, 99th, 99th-1st percentile of Stroke no., size, duration, speed, height, width, Displacement, Velocity, Acceleration, NCA, NCV, On surface, In-air & total time, Pressure, NCP, Shannon & Renyi ENT, Signal:Noise
Ali et al. (2019)	Alleviate the class imbalance problem	(Pre-P) Filled form was segmented into 8 parts, Automated method to separate HT from ET, (FE) Statistical features by comparing ET and HT, (FS) CS, (PP) Undersampling, Oversampling	LDA, KNN, Gaussian NB, DT, AdaBoost, LSVM, RSVM	RMS, Max, Min, SD of difference between ET and HT, Min, Max, SD of ET, Number of times the difference between HT and ET, radius changes from negative to positive and vice versa, Mean Relative Tremor
Pereira et al. (2018)	Features from hand-written dynamics	(Pre-P) Rescaling, Normalization, Images of 64×64 and 128×128, (FE) Time series data in the form of images, Gray Level Co-occurrence Matrices (GLCM), Local Binary Patterns (LBP), (PP) Wilcoxon signed rank test with significance of 0.05	OPF, RSVM, NB, CNN (ImageNet & Cifar-10)	Energy, ENT, Contrast, Homogeneity, correlation for (θ as 0°, 45°, 90°, 135°), Recaps local structure by comparing each pixel with its neighbors
Rios-Urrego et al. (2019)	Kinematic, geometric and Non-Linear Dynamics (NLD) features to discriminate between PD and HC	(FE) x, y, z coordinates, FFT, Trajectories of the spiral, (FS) PCA, (PP) Kruskal–Wallis test	KNN, RSVM, RF	Speed, Acceleration, Pressure, 1st, 2nd derivative, Distance from tablet surface, 1st derivative of z(t) with six functions i.e. mean, SD, Max, Min, skewness & kurtosis, MSE, Coefficients of 3rd order polynomial, amplitude of 1st five spectral components, slope, ApEn, SampEn, ApEn & SampEn with Gaussian kernel, CD, Hex, LLE, LZC
Bernardo et al. (2019)	Develop software to select drawing patterns and collect data	(Pre-P) Grayscale conversion, Skeletonization process, (FE) Extraction from images, (PP) Mindwave EEG is used to detect attention, meditation and eye blink	OPF, SVM, NB	Euclidean, relative, circular, Manhattan distance, Mouse pointer speed, Similarity between pixels, design speed & time

ApEN—Approximate ENtropy CD—Correlation Dimension Hex—Hurst Exponent LLE—Largest Lyapunav Exponent LZC—Lempel–Ziv Complexity NCA—Number of Changes of Acceleration NCP—mean Number of local extrema of Pressure NCV—Number of Changes of Velocity SampEN—Sample ENtropy

6. Software, Tools, and Libraries used in Parkinson's disease diagnosis research

Machine learning and deep learning-based diagnosis of Parkinson's disease involves Pre-Processing, Feature Extraction, Feature Selection, Post-Processing, and Classification with or without cross-validation. Each step involves the processing of data which can be done through some programming or automated software, tools, and libraries. The software like MATLAB, Python, Weka can provide a platform for feature extraction and classification purpose. Some libraries and toolboxes can be integrated with these softwares to increase the functionality of these softwares.

Table 9
EEG-based datasets for Classification, Prediction, and Monitoring of PD.

Reference	Description	Device used	Sampling Rate
Oh et al. (2018)	20 PD + 20 HC	Emotive EPOC neuro headset of 14 channels	128 Hz
Betrouni et al. (2019)	118 PD (Dujardin et al., 2015)	Waveguard, ANT software BV (Enschede, Netherlands), high resolution, 128 channels, resting state protocol	512 Hz
Ruffini et al. (2019b)	114 RBD + 83 HC, Out of 114 RBD within 10 years 19 developed PD and 12 Lewy Body Dementia (DLB) (Brazète et al., 2016)	Full EEG montage for Resting state EEG. Collected data within 30 min of waking up using 14 scalp electrodes	256 Hz
Ruffini et al. (2019a)	121 RBD + 91 HC, Out of 121 after 10 years 14 developed PD and 13 developed DLB	Resting state EEG collected from awake subjects using 14 scalp electrodes, Contains period of eyes open followed by eyes closed digitized with 16 bit resolution	256 Hz
Yuvaraj et al. (2018)	20 PD + 20 HC	Emotiv EPOC neuroheadset, Wireless, 2.4 GHz band, 14-channels, eyes-closed state EEG for 5 min	128 Hz

Table 10
Classification, Prediction, and Monitoring of PD using EEG signals.

Study	Proposed work	Signal Processing	Classification	Features
Oh et al. (2018)	Deep learning based early diagnosis	(Pre-P) Segmentation (2 s window), 6th order BPF, BF (1-49 Hz)	CNN	weights of CNN as features
Betrouni et al. (2019)	Differentiate between severity of cognitive impairments in PD patients	Brain Analyzer software, Gratton & Coles method, 50-Hz filter — remove residual noise, segmentation (4 s), (FE) FFT (2 s, 50% overlap), (FS) CFS (Pearson correlation), (PP) ANOVA	RSVM, KNN	Absolute power, Relative power, Peak frequency
Ruffini et al. (2019b)	RBD analysis for prediction of PD	BPF (0.3-100 Hz), line-noise notch filter (60 Hz), Sliding window (1 s), HW (50% overlap), Data Flattening, Binarization, (FE) FFT (1-50 Hz), (FS) Lempel–Ziv–Welch Complexity, ENT Rate, (PP) Kruskal–Wallis test, Wilkoxon ranksum statistic test, Mutual Algorithmic Information	RF	Average PSD
Ruffini et al. (2019a)	Deep learning to find clinically relevant biomarkers	(Pre-P) BPF (0.3-100 Hz), Notch filter (60 Hz), HW (1 s), (FE) FFT (4-44 Hz)	CNN, RNN with stacked LSTM, GRU, SVM	Images of spectrograms
Yuvaraj et al. (2018)	Higher Order Spectra (HOS) for automatic diagnosis of PD	(Pre-P) Discarding amplitudes more than 80 μV, Forward and reverse 6th order BF, BPF (1-49 Hz), Segmentation (2 s, HW with 50% overlap), (FE) HOS, (FS) Student's t-test	DT, KNN, NB, Fuzzy-KNN, PNN, SVM (RBF, Poly)	Mean, bispectral & Phase ENT, Bispectral Moments, Sum of logarithmic amplitude, 1st & 2nd order spectral moment, Weighted center, Absolute weighted center

Table 11
Clinical data based datasets for Classification, Prediction, and Monitoring of PD.

Reference	Description	Type of Clinical data
Gao et al. (2018)	Michigan Data: 148 PD + 77 HC, 207 variables	Demographics, PET, Behavioral and sensory assessments, Mattis Dementia Rating scale, Sleep questionnaire, Genetics, Number of falls, Clinical measures, MRI
Gao et al. (2018)	Tel-aviv data: 110 PD	Demographic, Clinical, Gait, Balance, Imaging data
Peng et al. (2017), Sivaranjini and Sujatha (2019), Oliveira et al. (2018), Lei et al. (2018), Prashanth and Roy (2018), Lei et al. (2017)	PPMI database: (0000c; Marek et al., 2011) (Peng et al., 2017): 69 PD + 103 HC (Sivaranjini and Sujatha, 2019): 82 HC + 100 PD (Oliveira et al., 2018): 209 HC + 443 PD (Lei et al., 2018): 238 baseline subjects (62 HC, 142 PD, 34 SWEDD), 186 subjects (12 months) (54 HC, 123 PD, 9 SWEDD), 127 subjects (24 months) (7 HC, 88 PD, 22 SWEDD) (Lei et al., 2017): 208 subjects (56 HC + 123 PD + 29 SWEDD) (Prashanth and Roy, 2018): 197 HC + 434 PD (1025 + 3020 observations)	(Peng et al., 2017; Sivaranjini and Sujatha, 2019; Lei et al., 2018, 2017): T1 weighted brain MRI images are acquired by a 3T SIMENS MEDICAL SYSTEM with 2300 ms repetition time, 2.98 ms echo time, 9° flip angle, 1 mm slice thickness, 256 mm field of view and 240×256 matrix size (Oliveira et al., 2018): SPECT scan images lasted for 30 to 45 min, saved in DICOM format using $91 \times 109 \times 91$ cubic voxels with 2mm wide (Prashanth and Roy, 2018): MDS-UPDRS scores from 59 activities from different parts of MDS-UPDRS scale (Lei et al., 2017): Sleep scores from ESS, olfactory scores from UPSIT
Yao et al. (2018)	12 PD	16 LFPs (1.5-10 min) from 7 channels (4 Monopolar & 3 bipolar) (2048 Hz)
Abós et al. (2017)	Training: 38 HC + 70 PD (27 PD-MCI and 43 PD-Non-MCI) Validation: 25 PD (8 PD-MCI and 17 PD-Non-MCI)	Three-dimensional structural T1-weighted images, functional resting state images (Training: 10 min duration, 300 volumes, Validation: 6 min, 180 volumes) and FLAIR images were acquired from 3T Siemens MRI Scanner

Pre-processing of the data is a very important step as it directly influences the performance of the system. It involves the processing of brain images, filtering signals, noise removal, motion analysis. Motion data analysis includes gait events, FoG, bradykinesia, activity segmentation, balance analysis, and others. Some of the related softwares and tools to measure and pre-process the motion-related data include ELAN Annotation software (Tahavori et al., 2017), OpenSim (McKay et al.,

Table 12
Classification, Prediction, and Monitoring of PD using Clinical data.

Study	Proposed work	Signal Processing	Classification	Features
Gao et al. (2018)	Investigate falls using clinical, demographics and neuroimaging data	(Pre-P) Data Aggregation, q-values (Benjamin/Hochberg False Discovery Rate adjusted p-value), Normalization, Harmonization, MultiDimensional Scaling, t-SNE, (FS) RF, Least Absolute Shrinkage and Selection Operator (LASSO), KnockOff, (PP) t-test, MWW, KS	LR, RF, RSVM, NN, Ada & Gradient Boost, super learner	Clinical data features
Peng et al. (2017)	Multi-level ROI features to detect sensitive biomarkers	(Pre-P) Resampling, reorientation, intensity correction, brain label & extraction (scalp, skull & dura), tissue segmentation (Gray Matter (GM), White Matter (WM), CSF), cortical surface reconstruction, (FE) ROI features (BrainLab software), (FS) t-test, mRMR, RFE	Multi-kernel SVM	GM, WM, CerebroSpinal Fluid (CSF), cortical thickness & surface area (78 each), 78×78 correlative matrix on cortical thickness values
Sivaranjini and Sujatha (2019)	Deep learning based classification of MR images	(Pre-P) Normalization, 2D Gaussian filter (size 5×5 & SD 0.8)	CNN AlexNet	weights of AlexNet as features
Oliveira et al. (2018)	Potential of [^{123}I] FP-CIT SPECT brain images	(Pre-P) Registration Algorithm (Powell's and Brunt's Method), Resampling (2.2 mm), Gaussian filter (16 mm), Binarization (threshold level 25%), Morphological erosion, (FE) 7 ROI's, (PP) t-test, Cochran's Q test, Post hoc Dunn's Test with Boniferroni correction	SVM, KNN, LR	Specific Binding Ratio, Caudate, Putamen & Striatal Binding Potential, Putamen-to-Caudate Ratio, Volume, Length
Yao et al. (2018)	LFP based biomarkers to detect tremor	(Pre-P) Notch filter (50 Hz), 2nd order BF BPF (2 Hz), Segmentation (2s), 2nd order Kalman filtering, (FE) FFT (1-10 Hz), Hilbert transform, Hjorth, Threshold, (PP) Biserial correlation coefficient, ANOVA, Post hoc	LDA, KNN, LR, LSVM, RSVM, MLP, RF, eXtreme Gradient (XG)	phase–amplitude coupling, high frequency oscillations ratio & Power, Tremor, Power (M, Max, Gamma, Beta), Wavelet, ENT, Hjorth (Activity, mobility, complexity)
Lei et al. (2018)	Un-supervised FS based on joint embedding & sparse regression	(Pre-P) Anterior Commissure-Posterior Commissure reorientation (ACPC), FSL toolbox, (FE) Voxel-Based Morphometry toolbox- GM features, (FS) joint embedding learning & sparse regression	SVR, SVM	116 dimensional features
Prashanth and Roy (2018)	Staging of PD with MDS-UPDRS and HY scale	(FS) Filter method, (PP) Kruskal–Wallis, Wilcoxon rank sum tests, Spearman's rank correlation coefficient, GA, boxplots	NN, Ordinal LR (OLR), SVM, PGM, KNN, RF, AdaBoost, DNN, RUSBoost, NB	UPDRS scores of 59 features from different sections of MDS-UPDRS scale
Abós et al. (2017)	Connection-wise patterns of functional connectivity to find cognitive status (with/without MCI)	(Pre-P) Anatomical component-based noise correction, stabilization, De-spiking, motion-correction, grand-mean scaling, detrending, BPF (0.01-0.1 Hz), (FE) principal components from CSF and WM time series & 6 motion parameters from motion correction step to find 246 nodes & 30135 edges, (FS) Randomized LR, (PP) z-score, regularization, Network based statics, Monte Carlo, F-thresholds	LSVM	21 edges connected with 34 nodes were used as features
Lei et al. (2017)	Multi-modal neuroimaging data to classify and predict PD	(Pre-P) ACPC correction using COM algorithm, Resampling, Normalization, Segmentation, (FE) 116 ROIs, (FS) Novel Objective function ($l_{2,1}$-norm using LASSO), (PP) Pearson Correlation Coefficient	SVM, SVR	GM ,CSF, Fractional Anisotropy

2019), Mobility Lab systems (Ramdhani et al., 2018), IGS bio and motion capture software (Delrobaei et al., 2018; Nguyen et al., 2017), Motion Studio (di Biase et al., 2018), Motive Tracker (Dang et al., 2019), Tech MCS software (Caramia et al., 2018), Faceshift (Bandini et al., 2017), LMC-SDK (Butt et al., 2018). Processing brain images include template matching, find ROI's de-noising, filtering surface reconstruction rendering, and others. Some of the tools to process brain images include MRICon software (Peng et al., 2017), BrainLab software (Peng et al., 2017), Insight toolkit (Oliveira et al., 2018), CImg library (Oliveira et al., 2018), Visualization toolkit (Oliveira et al., 2018), VBM (Voxel-Based Morphometry) toolkit (Lei et al., 2018), AAL atlas (Lei et al., 2018), FSL toolbox (Lei et al., 2018; Abós et al., 2017), brainnetome atlas (Abós et al., 2017), SPM, FLIRT, brainnet viewer (Lei et al., 2017), brain analyzer software (Betrouni et al., 2019).

Feature extraction is also very important to extract discriminative features for robust classification. There are various feature extraction techniques and different toolboxes that are available to decrease the manual process of extraction. Some of them are openSmile (Braga et al., 2019), Voice analysis toolbox (Sakar et al., 2019), Praat (Braga et al., 2019; Sakar et al., 2019; Almeida et al., 2019; Haq et al., 2019), OpenPose (Li et al., 2018), OpenCV (Khan et al., 2014; Almeida et al., 2019), OPENNI (Bandini et al., 2017), OpenFace, Librosa (Joshi et al., 2018).

Post Processing includes statistical analysis of data and features to understand the statistical significance of features. Some of the post-processing tools include SPSS software (Delrobaei et al., 2018), t-SNE (Almeida et al., 2019), Circos (Peng et al., 2017), TEEM tools (Lei et al., 2017).

Classification involves the implementation of different algorithms of the machine and deep learning and analyzing the results and features through some visualization tools. Some of the related tools include Statistics and Machine Learning Toolbox (Camps et al., 2018; Prashanth and Roy, 2018; Caramia et al., 2018), classification Learner toolbox (Tuncer et al., 2019; Tuncer and Dogan, 2019; Betrouni et al., 2019), Alyuda NeuroIntelligence (Parisi et al., 2018), Caffe library

Table 13
Comparative Analysis.

Feature	Voice	Wearable	Non-Wearable	Handwriting	EEG	Clinical
Description	Voice becomes slurry, blurry and monotonous	tremor, FoG, bradykinesia, motor impairments can be captured	motor impairments and facial expressions can be captured	Handwriting becomes smaller, crooked due to tremor	cognitive impairments can be captured	Images from MRI, PET, DATSCAN, f-MRI can capture cognitive impairment, automating UPDRS scores from Part I, II, IV
Type of Data	Signals, Images (from signal)	Signals, Images (from signal)	Images, Video Recordings	Images, Signals	Signals, Images (from signal)	Images, Clinical Scores
Sensor Type	Microphone (Headmounted/ smartphone)	Force, Accelerometer, Gyroscope, Magnetometer, Geomagnetic, Telemeter, Goniometer	Laser, Camera, Video Recorder, Infrared Cameras, Microsoft Kinect, LMC, Force Plates	Tilt, Acceleration, Refill, Grip, Pressure	✗	✗
No. of Studies	Signal - 21 Images - 0	Motor Fluctuations - 2 Tremor - 7 FoG - 7 Bradykinesia - 3 Gait - 1 Rigidity - 1 Activity Recognition - 2 Activity Segmentation - 1	Facial Expressions - 2 Motor Fluctuations - 2 Activity Segmentation - 2 Gait - 1	Signal - 3 Images - 6 Signal to Image - 3	Signal - 2 Images - 3	MRI - 3 f-MRI - 1 FP-CIT-SPECT - 1 Clinical Scores - 3 UPDRS Scores - 1
Prediction	UPDRS- (Nilashi et al., 2018; Yoon and Li, 2018)	✗	✗	✗	✗	Fall - (Gao et al., 2018) Depression, Sleep, Olfactory Scores - (Lei et al., 2018) Sleep, Olfactory Scores - (Lei et al., 2017)
Monitoring	(Zhang, 2017; Yoon and Li, 2018)	(Camps et al., 2018; Samà et al., 2018)	✗	✗	✗	✗
Stage Estimation	(Oung et al., 2018b)	(Kim et al., 2018)	✗	(Rios-Urrego et al., 2019)	(Betrouni et al., 2019)	(Prashanth and Roy, 2018)
Public Dataset	19	6	1	8	✗	6
Private Dataset	3	20	5	3	3	3
Other Datasets	3	2	2	3	2	✗

(Afonso et al., 2019; Naseer et al., 2019; Pereira et al., 2018), LIBSVM, LIBOPF (Pereira et al., 2018), LIBLinear (Abós et al., 2017).

7. Comparative Analysis

Parkinson's Disease is a combination of multiple symptoms that can be broadly divided into motor and non-motor symptoms. These symptoms vary from patient to patient. Based on the symptom, type of data, and source of data, we have divided our analysis into six sub-categories including voice-based analysis, wearable, and non-wearable devices-based analysis, handwriting based analysis, EEG signals-based, and Clinical data-based analysis. All the work collected is from recent years basically from 2017, 2018, and some work of 2019. Apart from these six sub-categories, some review articles are also included to collaborate the research work done before 2017. Some of the work done for the rehabilitation of Parkinson patients is also included in the survey. As there is no cure for this disease, rehabilitation is very important to improve the quality of life of Parkinson patients.

The voice-based analysis provides the measure for early diagnosis as most of the Parkinson patients have a voice disorder. Wearable and non-wearable devices can measure motor symptoms like tremor, FoG, bradykinesia, dyskinesia, and body movements. Handwriting provides the diagnosis process as well as the measure of tremors in patients. EEG signal data provides cognitive biomarkers to check the progression of the disease. Clinical measures provide clinical data, sleep scores, olfactory scores, brain images from MRI, f-MRI, PET, etc.

The comparative analysis of the work done in each of the sub-categories is provided in Table 13. It contains a description of each sub-category, type of data used, type of sensors, number of studies based on public datasets, private datasets or datasets taken from other studies. The number of studies shows the sub-division under each category. It can be observed that in the voice-based sub-category, no work has been found using images to the best of our knowledge. Signal-based images can provide rich information for the diagnosis process and can also reduce the time of the feature extraction as the feature extraction process will become automatic. From the wearable category, less work has been done to access gait. Gait is also one of the major symptoms in Parkinson patients which needs more attention. The activity segmentation process is very important to measure gait, FoG, turning and this process should be automatic to reduce the manual work and very little work has been done in this field. Prediction of UPDRS scores, falls, clinical scores can help to quantify severity in Parkinson patients. Only work in this area has been done using voice signals and clinical data. There is a lot of potential in this area as prediction can be done using wearable and non-wearable devices as well as from EEG signals. Wearable devices with the help of accelerometer, gyroscope can predict falls and helps to stop them. Remote monitoring of patients is a very trivial task as symptoms vary with the time of the day. 15–20 min

Table 14
Comparison of Feature Extraction methods.

Method	Description/ Pros	Challenges/ Cons	Voice	Wearable	Non-Wearable	Handwriting	EEG	Clinical
Spectral Analysis	• Transform a time-series data into its coordinates in the space of frequencies, and then analyze its characteristics in this space. • Capture local temporal effects • Discover periodicities in the data	• Correlated features • Good only for stationary signals • Concept of windowing is needed	✗	✓	✗	✓	✗	✗
EMD	• Works in temporal rather than frequency space • Can decompose any complex dataset into finite and complete small number of components • Good for natural signals (Non-Linear & Non-Stationary) • Can separate stationary and non-stationary components from a signal • Self-adapting according to the input signal i.e. basic functions are derived from the signal itself • Highly efficient	• Difficult to interpret and understand the output • Lack of mathematical theory i.e. mathematically difficult to model • Less robust • Sensitive to noise • Give error points at the end of the signals which gives a wrong interpretation of the signal	✓	✗	✗	✓	✗	✗
FFT	• Process stationary signals i.e. combination of sine and cosine signals • Localized in the frequency domain • Can convert discrete data into continuous data at various frequencies • Efficient matrix–vector multiplication • Achieves high-frequency resolution	• Discontinuous signals cannot be represented properly • The problem of power leakage • Large bias or variance in estimates • Unable to process non-stationary signals • Has zero temporal resolution	✗	✓	✗	✓	✓	✓
WT	• Provides multiple levels of details and approximations in time–frequency domain so that transient features of the data series can be retained. • Uses functions that are localized in real and Fourier space • No redundant information • Fast computation • Non-stationary dynamic signals • De-noise a signal without appreciable degradation.	• The issue with the self-adaptability of wavelet transform due to the presence of wavelet function • Leakage problem • Low-frequency components are smeared • Computationally intensive for fine analysis	✓	✗	✗	✗	✗	✗
DWT	• Time and frequency analysis • Flexibility • Easier to filter in and filter out non-stationary waveform • More levels of decomposition provide more detailed depictions • Common mother wavelets: Haar, Daubechies, biorthogonal, coiflets, symlets, discrete Meyer • resolution of time and frequency can be adapted to the frequency content of the examined patterns, leading to an optimal time–frequency resolution across all frequency ranges (Chen et al., 2017) • Can be used to denoise the real signal	• Greater complexity • More difficult to understand • Difficult to choose appropriate wavelet • Very sensitive to the alignment of the signal in time • More levels of decomposition can lead to feature redundancy leading to accuracy reduction and computational cost increasing (Chen et al., 2017) • Optimization of mother wavelet is very difficult	✗	✗	✗	✗	✗	✗
EWT	• Combination of EMD and wavelet theory • First extracts frequency components and then extract oscillatory components from boundaries • Works in frequency space • More consistent decomposition than EMD • Adaptable wavelet filters to extract components • Strong mathematical background • Simple and fast • Good for non-linear and non-stationary signal	• Cannot separate two signals if they overlap in time and frequency domains • Difficult to find boundary for Fourier segments in a noisy environment • Slow computation • Decomposition into too many invalid components • Parameter setting is difficult • Decomposition is done only on approximate coefficients	✓	✗	✗	✗	✗	✗

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of the clinical visit is not sufficient to measure symptoms accurately. Moreover, the effect of the medicines can be monitored remotely as effect depends on the time of the day. Only work in monitoring has been done using voice signals and wearable devices. Non-wearable devices can also provide a non-invasive way of monitoring which is yet to be explored. Symptoms of Parkinson's disease worsen with time.

Table 14 (*continued*).

Method	Description/ Pros	Challenges/ Cons	Voice	Wearable	Non-Wearable	Handwriting	EEG	Clinical
EWPT	• Extension of EWT • Decomposition is done on both detailed and approximate coefficients giving rich signal analysis • Reduces computational overhead in terms of reducing the number of wavelet decomposition levels	• Lacks improved directionality • Sensitive to location • Involves complex data structures	✓	✗	✗	✗	✗	✗
LPC	• Efficient computational model of speech • Provides an accurate estimate of speech parameters known as cepstral coefficients • Spectral coefficients are represented with low dimensional feature vectors • Good source-to-vocal tract separation • Simple to implement • Mathematically precise	• Features vectors are highly correlated • Does not link speech information with former speech in time	✓	✗	✗	✗	✗	✗
PLP	• Combination of spectral and linear prediction analysis • Effectively compress high frequencies into a narrow band • Reconstructs the autoregressive noise component accurately (Thomas et al., 2008) • More consistent with human hearing • Low dimensional representation of a signal	• Sensitive to any change in the formant frequency. • Feature vectors are dependent on spectral balance of formant amplitudes. • The formant amplitudes are easily affected by factors such as the recording equipment, communication channel and additive noise (Hermansky, 1990) • Sensitive to noise and variations in the channels	✓	✗	✗	✗	✗	✗
MFCC	• Robust due to its accurate estimate of the speech parameters and efficient computational model of speech • Discrete Fourier Transform (DFT) is used to calculate the magnitude of spectra. • Approximates the human system response more accurately • Gives good discrimination • Less correlation between cepstral coefficients	• Phase information is not present. Both phase and magnitude are complementary to each other and one of two should not be ignored. • The performance is not superior in noisy environments • Selecting the filter shape at every step with the changing environment is very difficult. • Does not work well in continuous speech environments • Not flexible	✓	✓	✓	✗	✗	✗
DFA	• Random and non-stationary time-series data • Can detect the long-range correlations embedded in data • Avoid the spurious detection of the apparent long-range correlations which are an artifact of non-stationary data (Wang et al., 2016) • Simple and utilizes fewer parameters	• Discontinuities between trends of two neighboring data segments • Practically difficult to find the type of fitting polynomial • Difficult to determine appropriate data size for DFA. Small data size lead to poor results and large data size increases the time cost (Lin and Chen, 2014)	✓	✗	✗	✗	✗	✗
TQWT	• Fully discrete, over-complete, modestly oversampled • Three input parameters: Q (quality factor), r(redundancy), J (Number of levels) • Formulas for calculating sub-bands provide deep information • Higher frequency resolution than DWT • Can be implemented efficiently with FFTs • Faster implementation using radix-2 FFTs • Q-factor and redundancy can be easily tuned. • Easily invertible	• It is very difficult to find the appropriate value of J. Higher value of J may result in difficult analysis and poor computational efficiency	✓	✗	✗	✗	✗	✗

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Stage estimation is an important aspect to measure the progression of the disease. Less work has been done to estimate the stage in each category. No work has been found to estimate stage using non-wearable devices as per the best of our knowledge. Non-wearable devices can serve as an important biomarker to estimate the stage in a non-invasive way.

Table 14 (*continued*).

Method	Description/ Pros	Challenges/ Cons	Voice	Wearable	Non-Wearable	Handwriting	EEG	Clinical
RPDE	• Determine the periodicity or repetitiveness of a signal. • Does not require the assumptions of linearity, Gaussian or dynamical determinism • Can detect subtle changes in the time-series, non-linear, non-stationary data • Reliable	• Ineffective in longer time-series data	✓	✗	✗	✗	✗	✗
Hilbert Transform	• Takes a function X(t) and transforms into H(X(t)) in the same domain • Non-parametric spectral estimation method • Eliminate the negative frequency part and double the magnitude of positive frequency part • Time-domain analysis i.e. preserve temporal characteristics of a signal • Process non-linear, non-stationary and narrow band signals	• Unable to decompose signals with closely spaced frequency components • Unable to separate small fluctuations • Unable to track the time-varying change between two modes of vibration	✓	✗	✗	✗	✗	✓
Hjorth Parameters	• Serve as a bridge between a physical time domain interpretation and the conventional frequency domain description • Analyze signals in the time domain but also contain information about the frequency spectrum • Three parameters: activity, mobility, complexity • Low computational cost, simple processing • High accuracy parameters	• Lack of clarity if the input signal has more of a peak in the power spectrum. • Suspectable to noise • Requires signal segmentation	✗	✗	✗	✗	✗	✓
GLCM	• Extract second-order statistical texture features • Show good results for easily separable textures • Easy implementation • Less processing time and complexity • Provides spatial information from pixels	• The high dimensionality of the matrix • The high correlation between features • Consumes high amount of memory • Sensitive to the size of textures (Mohanaiah et al., 2013)	✗	✗	✗	✓	✗	✗
SCM	• Identify multiple patterns simultaneously using image as input • More useful for image synthesis • Rotation invariant • Can find structural differences between two input images easily • Ability to detect details	• Not appropriate for natural textures because of the variability of micro-texture and macro-texture • Finding the appropriate filter is difficult	✗	✗	✗	✓	✗	✗
LBP	• Combine structural and statistical methods for texture analysis • Resistant to light variations • Simplicity in computation • Low computation cost • Invariant to monotonic illumination changes (Humeau-Heurtier, 2019)	• Sensitive to image rotation • Large memory requirement • Highly sensitive to noise and blurring	✗	✗	✗	✓	✗	✗
HOS	• Analysis of non-linear vibrations where the generation and interactions of non-linear resonance modes are of major concern (Rivola, 2000) • Retain both amplitude and phase information • High noise immunity • Yields good results for weak signals also • Very limited correlation between features • Translation invariant (Chua et al., 2010)	• Choosing data length is a major problem (Rivola, 2000) • Over-parametrized	✗	✗	✗	✗	✓	✗

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The work that is considered in this analysis is based on machine learning and deep learning. Machine learning based diagnosis includes pre-processing, feature extraction, feature selection, post-processing, and classification task. The details of the methodology of each sub-category are mentioned in Tables 2, 4, 6, 8, 10, and 12. Pre-Processing is a very important process to remove noise from the dataset, remove

Table 14 (*continued*).

Method	Description/ Pros	Challenges/ Cons	Voice	Wearable	Non-Wearable	Handwriting	EEG	Clinical
SAE	• Axisymmetric single hidden layer neural network • More robust data features • Reduce the effect of overfitting in feature learning • Easily reconstruct input data with high precision • Encodes the input sensor data and approximates the minimum error features • Sparsity constraint improves the generalizability of features • Minimum loss of data when converting original data to its decoded form	• Does not consider the relationship of data samples • Computational complexity is higher than PCA • Longer time to train • Not sensitive to slight variations	✓	✗	✗	✗	✗	✗
PCA	• An unsupervised method which converts original data into principal directions by maximizing the variance • Transforms data linearly into new properties that are not correlated with each other • Reduce storage space needed to store data as dimensionality is reduced • Speeds up the learning process • Address the multicollinearity issue	• Projects data in linear fashion only • Skips less significant components which may be useful in some applications • Hard to maintain the relationship among data samples • Less efficient than SVD	✗	✓	✗	✗	✗	✗
SVD	• Time-frequency analysis • Efficient (can be applied to a big matrix of feature set) • Hierarchical based on the relevance of features • Works well with images (provides optimal representation with few coefficients) • More robust to numerical errors • Singular Values (SVs) are highly stable, rotation and ratio invariant (Zhang and Wang, 2016)	• Non-linear data does not work well • Strongly based on variance and can discard other useful information • Difficult to interpret • Difficult to choose reconstruction parameters • Computationally expensive • The appropriate number of SV are difficult to find (Gan et al., 2015)	✓	✗	✗	✗	✗	✗
RBM	• The strong power of representation • Consist of a visible and hidden layer without connecting units within the same layer • Extract discriminating features from complex dataset • Extracted features from one RBM can be used as input to train another RBM to capture higher-order abstract features (could be repeated multiple times to build a deeper network) (Cai et al., 2012) • Ability to reconstruct images • Global gradient-based optimization	• Complex computation • Less efficient for full size natural images • The spatial relationship between different image patches are not considered (input image is treated as a vector) (Gao et al., 2016) • Tricky to train well, as algorithm Contrastive Divergence requires sampling from a Monte Carlo Markov Chain, which requires care to get things right	✗	✗	✗	✓	✗	✗
CNN	• Automatic feature extraction • Does not require any expert background knowledge of features • Handcrafted features are limited by human time constraint and imagination but CNN is not • No human Biasing • Optimally tuned features	• Time Consuming • Requires a lot of training data • High Cost • Weight initialization is difficult	✗	✓	✗	✓	✗	✗
Pre-Trained Models	• Fast training • Require lower training data • No need for labeling data to increase the size of the dataset • Avoids overfitting • Adaptable to the existing pipeline • Useful in imbalanced data distribution • Examples: ResNet-50, AlexNet, VGGNet, MobileNet, GoogleNet	• Reduces flexibility for the new dataset • The problem of negative transfer • Cannot remove layers with confidence to reduce the number of parameters.	✗	✗	✗	✓	✗	✗

unwanted signals, peaks, and frequency for robust diagnosis. Some of the important frequency ranges for this process are mentioned below.

- Rest tremor frequency ranges from 4–6 Hz (Abdulhay et al., 2018; Kim et al., 2018).
- The ratio of Stance time: Swing time is 3:2 for a healthy person, which is not the same for Parkinson patients (Abdulhay et al., 2018).
- Gait patterns have a frequency lower than 20 Hz (Camps et al., 2018).

Table 15
Comparison of Classification techniques.

Classifier	Description/Pros	Challenges/Cons	Applications
Traditional Machine Learning Techniques			
SVM	• Non-Parametric, Linear and Non-Linear • Effective in high dimensional data • Capable of evading local minima (Lahmiri et al., 2018) • High generalizability (Khan et al., 2014) • computationally efficient (Parisi et al., 2018), fast • Less prone to class imbalance problem (Prashanth and Roy, 2018)	• Performance reduction if data is not scaled • Poor performance if attributes are greater than the sample size • Difficult to estimate kernel function & penalty constant (Avci and Dogantekin, 2016)	
KNN	• Non-Parametric, Non-Linear • Data-driven learning • Fully based on memory, without model usage indicates good performance in short training time (Oung et al., 2018b) • No training period (learns at the time of predictions) • New data can be added seamlessly, easy to implement	• Does not work well with large datasets • Does not work well with high dimensions • Sensitive to noisy data, missing values, and outliers • Need feature scaling	
LR	• Parametric, Linear • Does not require too many computation resources • Highly interpretable, easy to regularize • Does not require feature scaling • easy to implement, fast	• Highly reliance on proper presentation of data • Prone to overfitting (if the number of observations are less than features) • Can only predict discrete functions	
NB	• Parametric, Linear • Requires one iteration to learn (simple) (Lahmiri et al., 2018) • Strong independent assumptions about predictors (de Souza et al., 2018) • Does not require much training data • Fast and make real-time predictions • Handles both continuous and discrete data	• Assumes all attributes are mutually dependent (almost impossible practically) • Zero frequency problem: If there is unseen testing data, it assigns a probability of zero	
DT	• J48 (C4.5): algorithm to generate DT • Non-Parametric, Non-Linear • Less effort for data pre-processing • Does not require feature scaling • Robust to outliers, missing data • Transparent, clear visualization	• Unstable-Small change in data leads to a large change in structure • Complex calculations, high training time • Prone to overfitting, high variance • Sensitive to noise, relatively inaccurate • Not suitable for larger datasets	
CART/ RT	• Non-Parametric, Non-Linear • Does not require assumptions regarding the distribution of predictors (Lahmiri et al., 2018) • Can grip skewed numerical, categorical & missing data • Fast prediction, Easy to understand which variables are important	• Overfilling • High variance, low bias • Lack of locality, discontinuity	
LDA	• Parametric, Linear • Simplicity, interpretability • Also a dimensionality reduction technique • Fast, portable • Extensions: Quadratic, Flexible and Regularized Discriminant Analysis	• Only for binary classification • Unstable when there are few examples to estimate the parameters	
OPF	• Non-Parametric • Fast, simple, real-time detection • Does not make any assumptions about the shape of the class • Can handle some degree of overlapping • Intrinsically multi-class	• Number of clusters should be known in advance which is practically not always feasible	
OLR	• Required when there are ordered multiclass variables • Ease of collation and categorization	• Strong assumptions that may lead to incorrect interpretations if assumptions are violated • Large bias	
MDC	• Based on Probability statistics • Fast as it assumes all classes have the same co-variance • Works well with highly imbalanced datasets • More accurate, simple, suitable to detect outliers (Lahmiri et al., 2018)	• Does not work well with highly correlated data • Computationally restrictive as it required inversion of the co-variance matrix	
PGM	• Describes the probability distribution of random variables • Fewer Parameters (can be estimated with less data) • Reduced computation cost • Less memory to store model • Works well with missing data • Two types: Directed, Undirected	• Lacks flexibility • Not good with large scale high dimensional data • Less accurate • Biased (make strong assumptions)	
GMM-UBM	• Parametric • Smooth approximation to arbitrarily shaped distributions • Fast (less time for recognition) • Can be scaled	• Requires large training data	

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Table 15 (*continued*).

Classifier	Description/Pros	Challenges/Cons	Applications
i-vector GPLDA	• Low-dimensional representation of speech segment • Assumes gaussian distribution of data • Use of large amount of data to attenuate the effect of adverse conditions	• Sensitive to noise, content, and number of features • Less reliable in case of short utterances	
Deep Learning Techniques			
NN/ ANN/ DNN/ MLP/ SLNN	• Can perform learning in real-time (Braga et al., 2019) • Exceptional generalizing capability (Sivaranjini and Sujatha, 2019) • feature extraction without the need of pre-processing (Kadam and Jadhav, 2019) • Data-driven • Robust to noise (Lahmiri et al., 2018)	• A large number of hyperparameters makes optimization time-consuming • Several local minima due to several hidden layers having non-convex loss function (Braga et al., 2019) • Long training time • Uncertainty in choosing activation function, number of hidden layers and number of neurons	
CNN	• Can perform complex classification task (Kim et al., 2018) • Automatically extract discriminative features • Adam optimizer has fast convergence, adaptive learning rate requires less tuning • Not constrained by engineering ability of handcrafted features (Camps et al., 2018)	• Data hungry (does not perform well with small datasets) (Camps et al., 2018) • A large number of hyperparameters • Non-deterministic • Laborious architecture, time-consuming (Sivaranjini and Sujatha, 2019)	
LeNet	• Low memory requirement • OCR and character recognition	• Sensitive to image resolution due to shallow architecture	
AlexNet	• Fast training time as it uses ReLU activation function • Allows Multi-GPU training • Overlapping pooling	• Overfitting due to a large number of parameters • Data duplication, more memory required	
VGGNet	• Small-sized kernels to learn more complex features at lower cost	• Huge computation requirement (both time and memory)	✗
GoogleNet	• Sparse CNN • New BottleNeck Layer: reduces the computational requirement and number of parameters	• Tedious parameter customization	✗
ResNet	• Solves degradation problem in optimization • Decreased error rate	• More training time • Complex architecture	
ZFNet	Deconvolution: Allows to go from output to input dimension	• Extra information processing is required for Visualization	✗
RNN	• Model Sequence of data in which each sample can be assumed to be dependent on the previous one • Potentially turing complete (Ruffini et al., 2019a)	• Difficult to train • Vanishing and exploding gradient problem	
LSTM	• Solves vanishing gradient problem (Hssayeni et al., 2018) • Efficiently handle dependencies, distributed representations • Can handle noise, continuous values	• Complex structure • Requires a lot of resources and time to get trained • Prone to Overfitting • Get affected by random weight initialization	
GRU	• Less training parameters, fast • Uses Less memory	Less accurate on longer sequences	
ELM	• Linear • A training algorithm for SLNN (Li et al., 2017a) • Fast learning capability, a single iteration • Solves the problem of over-fitting (Oung et al., 2018b) • solves the problem of trapping in local optima • Types: Online, Pruned	• No rule in the determination of the number of hidden neurons and activation function (Avci and Dogantekin, 2016) • Slow evaluation (faster in training but slow in interpolation) • Cannot go deep (cannot encode more than one layer of abstraction)	
PNN	• Non-Parametric, Non-Linear • Derived from the Bayesian model (Oung et al., 2018b) • Fast training as compared to other neural networks (MLP) • Confirmed to converge to an optimal classifier (Oung et al., 2018a) • Samples can be added or removed without re-training	• Accuracy depends on smoothening parameter/spread factor • More memory space to store model • Requires a representative training set	
GNN	• Automatically adjusts the number of neurons to reflect the complexity of data (Saad et al., 2017) • Easily generate non-linear separators • Fast learning ability • Requires fewer weights • Can build small networks • Autonomous adaptation process	✗	
HBNN	• Can detect subtle variations (Joshi et al., 2018) • Works well even with small datasets • Works well even if prior knowledge of classes is vague	• Sensitive to prior assumptions	

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Table 15 (*continued*).

Classifier	Description/Pros	Challenges/Cons	Applications
ANFIS	• Parametric, Non-Linear • Adaption capability due to NN, smoothness due to Fuzzy nature • High precision • Rapid learning capacity	• Output depends on type and parameters of membership function • Computation and spacial complexity • Sensitive to initial number of partitions • Partial loss of locality	Voice
Ensemble Methods			
RF	• Non-Parametric, Non-Linear • Extension over bagging technique • Do not need pruning to avoid overfitting (Braga et al., 2019) • Fewer hyperparameters to optimize (Braga et al., 2019) • Insensitive to outliers and noise	• Overfitting with datasets having fewer training examples • Does not perform well in regression • Likely to have elbow point-steep drop in slope with increase in number of trees	Voice, Wearable, Non-Wearble, Handwriting, EEG, Clinical
AdaBoost	• Convert weak classifiers or estimators into strong one (Ali et al., 2019) • Tackles class imbalance problem (Prashanth and Roy, 2018) • A high degree of Precision • Fully considers the weight of each classifier	• Number of iterations poorly set • Time-consuming training • Sensitive to noise and outliers	Wearable, Handwriting, Clinical
LogitBoost	• High Performance in poorly separable data (Camps et al., 2018) • Address multi-class classification problems • Smaller variance	• Overfitting problem	Wearable
RUSBoost	• Eliminate the data distribution imbalance and improve the performance of the weak classifiers • Reduced training time • Avoids biasing	• Random undersampling to reach the desired balance • Loss of information	Wearable, Clinical
RobustBoost	• Insensitive to outliers, noise • Non-convex loss function • Better average classification accuracy	• Computation overhead • Depends upon external parameters like target classification error, maximal classification margin which should be known beforehand	Wearable
Gradient-Boost	• Little training time, parameter tuning • Works well with limited data (Yao et al., 2018) • No data processing required • Handles missing data, flexible	• Less interpretative • Prone to overfitting • Computationally expensive • Tuning requires larger grid search	Clinical
XG Boost	• High computation speed and performance • Parallelization, Cache optimization • Distributed computing, Out of core computing (for very large datasets)	• Relatively slow • Lacks scalability • Sensitive to outliers	Clinical

— Voice — Wearable — Non-Wearble — Handwriting — EEG — Clinical

- Tremor frequency bands range between 3.5 Hz – 7.5 Hz (Rovini et al., 2018).
- Free Walking frequency bands ranges between 1 Hz-2 Hz (Rovini et al., 2018).
- Normal Gait has a frequency near 2 Hz (Han et al., 2003).
- Freezing of Gait has a frequency near 6–8 Hz (Han et al., 2003).
- Power in the locomotor band is between 0.5–3 Hz (Moore et al., 2008)
- The frequency of Freezing of Gait occurs in bandwidth 3–8 Hz (Punin et al., 2017; Moore et al., 2008).

Feature extraction is an extremely important process in the machine learning-based diagnosis. The choice of feature extraction method gives robust features that directly influence the classification and prediction accuracy. Some of the feature extraction techniques mentioned in the research articles are explored in Table 14. It gives the pros and cons of each feature extraction technique along with, whether its potential has been explored in a certain category or not. Different feature extraction techniques can be explored depending upon the type of requirement of the system like if the data signals are stationary or non-stationary, linear, or non-linear. They can also be explored based on which type of analysis will be useful like if the time-based analysis is required then EMD is a better option, if time–frequency based analysis is required Wavelet analysis like DWT, EWT, EWPT is a good choice.

Classification is the last and very important step in processing. After robust feature extraction, the performance of the system depends upon the choice of the classifier. Some of the classifiers that have been covered under the review are explored in detail in Table 15. The table contains the name, pros, and cons of the classifier. It also contains the applications in which a particular classifier has been explored. Applications are color-coded and explained as footnotes in the table.

It can be observed from the table that there is no single best classifier. The choice of the classifier depends upon the type of data that the researcher is working on, a tradeoff between the accuracy and time complexity of the classifier. The comparison of classification techniques is divided into three sub-categories which include traditional machine learning techniques, deep learning techniques, and Ensemble methods. The choice of the classifier can first be done by checking if the data is linearly separable or not. If data is linearly separable then algorithms like SVM, LR, and NB are better choices. Most of the practical datasets are non-linear then SVM, KNN, all deep learning classifiers are better choices. The choice of classifier also depends upon the tradeoff between good accuracy and computational complexity. If the system requirements are sensitive to accuracy, then deep learning methods are a good choice. If the system requires a balance between both, them ensemble methods are a great choice as some of them are fast and accurate. The choice of the classifier also depends on whether the data is noisy, missing, or consists of outliers. For example, if the data is noisy then KNN should not be applied as it is sensitive to noisy data. Similarly, if the data contains missing values then GradientBoost and PGM are better choices.

The pros and cons of each classifier are therefore discussed to make a clear and informed choice of the classifier. Some of the classifiers are still to be explored in different applications as shown in the last column of the table. Researchers can explore these classifiers in a particular application area as their future work.

Table 16
Research Gaps and Future Directions.

Research Gap/Future Direction	Explanation/Challenges
UPDRS Score Prediction	• Help in the automating the long and lengthy process of UPDRS prediction. • Predict the scores of PD patients using TQWT features (Sakar et al., 2019). • Different feature extraction techniques as shown in Table 14 can also be tested for better prediction results and to find the best feature extraction method.
The potential of feature selection methods are not fully explored (Lahmiri et al., 2018; Oung et al., 2018b).	• Feature Selection method can reduce the dimensionality • Extract the important features that are useful for diagnosis • Decreases computation cost and time. • Improve detection accuracy (Zhang et al., 2018). • Applying AutoEncoders right after CNN can reduce the dimensionality of feature space (Pereira et al., 2018)
Longer datasets are required for generalization.	• Deep Learning models are data-driven, also known as data consuming machines, therefore they require larger datasets for generalization purposes. • Overfitting can also be avoided with the use of a large sample size. • Less time will be employed in cross-validation techniques like Leave One Out cross-validation. • Most of the studies include very fewer data samples from later and moderate stages, extending the dataset with later and moderate stage patients help to improve the staging process (Yuvaraj et al., 2018). • Data samples from the diverse ethnic group (Oung et al., 2018b; Yuvaraj et al., 2018) to check whether socio-cultural differences may affect the disease (Bandini et al., 2017). • Gender balanced datasets are needed (Bandini et al., 2017). • If larger datasets are not available, we can utilize incomplete datasets with a large amount of information (Prince et al., 2018)
Data from multiple visits need to be included (Prashanth and Roy, 2018).	• Data from the same patient on multiple visits will help in the monitoring of patients. • Will help in checking if the medications are working properly or not. • Stage progression can also be checked.
• To develop a Computer-Aided Design (CAD) system (Lahmiri and Shmuel, 2019) • To develop a clinical decision-making support tool (Parisi et al., 2018) • Development of web and mobile platform (Afonso et al., 2019) • Implementation in a distributed environment (Cai et al., 2018) • On-chip integration of closed-loop DBS (Yao et al., 2018) • Implement system in a wearable computer Rasberry Pi (Saad et al., 2017) • Accommodate framework into the test-battery system (Khan et al., 2014)	• Testing in the real environment is needed as to help the clinicians with the diagnosis process. • To check real-time computation cost and time. • To includes run-time from the evaluation process (Mostafa et al., 2019). • To monitor PD patients using the Internet of Health Things. • Need to select features with high discriminative accuracy (Yao et al., 2018) • Low hardware cost (Yao et al., 2018) • To check if the system can handle big data (Zhang, 2017) • To check Resource utilization (Camps et al., 2018) • To check if the system is accessible from any location (Bernardo et al., 2019)
To develop a multimodal feature-based system for PD diagnosis (Lahmiri and Shmuel, 2019).	• PD is a combination of multiple symptoms that vary from person to person. • It may be the case that one may have voice distortion and others may not. • Combination of at least two of related symptoms is needed to serve as the criteria for disease diagnosis (Pedrosa et al., 2018). • Performance of PD can be strengthened by fusing different modalities. • Need to determine the relationship between different symptoms for robust diagnosis (Prince et al., 2018)
To develop machine learning-based Recommender Systems.	• To help PD patients overcome sadness, depression, real-time recommender systems can be made to improve the quality of life of PD patients. • Can provide a reminder to patients in case of stooped posture (Dang et al., 2019)
To develop an adaptive framework (Prateek et al., 2017)	• System should be able to learn parameters and dynamically adjusts them in real-time. • Development of a valid, reliable and dynamic method for real-time adjustment
To solve the class imbalance problem (Prashanth and Roy, 2018).	• As data collection from Parkinson's patients is difficult, there are a smaller number of instances of patients, so there is a class imbalance problem. • Machine learning-based systems need to developed to obtain high a detection rate of minority class without jeopardizing the accuracy of other classes. • There is usually a tradeoff between sensitivity and specificity and high values for both are required simultaneously (Impedovo et al., 2018)
To employ cost-sensitive learning techniques (Prashanth and Roy, 2018).	• Cost is an important factor in real-world diagnosis of PD. • Overall Cost of the system should be minimized. • Biasing of minority class is needed to improve the diagnosis process and to decrease the cost of the system.
To classify Parkinson patients from other disease patients.	• A lot of work is already done in classifying Parkinson patients from healthy controls. • Very few works have been done to classify Parkinson patients from other diseases having similar symptoms. • Examples include: • Progressive supranuclear palsy from PD by finger tapping as there is a decrement in amplitude/speed in PD whereas preservation of speed in Progressive supranuclear palsy (McKay et al., 2019) • Differentiate IH patients from PD patients to investigate the early onset of PD. Follow-up of IH patients to check for the development of PD (Rovini et al., 2018) • Distinguish RBD patients from PD patients as RBD is considered as an early stage of PD. Diagnosis can be done years before actual conversion to PD (Ruffini et al., 2019b) (may also help in prevention). RBD patients who later develop PD display diminished complexity as compared to HC as well as from RBD who remain disease-free. • Compare walking patterns of Huntington Disease, Knee Osteopsathyrosis with PD (Benson et al., 2018)

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Table 16 (*continued*).

Research Gap/Future Direction	Explanation/Challenges
To detect Subtle Instability (Stack et al., 2018).	• Sensitive algorithms need to be developed which can capture even subtle variations in the gait of PD patients as falls are extremely dangerous for PD patients.
To check the feasibility and effectiveness of proposed methods in free living environment (Son et al., 2018)	• Wide range of movements cannot be detected in laboratory settings • Remote monitoring needs to be done • Personalized care need to be provided • The requirement to check how patients react to the system after using it for a few hours (Oung et al., 2018a) • 15–20 min of clinic visits do not provide enough information for doctors to accurately access the patients (Zhang et al., 2017)
To check the Long-term feasibility (Son et al., 2018; Tahavori et al., 2017)	• Checking the symptoms in the long run is better than focusing on a short period • We can quantify responses to treatment and differentiate from day-to-day variations. • The severity of tremor varies with time, that cannot be quantified in a short period (Delrobaei et al., 2018) • To check worst and best performance throughout the day to check medication effects (Bernad-Elazari et al., 2016)
Speech denoising needs attention (Zhang, 2017)	• For remote monitoring, there should be strong and low-cost denoising techniques which can be either implemented on client-side or server-side.
To find the minimum number of sensors required to measure each symptom correctly (Daneault et al., 2017)	• The increase in the sensor number does not determine a direct increase in classification accuracy (Caramia et al., 2018)
Feature Extraction based on handwriting is very less explored (de Souza et al., 2018).	• As seen in Table 14 also, various feature extraction techniques have a lot of potential in analyzing handwriting signals and images like TQWT, HOS, Hjorth parameters, EWT, and others.
Exploration of sounds of writing (Pereira et al., 2018)	• Sounds of writing can enhance the classification accuracy of PD
Decreasing the number of EEG channels (Ruffini et al., 2019b)	• Motive is to maintain the relevant information but decreasing complexity
Very limited work to detect dyskinesia (Camps et al., 2018; Lonini et al., 2018)	• Refers to uncontrolled, involuntary muscle movement • One of the major symptom which needs more exploration
Exploration of diverse handwriting templates (Moetesum et al., 2019)	• Variant templates apart from spirals, meanders may further improve the diagnosis process
Analyzing Signals from handwritten exams (Passos et al., 2018)	• Most of the work in handwriting based classification is done on images. • Signals can provide much more detailed feature set which will improve the accuracy of the classification process
Explore the importance of the relation of velocity and motion curvature i.e. two-thirds Power Law (Impedovo et al., 2018)	• Two-Thirds Power Law states that there is an inverse relationship between tangential hand speed and the curvature of trajectory during curved motion (Maoz et al., 2006). • This relationship could prove useful in learning some handwriting features.
Differentiate between an episode of FoG from a voluntary pause in gait (Punin et al., 2019)	• FoG detection is needed to provide external stimuli to reduce the FoG time • Differentiation between the two is needed to reduce the false alarm rate. If false alarm rate is high then the wrong timing of external stimuli can cause sudden falls
Estimate stage of PD using gait patterns (Benson et al., 2018)	• Staging helps in estimating the severity of the disease. • Very less work has been found in stage estimation as shown in Table 13
Fully automated UPDRS-III evaluation using video recordings (Li et al., 2018)	• Will provide a non-invasive and computationally inexpensive calculation of UPDRS scores
Potential of LMC is not fully Explored (Butt et al., 2018)	• Updated Versions needs exploration
Development of Multiplayer Games (Pachoulakis et al., 2018)	• To improve communication and coordination among PD patients • To improve decision-making capabilities of PD patients
Staging using different standard Scales	• HY scale gives visual staging of PD patients whereas the UPDRS score gives a rating of pertinent features (Prashanth and Roy, 2018). • If we can map the UPDRS scores with HY scale stages, stage estimation of PD patients can be done. • Similarly, other scales can be mapped with stage estimation. **Examples include:** • Geriatric Depression Scale • ESS (Lei et al., 2017) • UPSIT (Lei et al., 2017) • Montreal Cognitive Assessment Test • Dynamic Gait Index • Berg Balance Scale • Freezing of Gait Questionnaire (FoGQ) (Punin et al., 2019)
Exploring other Deep architectures	• To check the sensitivity w.r.t size of data (Zhang et al., 2018) • Deep Belief Networks (DBNs) (Pereira et al., 2017)- For Feature Extraction and classification • Deep Boltzmann Machines (DBMs) (Pereira et al., 2017)-For Feature Extraction and classification • RBMs (Pereira et al., 2017) - For classification • RNN (Ruffini et al., 2019a) - For Feature Extraction and Classification • Extreme Gradient Boosting (Gao et al., 2018) • Knowledge-based machine learning (Gao et al., 2018) • non-encoding RiboNucleic Acid (RNA) (Gao et al., 2018) • micro RNA (Gao et al., 2018)
Advance spectral estimation	• State-space estimation (Ruffini et al., 2019a) • Multi-tapering (Ruffini et al., 2019a)

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Table 16 (*continued*).

Research Gap/Future Direction	Explanation/Challenges		
Adding new Sensing Modalities	Wearable	Non-Wearable	Clinical
	Inclinometers (Torres et al., 2017) Pressure Sensor (Benson et al., 2018) Pedometer (Benson et al., 2018) Barometer (Benson et al., 2018) GPS (Benson et al., 2018) Bending Sensor (De Lima et al., 2017) Potentiometers (Saad et al., 2017) Magnetic Sensors (Khan et al., 2014)	Compass Ambient sensors (Li et al., 2018) Optical Sensors (Torres et al., 2017) Environment Sensors (Torres et al., 2017) Touch-Based Sensors (Pereira et al., 2019) Sony Playstation EYE (Pachoulakis et al., 2018) Nintendo Wii (Pachoulakis et al., 2018) Sensorized Walkways (Caramia et al., 2018) Load Sensors (Caramia et al., 2018)	EMG (McKay et al., 2019) Facial-EMG (Bandini et al., 2017) ECG (Bandini et al., 2017) PCG (Tuncer et al., 2019) Polysomnography (Ruffini et al., 2019a)

8. Research Gaps and Future Directions

Machine learning and deep learning-based diagnosis system for Parkinson's disease has proved to be very helpful for robust classification, prediction, and monitoring of Parkinson's patients. It has also shown potential in estimating the severity of the disease, early diagnosis of the disease, and UPDRS prediction. Research articles showed the potential of different pre-processing, feature extraction, and classification techniques. A lot of work has been done to classify patients, stage estimation, remote monitoring. But there is still potential in each of the areas to be explored. Many sensors like accelerometer, gyroscope, magnetometer have been used and validated. Work has been done using EEG signals, MRI, f-MRI, DATSCAN images. Other brain signal images can also be analyzed to explore more research opportunities like ElectroCardioGram (ECG), ElectroMyoGram (EMG), and PhonoCardioGram (PCG). There are many more sensing modalities that have not been yet explored and their integration with the classification process can further improve the accuracy. Moreover, most of the work has been done on a smaller dataset. Large datasets are needed for generalization. A step toward this research gap is taken in Bot et al. (2016), where the authors build the "mPower" app to take the data from Parkinson patients from their iPhone. As smartphones are available with each individual, this technique can be extended to Android app users to collect data from the mass public. This would solve the problem of generalizability. Similarly, many other limitations and future directions are suggested which are summarized in Table 16. It gives the potential research gaps and future directions along with the suggested measures to work upon in the future.

9. Conclusion

Parkinson's disease is a neurological disorder which is caused due to the loss of dopamine-producing cells in the brain. These cells are responsible for maintaining coordination between brain and body parts. Therefore, patients suffer from various motor and non-motor symptoms. Clinical methods for evaluating the symptoms of Parkinson's disease i.e. UPDRS scale and HY scale are subjective in nature and suffers from the problem of inter-rater inconsistency. Therefore, computer-assisted diagnosis is necessary for the classification, prediction, and monitoring of Parkinson's disease. Moreover, there is no cure for this disease. Therefore, its early diagnosis is of utmost importance. The present study focuses on the machine and deep learning-based classification, prediction, and monitoring of Parkinson's disease. A comparative analysis has been done by dividing the analysis into six different sub-categories based on the symptom, type, and source of data. All the research articles are from the year 2017, 2018, and some articles of 2019. Each sub-category includes the exploration of public and private datasets available. Also, exploration is done to study work done in processing the signals starting from pre-processing, feature extraction, feature selection, and classification. Important features are also mentioned as used by the researchers. Some studies have also been done on the rehabilitation of Parkinson patients to improve the quality of life. Related software, tools, and libraries have also been explored for the researchers to use. Then a comparison has been done for each sub-category based on the type of data, the sensor used, whether prediction, stage estimation, and remote monitoring is done or not. Different feature extraction methods have also been explored with their pros and cons. It is also discussed whether a particular feature extraction technique has been studied for each sub-category or not so that researchers can explore the potential of these techniques in the future as per need. Different classification methods used by researchers are also discussed with their pros and cons so that proper and informed choice of selection of classification technique can be performed. Finally, research gaps and future directions are explored and elaborated with some suggestions so that the researchers can work upon them in the future.

CRediT authorship contribution statement

Jinee Goyal: Conceptualization, Writing - original draft, Writing - review & editing, Visualization. **Padmavati Khandnor:** Writing - review & editing, Supervision. **Trilok Chand Aseri:** Writing - review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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