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Sensor technology with gait as a diagnostic tool for assessment of Parkinson's disease: a survey

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Abstract
Parkinson's Disease (PD) is the most precarious chronic disorder of the human brain affecting millions of people globally. In today's world of technical inventions, the diagnosis of PD at its initial stage is a serious issue. The high dependency on the patient's medical history and clinical rating scales have certain limitations as they are very tiring and include recall bias. Therefore, more stable and objective measurements are needed to execute automated and effective detection of PD. The biometric gait has been developed as a reliable diagnostic tool for such a purpose because of its unobtrusiveness. In past years, the applications of sensor devices have been utilized the most to evaluate PD via gait. So, the purpose of this article is to analyze the past and current research toward sensor-based (SB) diagnosis of PD motor symptoms. In this article, we provide a brief description of PD and the related concepts also defining its impact on human gait. This article comprehensively surveys the SB technology and the role of different sensors in PD gait recognition. This study investigates the machine learning paradigms used in PD analysis and their performance evaluation. Several SB PD gait datasets are surveyed and explored considering literature from the last ten years. Also, we exhaustively provide a discussion section in this article to give a clear picture of the results concluded from the analysis of prior sections. At last, this article examines some gaps in the existing studies that need to be addressed and also suggests some measures to tackle such issues using advanced paradigms.

Keywords Parkinson's disease · Sensor-based · Gait · Machine learning · Sensor datasets · Clinical gait analysis

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1 Introduction

The present age of digital scenarios demands more advanced and automated systems to identify the diseased state of a person to cope with the growing rate of pathologies. The evaluation of disease using a few subjective clinical scoring scales doesn't offer true reliability and hence fails to give accurate results. Therefore, to suppress such bottlenecks, the unique attributes of the human body either physiological (e.g. hand geometry, face, iris, etc.) or behavioral (such as speech, gait, etc.) named as biometric, plays an important role in clinical recognition and have shown efficacy over the decades [60, 202]. Among the highlighted traits, gait has been tremendously given more focus of interest by the researchers for clinical analysis because of its exceptional features. Gait simply means the walking pattern of a person and it can be effectively utilized for the purpose due to facilities it provides like being captured at a low resolution [35], easy setup requirements, and difficult to concealed easily [116]. These benefits of gait analysis in combination make it a useful tool to detect abnormal behavior that happened due to any cause involving factors like injury, age, or some disorder [193]. An estimate given by the study in [197] revealed a high burden of disease in deteriorating public quality of life (QOL) [79]. Neurological disorder (ND) can be seen as one of the most predominant causes resulting in great loss of healthy living. The data provided by the study in [183] based on an analysis made on 328 diseases showed a great rise in ND (approx. 5% growth) between 2006 and 2016 and a major reason for most of the deaths. Due to the prediction of higher growth in the number of aged people, this survey article takes PD among all the ND, in concern for its further investigation.

Parkinson's disease (PD), defined by James Parkinson in 1817 [133], is referred to as the most frequent movement disorder graded in second place after Alzheimer's disease. The real causes for the occurrence of PD are undiscovered but a chemical known as dopamine is primarily related to the degraded functioning of the human mid-brain. When a person is usually diagnosed with PD, almost 70% of dopaminergic neurons are already lost and thus most of the symptoms develop gradually. The occurrence of such signs (like slow movements, freezing of gait (FOG), small and fast steps, etc.) provides powerful clues regarding PD stages. One of the main causes behind the incidence of PD involves an increase in age so it can be considered an age-related disorder where the process of aging is unnatural. An incidence reported the effect of PD on different age groups (such as 1:1000 for population over 65 and 1:100 over 75) with its pick-up range of about 60–64 years [30]. In a study involving statistics of PD, it is analyzed that PD has a distinct impact on different countries. The pie chart plotted in Fig. 1 (left) shows the overall prevalence estimates indicating a great rise in the PD-affected

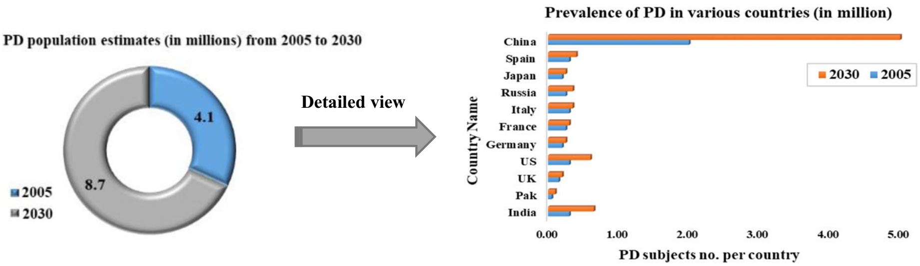

Fig. 1 (Left) Shows overall prevalence estimates of PD growth from 2005 to 2030. (Right) Depicts country-wise projected rise in PD (elaboration of left part) analyzing the gait parameter of an individual is necessary to accurately identify healthy and PD subjects to cure them adroitly

population from 2005 (4.1 million) to 2030 (8.7 million). The graph in part (right) provides a wider view of the left part which demonstrates the country-wise projected growth of PD where the highest rate is seen in China followed by other countries. The data also revealed that PD has more effect on men (about 63%) as compared to women (approx. 37%) [179]. To treat PD, doctors simply rate the disease on available scales and suggest medications to suppress their symptoms. The entire analysis involves the subjective evaluation which can be faulty if not performed by experts. Thus, the development of the automated analysis of gait parameters is necessary to accurately identify healthy as well as PD subjects and cure them adroitly.

1.1 Motivation

In recent years, gait analysis has contributed immensely to the medical field due to its unique usability. Despite having numerous pros, there exist certain cons such as occlusion, clothing, lighting factor, and other issues like use of the costly platform, small population size, heavy pre-processing requirements, etc. that have attracted huge numbers of researchers to provide more robust approaches to PD diagnosis. Working towards this direction, several survey/review articles have been published by various researchers. Recently, Brognara et al. in [20] performed a survey considering the last ten years of publications to inspect the efficiency and capability of inertial sensors in the evaluation of Spatio-temporal (SPT) gait features of PD subjects. Similarly, another review by Benson et al. in [17] explored various feature extraction techniques useful in PD evaluation and also discussed the role of wearables in PD analysis highlighting their advantages and gaps to be focused on. The summary of some important survey articles until 2019 (year-wise) is given in Table 1.

This survey article systematically goes through many publications in reputed journals and conferences and comes up with approx. 160 such articles that extensively concentrate on sensor data for PD evaluation. The article intends to keenly study PD detection based on gait data captured via sensor devices by exploring the past as well as current literature and also highlights the scope in the future. The fundamental objectives of this survey can be made clear by the points provided:

(1) The article briefly discusses the various aspects of PD and its relation to human gait considering SB analysis.
(2) Surveyed SB PD gait evaluation involving more than 150 research articles from reputed journals and conferences.

Table 1 Summarizes important survey/review articles (year-wise) on sensor-based PD gait detection

Ref./Year	Study purpose
[20]/2019	Focussed last ten years publications to inspect capabilities of IS in evaluation of SPT gait features of PD
[126]/2019	Reviewed the articles focussing PD FOG analysis via WS, also highlighting the gaps to be overcome in future
[17]/2018	Discussed PD feature extraction techniques and the role of WS in PD analysis
[146]/2018	Ascertained the factors causing PD instability to avoid falling risk of subjects
[201]/2016	Investigated the recent advancements in WS technology in PD motor funtion evaluation
[122]/2016	Keenly reviewed the WS methods and technology to analyze motion symptoms of PD subjects
[30]/2013	Focussed PD gait based on WS and advised PD cure strategies

(3) The article comprehensively investigates sensor modality/technology for PD gait acquisition giving its benefits and drawbacks.
(4) The article extensively provides the role of artificial intelligence (machine learning paradigms) in the analysis of PD with the help of a percentage usage graph of each as well as their performance analysis.
(5) The article inclusively surveys and presents an insight into PD SB datasets that can be helpful for further research studies.
(6) The article exhaustively provides the discussion explaining the outcome obtained from prior sections with proper graphs and charts.
(7) The article also highlights the gaps in the existing literature and gives possible suggestions to tackle them in the future more efficiently.

1.2 Article organization

After presenting the introduction and key aims of the article in Section 1, the other sections are organized as follows; Section 2 gives a brief description of PD and the associated concepts. The overview of human gait including its phases and gait parameter ranges is provided in Section 3. Section 4 outlines the literature search strategy and its outcomes in the respective sub-sections discussing sensor technology in detail. In Section 5, we investigate various machine learning paradigms (MLP) that have been used for PD diagnosis. Section 6 provides a view of public and private sensor gait datasets. The results obtained from each section are discussed and presented in Section 7, also giving the existing gaps and possible solutions. At last, Section 8 briefly provides the conclusion of the survey article.

2 Parkinson's disease (PD)- a progressive ND

Parkinson's disease, widely referred to as chronic degenerative movement disorder, has been identified as the second most precarious neurological disbalance worldwide [15, 127]. This section provides the general scenario in PD as depicted with the help of Fig. 2. and gives a brief description of PD related concepts that include the following.

PD brain degeneration and etiology PD generally occurs when cells in a particular part of the brain known as substantia nigra stop working in the usual manner. Due to the release of insufficient dopamine [15], a person starts developing symptoms of PD [36]. Figure 2 clearly shows the deviations in the presence of dopamine amount both in healthy and PD pruned brain that results in improper body functioning. Research related to PD isn't able to identify its actual causes [77, 96] and mainly involves genetic, metabolic, environmental, and other factors. Evidence shows that the presence of environmental toxins such as manganese, carbon monoxide, other pesticides, and herbicides are the major cause of PD. The entire destruction results in faulty mutations in the alpha-synuclein genes which is the key component of Lewy bodies in almost all PD clients.

PD outcomes/symptoms The age range of people who are affected by PD is not fixed, but it can affect people of all ages [153, 154]. Two signs either on one or both portions of the body start developing when a person comes under the impact of PD i.e. motor and non-motor

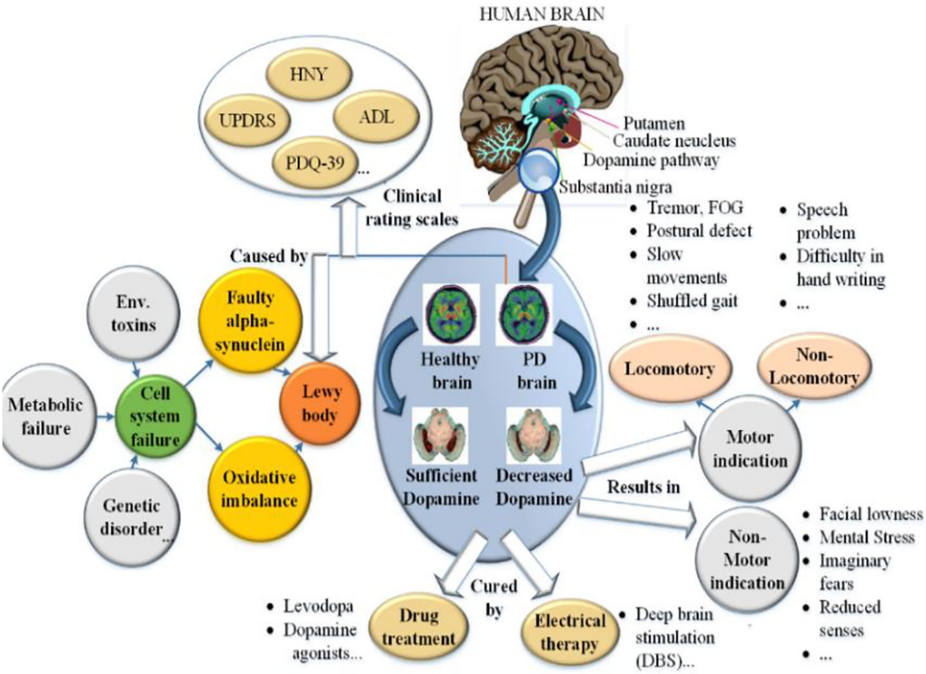

Fig. 2 A pictorial representation of PD with its related concepts (brain damage, causes, symptoms, clinical scales, treatment) [127, 154, 172]. Some of the images used in this and other figures of this article are taken from the internet whose proper URLs are provided in the Appendix

indications [68, 154]. Further, under motor classification, two subcategories are defined i.e. locomotory which happens when a person is moving, and non-locomotory which involves speech problems, and handwriting issues.

Clinical measures for PD and cure Till now, there is no specific test for PD diagnosis. Initially, a combination of tests is recommended such as medical resonance imaging (MRI), and positron emission tomography [127]. Then, several scales including the Hoehn and Yahr scale (HNY), Activities of Daily Living (ADL), etc., and some questionnaires are used for evaluation of PD severity [51, 68, 122]. PD being a non-curable brain disorder can be controlled through medications including levodopa, duodopa, dopamine agonists, anticholinergic medicines, etc. [172]. Similarly, some therapies and surgical cures like physiotherapy (to increase muscle flexibility), speech (vocal clarity) and dance therapies, deep brain stimulation, pallidotomy, thalamotomy, etc. are available for PD patients.

3 Human gait as a diagnostic tool

Ambulating on two limbs smoothly is the most significant and proficient physical exercise that has attracted huge researchers in the world for pathological analysis. Human gait, being the most decisive biometric came into reflection from the period of Aristotle [12] and demonstrated its importance to the modern era of advanced technology too in several fields [167, 195]. This section gives a brief introduction to the human gait and its crucial need in PD monitoring.

The events of walking appear in the form of a series called gait cycle (GC). The aggregation of two main phases of the gait cycle and its subsequent sub-phases i.e. Stance phase (foot on ground, 60% share in GC- heel-strike, foot-flat, mid-stance, heel-off, and toe-off as sub-phases) and Swing phase (foot in air, 40% share in GC- initial swing, mid-swing, and terminal-swing as sub-phases) in whole completes the total GC which begins from initial contact and further goes on [141]. Every single phase of the GC has its significance and captures three tasks including Weight acceptance (for limb balancing and shock absorption, by the first 2 sub-phases of stance), Single limb support (for load stability, by the next 2 sub-phases of stance), and limb advancement (for body progression, by last stance sub-phase and continues to rest of swing sub-phases) [139, 182].

In the current scenario, the use of gait for clinical monitoring has become a popular research area. Gait analysis can be simply seen as the empiric screening to remark the deformities observable by naked eyes. To truly understand the pathological conditions, it provides a consistent way to analyze the asymmetries while walking [167, 182]. Gait measurements of PD-affected subjects can be performed using different information such as kinetic, kinematic, spatiotemporal, etc. If these parameters are crucially analyzed in-depth, they can provide solid clues for the presence of PD as they differ a lot from the healthier gait. A representation of some important gait parameters is provided in Fig. 3 and Table 2 highlights their respective meaning and their ranges for normal gait.

Firstly, the walking features for normal and abnormal PD subjects are recorded and then compared to note the number of deviations between them. As seen in the table below, there are predefined ranges for every normal gait parameter such as gait speed/velocity (2–3 miles per hour), cadence (80–110 steps per minute), step length (28 in.), etc. So, the alterations (high or low) in a person's gait from the average ranges give indications for the presence of the diseased state. E.g. PD, in which the person has slow walking speed, large cycle time, stooped posture, etc. Therefore, to make an effective diagnosis of gait abnormalities, it is necessary to evaluate at least one GC which is often used by the clinicians for proper treatment of people with such unusual conditions as PD [71, 191].

4 Literature search plan

To achieve the basic motive of this article, we performed a comprehensive state-of-art literature search from 2010 to 2020. Several journals of repute such as Springer, sensors, IEEE, Elsevier, Gait & Posture, etc., were explored and simple keywords were used within the

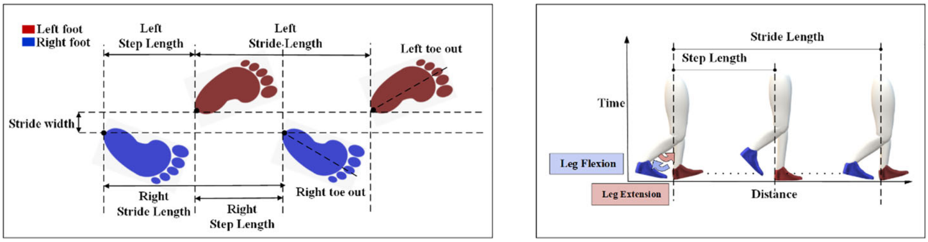

Fig. 3 A depiction of some crucial gait parameters (left) and right- figure detailing the leg flexion and extension)

Table 2 A list of mostly used gait parameters with their meaning and normal range [71, 191]

S.No.	Parameter	Meaning	Normal Range (avg.)
1	Walking speed/ velocity	Distance travelled by a person in the specified duration. The average speed can be defined as the product of cadence and stride length as: Speed = stride length × cadence/120	2–3 mph (60-80 m/min)
2	Cadence	The rate at which a person walks or the no. of steps taken in a given time	80–110 steps/min
3	Step length	Distance covered by a person while taking two steps (one with left foot and other with right). Step length can be defined as: Step length = Distance / no. of steps	(28–30) inches
4	Stride length (Gait Cycle)	Distance between heel strike of one foot to the heel strike of same foot. It comprises of two step lengths i.e. left and right and can be given as: Stride length = 2* step length	(56–60) inches
5	Stance/Swing ratio	The ratio of stance period to the swing period	60/40
6	Leg Flexion	The range of leg to flex backward. Flexion movement reduces the angle between two joints	0–60 deg.
7	Leg Extension	The range of leg to extend in forward direction thus increasing the angle between two joints	15 deg.
8	Stride width	Side to side distance between lines of two consecutive foot (generally calculated from the center of ankle joint)	(1–3) inches or (3–8) cm
9	Toe out angle	Made by foot ling axis and forward progression's direction intersection	7 deg.
10	Stride period/time	Time taken from heel strike of one foot to the heel strike of same foot and can be calculated as: Stride time = 120/ cadence	1 sec.

search box such as "PD Gait", "Gait based PD analysis", etc., yielding an approximation of (5000–7000) related articles. After refining the search string and following the screening and acceptability benchmark, finally, the most relevant and meaningful articles (160–170) were selected to delve into for further PD analysis.

4.1 Search results/outcomes

Traversing and surveying through the selected articles result in the usage of two broad categories of sensor technology for PD appraisal i.e. wearable and non-wearable. Four main types of sensors under the wearable class seem to be significantly utilized including Inertial, Insole shoe, Clothing, and Electromyography (EMG). Also, Floor sensors have contributed a lot toward non-wearable PD assessment. Similarly, some studies employed the combination of one or two sensors by hybridizing them for better results and accuracy as shown in Fig. 4. To scrutinize the sensor technology in PD monitoring, this sub-section provides a vision towards mostly adopted such sensing devices and various research studies contributing as an important part.

4.1.1 Wearable sensor technology (WST)

Wearable sensors (WS) are devices that are directly integrated into the subject's body to measure motor symptoms [53]. To enable gait monitoring in a daily living environment, the

Fig. 4 Mostly adopted sensor-based devices (wearable and non-wearable) used in PD monitoring

use of wearable sensors fixed to any part (e.g. ankle, foot, leg, arm, etc.) has advanced this research area nowadays [24]. Different types of wearable sensors as presented in Table 3 are adopted to enhance the clinical gait diagnosis.

I. Inertial Sensors (IS)

Inertial sensors abbreviated as Inertial measurement unit (IMU) is the amalgamation of a tri-axial accelerometer, gyroscope, and magnetometer where the accelerometer can compute velocity, as well as position, and gyroscopes are rich in calculating angular position [24, 111]. Several researchers used IMUs to capture the gait Spatio-temporal and kinematic features.

The study by Heijmans et al. in [62] developed a new IMU-based system, consisting of an accelerometer with ±8 g of amplitude range and a gyroscope having ±2000 deg. of range considering 20 subjects with idiopathic PD. The results revealed a high consistency of the new system in monitoring the PD population easily. Another work by Amigo et al. in [104] analyzed the gait variability among PD (22 early, 27 moderate) and 25 healthy groups using an inertial measurement sensor (a tri-axial gyroscope and an accelerometer having a range and resolution of ±19.62 ms^2 and 0.00981 m\s^2). Butt et al. in [22] proposed a system by introducing machine learning-based computer-assisted techniques for PD investigation of 59 participants and two IMUs (one positioned at the foot and the other at hand) were utilized to gather the motion features. To diversify the values among 0 and 1, linear scaling was adopted which can be represented as.

$$V' = \frac{V - min(V)}{max(V) - min(V)} \quad (1)$$

Here, V and V'denotes original and normalized feature values. At last, applying a support vector machine (SVM), regression, and neural network (NN) for the purpose yielded the best

Table 3 Shows some recent studies on the sensor technology used for PD gait collection. Acronym of terms used in the table: Number (N), Healthy controls (HC), Amyotrophic lateral sclerosis (ALS)

Authors (Year)	No. of Sensors	Sensor Location	Study Population (N)	Performance	Conclusion	Study Limitations	Related Studies Ref.
Chomiak et al. [32]	One (a tri-axial accelerometer, gyroscope)	Thigh	• N=30 (21 PD and 9 HC)	• 0% mode error rate • <5% mean error rate	• Combination of advanced AI can improve the efficacy of WS for PD analysis	• Window size limitation • Small sample size	[5, 9, 10, 13, 14, 25, 27, 37, 42, 43, 47, 52, 55, 63, 64, 70, 74, 76, 82, 86–89, 93, 97, 98, 101, 103, 108, 110, 117, 119, 124, 130, 131, 134, 137, 142, 145, 147, 155–157, 162, 163, 165, 168, 170, 171, 175, 178, 180, 181, 184, 185, 187–189, 192, 194, 199, 200, 204, 206]
Masiala et al. [94]	Three (accelerometer sensors)	Leg, Thigh and Trunk	• N=10 (PD)	• AUC=97% • Sen.=87% • Spec.=96%	• The use of RNN with LSTM using IS outperforms the existing methods for FOG detection	• Non- evaluation of dependencies among sensors	
Punin et al. [143]	One (a tri-axial accelerometer device)	Both Legs	• N=8 (7 PD and 1 HC)	• Effc.=80% • Sen.=60.6% • Spec.=86.6%	• Amalgamation of stimulation and detection provided reliability in PD monitoring	• Less number of patients data	
Borzi et al. [19]	One (an accelerometer + gyroscope)	Thigh, Waist	• N=93 PD (for LA exp.) and N=38 (for FOG study)	• AUC=0.92 (for LA) • AUC=0.97 (for FOG)	• The use of IMU-based smartphones proved to be helpful to estimate motor fluctuations in PD subjects	• Less training data • Negligence on the disease severity level	
Din et al. [41]	One (Dynaport/ Opal)	Fourth and Fifth Lumbar	• N=696 (HC)	–	• Large variability in step time and gait asymmetry seemed to be the best indicators for the presence of PD	• Consideration of only a single gait model • Infeasibility of used statistical models	
Boli et al. [84]	One (a nine-axis inertial accelerometer)	Lower Back	• N=10 (PD)	• AUC=93.2% • Sens.=92.4% • Spec.=94.9%	• The use of sensor and k-means algorithm can successfully determine FOG events automatically	• Data need to be updated for the designed system due to low sampling frequency	
Campas et al. [26]	One (inertial measurement unit)	Waist (left side)	• N=21 (PD)	• 90% (for G. M between sens. and spec.)	• Deep learning model showed high significance in accurate FOG detection by improving accuracy	• Computationally expensive for real-time implementation • Insufficient sample size	
Rovini et al. [159]	One (inertial measurement unit)	Foot	• N=90 (30 HC, 30PD and 30 IH))	• Recall: 96.7% • Acc.=78% • Spec.=96.7%	• The acquired system using machine learning can be helpful in clinical analysis	• Fewer data samples • Non-consideration of upper limb movement	
Sama et al. [163]	One (a tri-axial accelerometer)	Waist	• N=15 (PD) MASPARK	• Sens.=91.7% • Spec.=87.4%	• The use of a new FOG detection approach may enhance the true positive rate in PD analysis	• Less sample size	

Authors (Year)	No. of Sensors	Sensor Location	Study Population (N)	Performance	Conclusion	Study Limitations	Related Studies Ref.
Ahn et al. [2]	One (smart glass IS system)	Eyes	• N=10 (PD FOG)	• Acc.=92.86%	• The proposed system can efficiently improve the gait speed as well as step length of PD patients	• Few sample size	[5, 9, 10, 13, 14, 25, 27, 37, 42, 43, 47, 52, 55, 63, 64, 70, 74, 76, 82, 86–89, 93, 97, 98, 101, 103, 108, 110, 117, 119, 124, 130, 131, 134, 137, 142, 145, 147, 155–157, 162, 163, 165, 168, 170, 171, 175, 178, 180, 181, 184, 185, 187–189, 192, 194, 199, 200, 204, 206]
Pham et al. [136]	Three (tri-axial accelerometer)	Shank, Thigh and Lower Back	• N=34 (10 for development set and 24 for test set)	• Sens.=96% • Spec.=79%	• The used subject-independent method provided more accuracy and tolerance	• More elaborated techniques for ASD threshold need to be studied for better PD assessment	
Capecci et al. [92]	One (inertial sensor based smartphone)	Hip joint	• N=20 (PD)	• Sens.=70.1% • Spec.=84.1%	• Study showed the relevance of the Moore-Bachlin algorithm for FOG detection	• Small size of the sample can decrease the Sens. and Spec. values for PD subgroups comparison	
Nguyen et al. [115]	Two (a three-axis accelerometer and a three-axis gyroscope)	Lateral Side of shoe	• N=119 (PD)	• Increase in AUC up to 19%	• In-depth gait clusters analysis of systematized gait tests is helpful for clinicians to monitor PD	• The used approach required manual labeling work • Constrained number of strides	[1, 6, 29, 48, 57, 58, 72, 81, 83, 91, 102, 109, 129, 149, 150, 164, 173, 174, 176, 177, 205, 208–210]
Khoury et al. [73]	Sixteen	Both feet	• N=165 (93 PD and 72 HC)	• Avg. Acc.=83%	• The results obtained for features based proposed methodology can help to differentiate PD and HC	• Use of a few gait features for evaluation	
Zeng et al. [207]	Sixteen	Both feet	• N=165 (93 PD and 72 HC)	• Acc. Rate: 91.4%-98.8%	• The proposed combination of PSR, EMD, NN, and ED has a high potential to automatically classify PD and HC	• Limited dataset size • Negligence of PD severity level	
Asuroglu et al. [8]	Sixteen	Both feet	• N=165 (93 PD and 72 HC)	• Acc.=99% • Spec.=99.5%	• The approach used had the high potential to derive the exact value of PD severity level	• Fewer data samples of PD subjects • Diversity in a dataset in terms of PD stages	
Elde et al. [45]	Sixteen	Both feet	• N=64 (15 PD, 13 ALS, 16 HD and 20HC)	• ROC=0.861 • Acc.=90.6%	• SVM with RBF shown reliability in differentiating normal and abnormal subjects for PD inspection	• Negligence of PD severity level	
Paragliola et al. [125]	Sixteen	Both feet	• N=64 (15 PD, 13 ALS, 16 HD and 20HC)	• Acc.=90% • Acc. Improvement: 4.28%	• Deep time-series based approach can successfully detect the walking anomalies	• Time-consuming approach • Off-line consideration of classification process	

Authors (Year)	No. of Sensors	Sensor Location	Study Population (N)	Performance	Conclusion	Study Limitations	Related Studies Ref.
Alam et al. [4]	Sixteen	Both feet	• N=165 (93 PD and 72 HC)	• Acc.=93.6% •Sens.=93.1% • Spec.=94.1%	• VGRF data acquired from WS with SVM can be a useful tool for PD analysis	• Investigated only VGRF data	[1, 6, 29, 48, 57, 58, 72, 81, 83, 91, 102, 109, 129, 149, 150, 164, 173, 174, 176, 177, 205, 208–210]
Ertugrul et al. [49]	Sixteen	Both feet	• N=165 (93 PD and 72 HC)	• Acc.=87.58% (Highest by Random Forest)	• The proposed Shifted 1D-LBP can be used to analyze complex signal data	• Determining optimal P values was difficult as well as time-consuming	
Rennie et al. [152]	One (10 m pressure sensor mat-GaitRite)	Under foot	• N=54 (29 PD and 25 HC)	• p<0.0001	• Difference among gait speed and other gait irregularities can estimate the PD and healthy subjects	• Data collection during an irregular walk • A large amount of gait variability	[34, 50, 107, 132, 151, 158, 198]
Myers et al. [112]	One (GaitRite)	Under foot	• N=37 PD (13 F and 24 NF)	• ROI analysis:- 0.01–0.004 and p<=0.0001 (for velocity, step length)	• The study suggested the relevance of the BOLD signal in the analysis of PD gait	• Drawback of small sample size • Not valid for PD with a severe level	
Chen et al. [31]	One (U-shaped sensing mat)	Under foot	• N=23 (12 PD and 11 HC)	• Acc.=87.1%–95.6%	• The use of SVM based PSO for PD detection seems to be the reliable method	• Consideration of a few gait features • Less sample size	
Kliener et al. [75]	Two (force plates)	Under foot	• N=44 (22 PD and 22 HC)	• Positivecorrelation: 90.3%	• COF's pattern can be an efficient tool to analyze the gait deviations among PD and HC	• Small sample size of PD	
Young et al. [50]	Two (AMTI force plates)	Under foot	• N=19 PD	• Confidence interval of 95% • In PD-FOG, p=0.039, r=−0.432	• Study revealed the capability of sounds as FOG sensing cues	• Spatial conflict issue • Consideration of only sound action to study FOG	
Okuma et al. [118]	One (body-worn sensor)	Full body	• N=36 PD	• Increase in freezing index	• Study shown significance of wearable sensors for PD FOG detection	• Small PD sample size	–
Niazmand et al. [186]	One (body worn sensor garment)	Full body	• N=6 PD	• Sensitivity=88.3% • Specificity=85.3%	• The use of sensor-equipped body garment can efficiently detect FOG	• Very few sample sizes of PD subjects	

Authors (Year)	No. of Sensors	Sensor Location	Study Population (N)	Performance	Conclusion	Study Limitations	Related Studies Ref.
Putri et al. [144]	One	Leg	• N=23 (15 PWP and 8 HC)	• Acc.=88.4%	• The sensor-based analysis of PD can be helpful to explore its stages	• Severity level of PD was not considered	–
Lima et al. [38]	Two (a tri-axial accelerometer and a barometer)	Neck	• N=4126 (2063 PD and 2063 HC)	• 95% confidence interval • $p<0.0001$	• PD patients have double falling risk as compared to normal's • Study shows the feasibility of the used sensor in daily life	• Self-reported fall events by patients • Lack of separate fall detection data	[23, 39, 40, 100, 106, 114, 160, 211]
Rehman et al. (2019) [148]	Two (a GaitRite mat and a tri-axial accelerometer)	Lower Back, Under foot	• N=196 (93 PD and 103 HC)	•AUC: 87.83±7.81%	• Study suggested the relevance of testing protocol choice and gait sensing system	• Only SVM and RF models were compared • Consideration of only young subjects	
Chan et al. [28]	Two (3 MEMS unit and an AHRS -IS unit)	Upper Limbs (left and right)	• N=38 PD	• Variability: 64%–80%	• The sensor-based analysis of PD can be helpful to explore it efficiently	• Considered only PD subjects • Small sample size • Outliers in scores	
Jehu et al. [69]	Seven (6 accelerometers and a force plate)	Both Wrists, Ankles, Lumbar spine, sternum, and underfoot	• N=42 (25 PD and 17 HC)	• $p<0.05$ (fallers vs. non-fallers)	• Study revealed the capability of IS in diagnosing fallers and non-fallers	• Non-consideration of patient's disease severity levels	
Bertoli et al. [18]	Two (2 MIMUs with IS and an instrumented mat)	Both Ankles, under foot	• N=236 (PD, CI, and HOA)	• Avg. stride mean absolute error=2%	• The sensor-based PD evaluation can be helpful in the treatment of patients	• Only shorter walks of the subjects were instrumented	
Buckley et al. [21]	Two (3 IMUs and a GaitRite mat)	Lumber and cervical vertebra, Back	• N=114 (60 PD and 54 OA)	• $p<0.05$ and $d=-0.10$	• Study shown significance of IS for PD detection	• Uncontrolled gait speed • No data recording for standard alignments	
Perumal et al. [135]	17 (16 inertial sensors and a pressure sensor)	Both feet	• N=165 (93 PD and 72 HC)	• Acc.=86.9% • Sens.=0.72 • Spec.=0.81	• The analysis based on the sensor can be helpful in PD inspection	• Small data samples of PD patients • Heterogeneity in dataset among PD stages	

results using SVM with a classification accuracy of 79.66%. Similarly, Prateek et al. in [140] adopted inertial sensors (a 3-axis accelerometer and gyroscope) and have achieved a higher accuracy of the proposed method i.e. 81.03% in determining the true FOG events.

The application of IS for monitoring PD symptoms has been seen in other research work by Piro et al. in [138] using 3D Avatar. Four MARG (Magnetic, Angular Rate, and Gravity) sensors were attached to the wrists and arms of PD as well as normal subjects. The results achieved for Unified Parkinson's Disease Rating Scale (UPDRS = 0.48) and 3D Avatar = 0.47 revealed the effective agreement between both. Another effort by Hao Hu et al. in [65] used the Freezing index (FI) to analyze the FOG frequency between PD and normal gait (with one accelerometer frequency from 0.5 to 3 Hz and another from 3 to 8 Hz).

$$FI(t_m)_{new} = \frac{\int_3^8 |W(t_m, f)|^2 df}{\int_{0.5}^3 |W(t_m, f)|^2 df} \tag{2}$$

where $W(t_m, f)$ denotes the short-time Fourier transform (STFTM). This study by Hu redefined FI and generalized the spectrogram $GSPG_x\ (t_m,f)$ which can be presented as.FI(t).

$$GSPG_x(t_m, f) = STFTM_{wn_1}(t_m, f)^{\alpha_1} \cdot STFTM^*{}_{wn_2}(t_m, f)^{\alpha_2} \tag{3}$$

Here, α_1 and α_2 are the STFTM powers and wn_1, wn_2 denotes the window size where one is wider and the other is narrower. The experimentation results showed the specificity, sensitivity, and accuracy of 81.83%, 82.66%, and 82.83% respectively. The other work by Yoneyyama et al. in [203] and Gaßner et al. in [56] determined the capability of inertial sensors in future PD detection to help clinicians and for further treatment.

II. Shoe Sensors (INS)

Pressure shoe technology, mostly used in clinical research, comprises force-sensitive resistors embedded into foot insoles or fixed directly to the shoe. The key purpose of such a device is to perform spatial and temporal pressure distributions during walking activity [85, 90]. Zeng et al. in [207] proposed a novel methodology to classify the patterns among PD and healthy subjects by utilizing the concept of phase space reconstruction (PSRN), empirical mode decomposition, and NN. Initially, the vertical ground reaction force (VGRF) data was collected from the Physionet dataset (93 PD and 73 normal subjects) using 16 force-resistive insole shoes (8 under each foot). Then using PSRN and empirical decomposition with a neural network for pattern distinction provided the highest accuracy of 81.1%. The use of insole pressure shoe sensors can also be seen in the study by Alafeef et al. in [3] using Physionet. The study aimed to develop a novel wavelet transform-oriented method to identify the subjects with PD by analyzing signals from the mixed frequency-time domain and comes up with an accuracy rate of 97.6% with Artificial NN (ANN).

Ota et al. in [123] aimed to elucidate the connection between some significant PD indicators including stride time fluctuations and PD severity levels. Forty-five PD subjects (24F, 21 M) participated and footstep timing was gathered via footswitch sensors and the collected time series data were evaluated which can be presented as.

$$s(i) = J(i+1) - J(i) \tag{4}$$

where $s(i)$ is the i-th stride spell and $J(i)$ means i-th step timing and the procedure shows an accuracy, specificity, and sensitivity of 0.76, 0.86, and 0.93 respectively.

III. Clothing Sensors (CS)

Clothing sensor also named the smart fabric is another technology that has contributed immensely to clinical gait evaluation. These devices are equipped with a group of inherent sensors along with cable connections and are capable of measuring entire body movement as well as joint angles. Sensing fabric technology proved to be very robust as it is comfortable and provides better mobility to the user [7]. Okuma et al. by the study in [118] intended to objectively identify the FOG and fall events in subjects with PD in day-to-day activity using a full-body garment. The results obtained by FI in both groups provided reliable detection of FOG as well as fallers.

Similarly, Niazmand et al. in [186] proposed a FOG detection method by adopting a body-worn garment consisting of coherent acceleration to evaluate PD patients. The measurement values fell in the range of ±2 gm_u with 0.004 gm_u resolution and the relative acceleration was computed as.

$$u[l] = a[l] - gm_u \tag{5}$$

$$u[l]' = u[l] - \frac{1}{20} \sum_{l=1}^{l=20} u[l] \tag{6}$$

$$u[l]' = \left\{ \frac{u[l]', u[l]' > N_{THLDE}}{0, u[l]' \leq N_{THLDE}} \right\} \tag{7}$$

where denotes activity value,$u[l]$is the relative, and $gm_u$is the gravity acceleration, and N_{THLDE}represents the noise range (max). The new method provided a sensitivity of 88.3% and specificity of 85.3% which indicates the effectiveness of the considered mechanism without any requirement of heavy installations and set-up for FOG inspection.

IV. EMG Sensors

In PD, the muscle electrical pattern of a patient differs significantly with disease severity as well as from healthy subjects. Therefore, EMG also named electromyography sensors are the devices employed to act as a diagnostic tool to identify various disorders such as PD [54, 169]. These devices are available in two forms: surface (take measurements directly from the skin surface) and intramuscular (require needle insertion into the skin) EMGs. Former EMG is more user-friendly, less painful, and simpler to use but is restricted only to particular muscles while later can cause discomfort to patients. Putri et al. in the study [144] analyzed the EMG signals using a pattern recognition technique to further differentiate 15 PD and 8 healthy controls. Surface EMG electrodes with a sampling frequency of 100 Hz were placed on three muscles of the subjects. Twelve time-frequency domain features of EMG were considered, as in the example, the integrated EMG (*IEMGc*) and mean absolute value (MAV_l) features were computed as.

$$IEMG_c = \sum_{i=1}^{M} |w_i| \tag{8}$$

$$MAV_l = \frac{1}{M} \sum_{i=1}^{M} |w_i| \tag{9}$$

Here, M denotes the total number of patterns and w_i is a single signal. Using ANN for the purpose achieved an accuracy of 88.4% thus giving the relevance of EMG in PD diagnosis.

4.1.2 Non-wearable sensor technology (NWST)

Contrary to wearables, these types of sensors capture the forces when contact between foot and surface occurs. Non-wearable sensors are non-attachable to the body and make use of well-specialized laboratories having properly marked passages to enable gait recording of a subject. Under these sensors, floor sensor systems have been chiefly adopted to measure ground reaction forces (GRFs) produced during the subject's walk.

I Floor Sensors (FS).

Floor Sensors, the technology beneath our feet is the group of several lightweight sensors that are interconnected in the form of the instrumented walkway and are available in several forms like electronic mats, instrumented plates, etc. depending on the type of application [16]. Using such sensors in PD not only allows its detection but can also prevent the falling risk by monitoring the person's footsteps. Kleiner et al. in [75] proposed a study to outline the differences in the coefficient of friction (COFR) among 22 PD and 22 healthy subjects while walking barefoot. They employed two force plates (Kistler, Model 9286BA) and the ratio between shear force and the normal GRF was used to visualize the COFR curve which may be defined as

$$COFR = \frac{(FOY)^2 + (FOX)^2}{FOZ} \tag{10}$$

Here, FOY, FOX, and FOZ represent the antpost, medio, and VGRF. Using statistical analysis measures provided the significant differences among both the groups based on COFR. In another study, Christofoletti et al. in the study [33] made use of a GaitRite (4.8 m long) instrumented mat to conduct Time up and Go test and a six-minute gait test to identify PD gait impairment factors considering 144 PD subjects. The differences in variance and gait velocities with balance and age showed a positive relationship between these factors and PD mobility. Again, using two computerized force plates (at 100 Hz), Nantel et al. [113] tried to examine the relevance of repetitive stepping in place (SIPL) to identify the freezing events in 30 PD affected subjects as compared to 9 healthy controls. Applying the Spearman rank test yielded the specificity and sensitivity of 93% and 87% thus proving the usefulness of SIPL for the detection of FOG in PD. Results also showed a high correlation with the freezing of gait questionnaire ($r = 0.80$, $p < 0.001$).

4.1.3 Merged WST and WST + NWST fusion

Irrespective of using different sensors individually, some researchers adopted the concept of incorporating multiple sensors (either fusing WST or combining WST and NWST) to gain more profitable outcomes. Making an amalgam of sensors not only enhances the system efficiency but provides more reliability as they have very few connection points as well as a low risk of breakage [46]. Mileti et al. [105] tried to monitor the quality of gait for 26 PD patients and 11 healthy subjects in daily activities. The fusion of two IMUs (Xens Technology) and 8 force insole resistors (wireless) was used and the results obtained by measuring the gait phase quality index demonstrated good performance in threshold-based methods ($0.25 < G_p < 0.70$) for real-time gait analysis. Similarly, Kugler et al. in [80] proposed a work to perform an objective inspection of PD using the combination of surface EMG (consisting of four electrodes, an amplifier) and an IMU sensor.

Besides merging two same categories of sensors, few authors combined two different categories of sensors i.e. wearable and non-wearable sensor technology [18]. Research by Jehu et al. in [69] studied postural properties in PD by matching and comparing postural strategies among fallers (n = 11), non-fallers (n = 14), and healthy adults (n = 17). The mixture of six accelerometer sensors (at 128 Hz) and one force plate (Kistler, at 200 Hz) revealed the adoption of varying postural plans among the recruited groups that can provide useful information regarding falling risk. Similarly, the fusion of IMU (with size-4.2*4.6*1.5 cm and weight-43 g) and a pressure mat platform (4.27*0.61 m, at 120 Hz) can be seen in the study conducted by Hundza et al. in [66].

Table 3 provides a brief description of some recent studies purely focused on sensor-based modalities used for PD gait data acquisition including the number of sensors utilized, the accuracy achieved, and the respective drawbacks. The colors used in the second column in the table (i.e. author) denote the different types of sensors preferred under wearable and non-wearable categories for the purpose. Here, the green, blue, pink, orange, sea-green, and purple colors represent the studies that adopted inertial, insole shoe, floor, clothing, EMG, and finally the merged/combined sensors.

5 Role of artificial intelligence (AI) in gait based sensor paradigm for PD analysis- a narrow view

This section provides a brief introduction to MLP applied by the researchers in past years (2010–2020), also giving their accuracies in diagnosing PD. There are four main machine learning techniques (MLT):

5.1 Supervised Machine Learning paradigm (SMLP)

SMLP takes labeled datasets and gleans information from them to label new datasets to predict the function. For e.g. If I and O are the given inputs and outputs such as I = {1,2,3,4,5,6,7} and O = {1,4,9,16,25,36,49} then the predicted function will be:- $O(I)^2$. Several algorithms fall in this category consisting of SVM, ANN, Adaboost, K-nearest neighbor (KNN), Random Forest (RF), Decision Tree (DT), and Deep Learning (DL).

SVM is a MLT that map input vectors ($y_j \in R^M$, $1 \leq j \leq 1$) to some high dimensional space of features $\psi(y_j)$ and uses the concept of the hyperplane. Martin et al. in [157] used the SVM classifier and the results obtained showed the highest efficacy of SVM with an accuracy of 99%. ANN [144] is a widely preferred brain-inspired system used by Zeng et al. in [207] (RBF NN) to classify data from the Physionet dataset and gained an accuracy, sensitivity, and specificity of 96.3%, 96.7%, and 95.8%. DT is the tree-based model where each branch corresponds to a possible decision. Lima et al. in [38] studied the association between PD motor fluctuation severities with daily gait and achieved an accuracy of 98.5%. To avoid overfitting issues, RF is one of the best solutions that combine multiple DTs [177]. The concept of Adaboost was practiced by Kim et al. in [74] to classify PD and normal subjects and has shown the best sensitivity of 86%. Toro et al. in [134] performed a study to automatically diagnose the PD using SVM, ANN, and KNN, and accuracy from 86% to 92% was obtained. Apart from classification algorithms, regression models such as linear [192] and logistic [205] have been utilized for PD investigation which involves modeling between a dependent and an independent variable [150, 162].

The decrease in accuracy of the MLT when trained with a large amount of data leads to the development of a more supreme platform known as deep learning (DL) [26, 87] such as recurrent neural networks (RNN), convolutional neural networks, etc. [199]. The use of RNN can be seen in the study by Torvi et al. in [187] to determine PD FOG events. This platform has advanced the area of ML to a new level but also suffers high computational complexity, lack of transparency, etc.

5.2 Unsupervised Machine Learning paradigm (UMLP)

With an unsupervised machine learning paradigm (UMLP), the model is given the unlabeled dataset. In PD research, the k-means algorithm has been used to classify data based on similarity and distinctive nature. Boli et al. in [84] proposed a new wearable system with a K-means algorithm to differentiate FOG and non-FOG events and achieved an accuracy, sensitivity, and specificity of 93.2%, 92.4%, and 94.9% without any need for labeling the training set.

5.3 Semi-supervised Machine Learning paradigm (SSMLP)

SSMLP can be seen as the middle ground between supervised and unsupervised learning techniques. One of the examples is the fuzzy rule-based systems that have been also practiced in PD inspection [119]. A novel fuzzy logic approach was utilized by Ciabattoni et al. in [130] to study FOG in PD in which the logic controller is applied to compute the geometric center for the area under the membership function.

5.4 Probabilistic Machine Learning paradigm (PMLP)

A type of ML platform that uses the mathematics of probability theory to represent all forms of uncertainty and thereby apply inverse probability is known as PMLP such as Naïve Bayes (NB) and Hidden Markov model (HMM). Ghassemi et al. [57] applied template matching and hierarchical HMMs to perform PD analysis. Two gait tests were conducted wherein 2nd one HMM achieved an F-score of 96%. Similarly, Raykov et al. in [147] used an NB classifier to evaluate the PD and yielded the sensitivity and specificity of 0.85 and 0.97.

6 PD sensor datasets description

In PD research, the patients and normal controls data play a crucial job in the diagnosis of disease as well as in the overall performance of the model. There are several forms of data available depending on different data types such as signal, videos, images, text, and fluid thus comprising gait (e.g. Physionet, Daphnet, INIT), speech (Parkinson's speech, oxford PD detection, etc.) [120, 190], handwriting (HandPD, PaHaw (Parkinson's disease *handwriting database)*, etc.) [44, 67, 196] and bio-specimen (^{18}F-DMFP-PET DS, PPMI (Parkinson's Progression Markers Initiative)) [128, 166] based PD datasets acquired using different criteria including subject count, frequency/sampling rate, access link and other related information as tabulated in Table 4. Since this article is intensively based on the usage of gait biometrics to analyze signal-based data, therefore in this section, we briefly discussed only those PD datasets which are created using the sensor platform. INIT is also the gait-oriented dataset but it contains video data so it is not considered. Finally, there are six such datasets (one self-created and not public and the other five publicly available) used in the aforementioned studies, presented in Fig. 5, and are highlighted in the table with color to cope with the growing rate of PD.

Table 4 Summarizes various datasets for PD research emphasizing the focus on sensor-based PD gait datasets (colored). Acronym of terms used in the table: Freezing of gait (FOG), Dataset (DS)

References	Dataset Type	Dataset (DS) Name	Equipment	Subject's Count	Capt. Condition	Other info.	Access Link
Goldberger et al. [59]		• Physionet	Sixteen shoe sensors	93 PD, 73 HC	Straight ground walk for two min.	100 Hz	https://physionet.org/pn3/gaitpdb/
Sinziana et al. [99]		• CUPID Multimodal DS	Nine Inertial sensors	18 PD	Straight and cross walk, 180 and 360 deg. turns	128 Hz	https://joinup.ec.europa.eu/collection/ehealth/document/cupid-closed-loop-system-personalised-and-home-rehabilitation-people-parkinsons-disease-cupid
Bachlin et al. [11]	Gait (sensor) based	• Daphnet FOG DS	Inertial sensor	10 PD	Straight and random walk with 180 and 360 deg. turns	64 Hz	https://archive.ics.uci.edu/ml/datasets/Daphnet+Freezing+of+Gait
MASPARK [95]		• Maspark DS	Inertial sensor	92 PD	FOG detection activities at patient home such as moving from one room to other	200 Hz	https://futur.upc.edu/15557508
Hausdorff et al. [61]		• Hausdorff's Gait Dynamics DS	Floor (Force) sensors	15 PD, 20 HD 16 HC, 30 LS	A walk for five min. in 77 m long path	300 Hz	https://physionet.org/physiobank/database/gaitndd/
Yoneyama et al. [203]		• Self Created	Inertial sensor	12 PD, 11 HC	Level ground walk, spot stepping, asymmeterical walk, jumping actions	100 Hz	–
Ortells et al. [121]	Gait (vision) based	• INIT	A video camera (2D)	10 HC	Lateral view walk	800*400 px	http://www.vision.uji.es/gaitDB
Sakar et al. [161]		• Parkinson's Speech DS	Trust MC-1500 microphone	20 PD, 20 HC	26 voice samples while speaking sustained vowels	50 Hz- 13 kHz	https://ieeexplore.ieee.org/document/6451090
Arroyave et al. [120]	Speech based	• New Spanish Speech Corpus DS	M-Audio, Fast Track C400	50 PD, 50 HC	Morning time recording in ON-state	SR=96 kbps	http://www.lrec-conf.org/proceedings/lrec2014/pdf/7_Paper.pdf

References	Dataset Type	Dataset (DS) Name	Equipment	Subject's Count	Capt. Condition	Other info.	Access Link
OPDC [190]		• Oxford PD Detection DS	Smartphone	334 PD, 104 iRBD, 84 HC	Seven tasks to evaluate voice	–	https://archive.ics.uci.edu/ml/datasets/Parknsons
Weber et al. [196]		• HandPD	Spiral, meander images	74 PD, 12 HC	Six different activities to record 368 samples	–	http://wwwp.fc.unesp.br/~papa/pub/datasets/Handpd/
Drotar [44]	Handwriting based	• PaHaw	Intuos 4 M tablet	37 PD, 36 HC	Word writing task	200 Hz	https://www.sciencedirect.com/science/article/pii/S0933365716000063?via%3Dihub
Isenkul et al. [67]		• PD Spiral drawings using digitized graphics tablet DS	Wacom Cintiq 12WX graphics tablet	62 PD, 15 HC	Static, dynamic and stability handwriting tests	110 Hz–140 Hz	https://archive.ics.uci.edu/ml/datasets/Parkinson+Disease+Spiral+Drawings+Using+Digitized+Grap
Michael Fox Foundation [128]		• PPMI	VMAT-2 scans	24 PD and HC	Follow-up after 3,6,12 month, MRI tests	–	https://www.ppmi-info.org/access-data-specimens/download-data/
Segovia et al. [166]	Bio-markers based	• 18F-DMFP-PET DS	PET radiotracer	87 PD	Data collection after insertion of radiopharma-ceutical injection	128*128 matric of 2*2 mm voxels	https://www.frontiersin.org/articles/10.3389/fninf.2017.00023/full

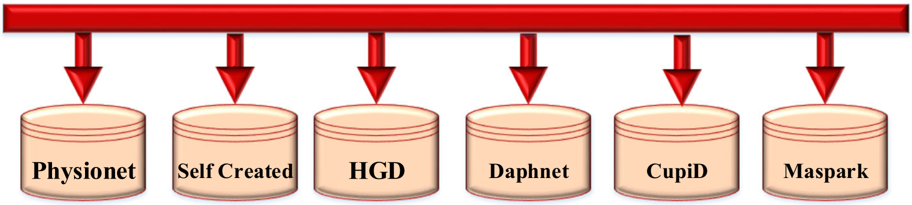

Fig. 5 Shows Sensor data-based PD Gait Datasets used in the literature

6.1 Physionet dataset

Physionet, the most popular PD signal gait DS, was given by Goldberger et al. in 2000 [59]. The dataset contains large data of VGRFs acquired from 93 subjects with PD and 73 HC via 16 shoe sensors (8 sensors each foot). To capture the data, the subjects were asked to perform a 2-minute walk on hurdle-free ground at a natural speed and the output of sensors was then recorded at 100 s/sec. Along with VGRF, the dataset also includes information about demographic data, PD severity levels, and other important measures. Wu et al. [205] used Physionet to evaluate the deviations among PD and HC and gained an accuracy of 95% using SVM. Similarly, other researchers of ref. [1, 72, 129, 174, 209] studied the gait variations in PD subjects using data from the most preferred Physionet to help clinicians for better PD detection.

6.2 CUPID multimodal dataset

CUPID is another sensor-based gait dataset that contains the data of 18 PD patients gathered using IMU. The sensors were attached to both the wrists of the subjects and straight, crosswalks were actioned with 180 and 360-degree turns while passing halls of hospitals and corridors [99]. The basic motive was to evaluate the relationship between hand motion and FOG events during gait. The 24-hour signal data in addition to nine IS was acquired via one galvanic skin sensor, an electrocardiogram, and a spectroscopy sensor. Many authors including [100] used such a setup (i.e. CUPID dataset) to analyze the FOG episodes during the walk and gained about 72% true prediction rate useful for PD investigation.

6.3 Daphnet FOG dataset

Daphnet FOG dataset was presented by Bachlin et al. in [11] which acts as a benchmark to evaluate the efficacy of various automated methods in FOG recognition. The signal data was captured using wearable IS at a frequency rate of 64 Hz. Three major tasks were performed by the subject i.e. straight walk, turning walk, and daily living activity task to keep a check on their gait performance. The dataset contains multivariate, time-series data with 237 instances and 9 attributes. The research work by Spyroula et al. in [94] used this DS to capture the acceleration data and to study the FOG effect on PD subjects. The used approach has given an accuracy of 97%. Similarly, ref. [7, 156] utilized Daphnet DS for PD classification to help clinicians.

6.4 MASPARK dataset

The collection of data in MASPARK Dataset was performed under the scope of ‘freezing in PD: Improving the quality of life with an automatic control system’ i.e. MASPARK project at 300 Hz

[95]. Almost 92 PD subjects were considered through the H&Y clinical rating scale. The data acquisition was done at the patient's home using wearable IS while performing many activities such as placing an object from one room to another, to represent FOG. Sama et al. in [162] used this dataset including 15 PD subjects with IS worn on their wrist. The evaluation of the subject's gait using Fast Fourier Transform and PCA achieved a sensitivity of 91.7% and specificity of 87.4%.

6.5 Hausdorff's gait dynamic (HGD) dataset

HGD Dataset or Gait in Neurogenerative disease dataset consisted of data collected from 15 PD, 20 Huntington's Disease (HD), 13 lateral sclerosis (LS), and 16 normal subjects. Force resistive sensors were employed at 300 Hz to capture signals during a 5-minute walk trailed on a 77 m long pathway [61]. So, by the force estimates, one can conclude the output which is proportional to the force recorded by these sensors. A proper format was used for the nomenclature of data present such as hunt, park, als and control means patients with HD, PD, LS, and normal subjects followed by a unique number. Proper suffixes were used to represent the file contents (e.g. Suffix 'rit' denotes right foot signal, 'let' means left foot signal, etc.). The dataset also includes demographic data of the subjects and disease severity rated using the H&Y scale. The use of such DS can be seen in a study by Pun et al. in [158] to analyze the SPT of PD subjects. The proposed system achieved an accuracy of 90% respectively.

6.6 Self-created datasets

Apart from the aforementioned publicly available datasets, a lot of researchers performed experimentation and evaluation on their own created datasets according to the requirements of the proposed model. The study by Arora et al. in [5] tried to analyze the gait variations in PD. The data from 10 PD and 10 HC was gathered using IS equipped smartphone and yielded a sensitivity of 96.2% and specificity of 96.9%. In another study by Wu et al. in [198], a U-shaped instrumented walkway was designed using flexible force sensor units. Almost 218 normal and 168 PD subjects were involved and their SPT gait features were extracted. The use of the created setup with RF showed a higher accuracy rate of 92.49%. Similarly, Cole et al. in [34] constructed their signal data by recruiting 10 PD and 2 HC. A 3-axis accelerometer device and an EMG sensor were attached to the subject's body to measure kinetic gait features. The proposed study gained a sensitivity of 83% and specificity of 97%.

7 Discussion

In this article, a thorough analysis of research work from the year 2010 to the current era has been done especially stressing sensor-based gait data for PD detection. Depending on the articles obtained and scrutinized, various findings have been reached that may be beneficial for future PD assessments. Here, in this portion of the article, we have made an effort to discuss such findings for every section presented above, with the help of proper analytical figures.

Section 4 of this article presents the outcome of the literature search performed on articles highlighting various sensors used for PD gait acquisition. Based on this systematic search strategy, we have come up with three major sensor categories i.e. wearable sensors (IS, INS, FS, CS, EMG, Hybrid), non-wearable sensors (FS), and sometimes the fusion of both. Concerning the usage aspect of such modalities, the art-of-literature reveals about 77% of research interest towards WST, 9%

towards NWST (14 articles), and 14% of studies used a combination of both the technologies. The reason behind heavy consideration of WST in this field is due to its more robust properties than NWST which are very expensive and need high maintenance and calibration. Amongst WST, out of a total of 160 research articles, 84 are IS oriented, 36 insole shoe-based, 2 on cloth sensors, and 1 on EMG sensor. Another important factor to consider was the efficacy of each sensor. The performance of a sensor-based gait system depends on various conditions i.e. type of sensor, number of sensors, and its pros and cons. A sensor should be easy to use, implement, and resource-efficient. From the exploration of existing data, it analyzed the IS has shown the highest performance (accuracy = 93%) followed by FS (about 87%) and other sensors. The reason for the superiority of IS observing its usage and high accuracy rate over others may include several advantageous factors such as simple deployment, cost-effectiveness, ease to carry on the body, low power requirements, high flexibility, portability, and better results. Besides, the signal data obtained using such sensors can be effective in solving complex gait problems which are being widely considered in PD research. Considering the combination of sensors, the fusion of IS and INS shows the best precision and recall when placed on the foot, back and leg together. Based on recent publications (2010–2020), the usage and performance comparison of each sensor can be visualized in the graph presented in Fig. 6.

The next part was to decide and select the machine learning paradigm which can provide more performance and reliability.

Section 5 talks about such concerns where various MLPs are looked over to find the most preferred and accurate one among SMLP, UMLP, SSMLP, and PMLP in PD diagnosis. From the literature, it is noticed that supervised learning has been pointed out the most. Considering the usage ratio of different MLTs from recent data, a pie-chart is constructed as presented with the help of Fig. 7. which indicates a high preference for SMLP i.e. 86.8% in which SVM classifiers are widely considered (21.3%) then ANN (16.5%) followed by RF (14%) and others. About 0.7% of UMLP, 1.3% SSLP, and 12.5% of PMLP are seen to be given a share in PD analysis. Also, focusing on the performance of these MLTs, the highest accuracy was shown by SVM (approx. 91%) as shown in Fig. 7. ANN also seemed to provide good results in this concern for PD investigation followed by KNN and other classifiers. The extraordinary characteristics of SVM such as high memory

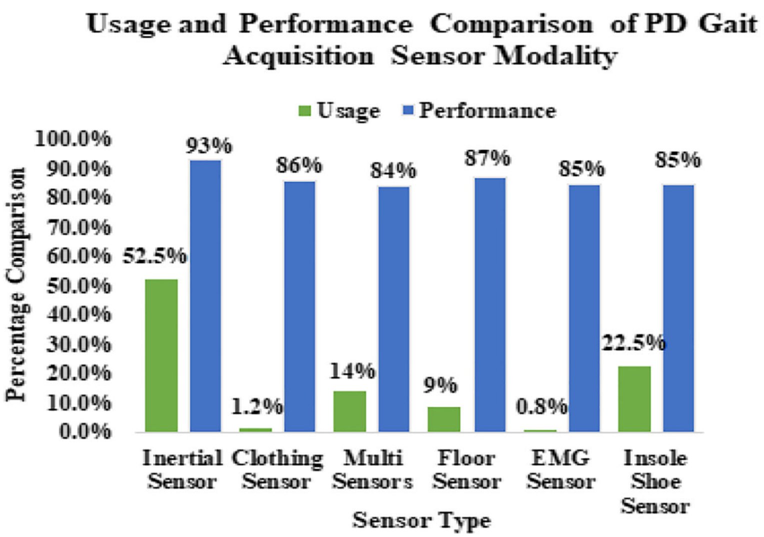

Fig. 6 Graphical representation of the percentage usage of different sensors and their performance comparison in PD data acquisition

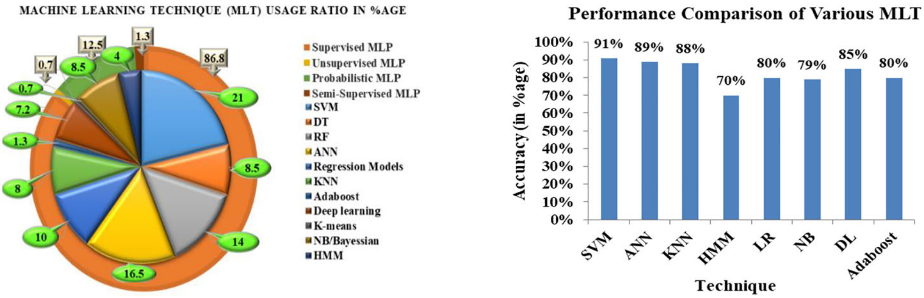

Fig. 7 Pie-chart representing the usage (left) and performance analysis (right) of various machine learning paradigms (MLP) used in PD analysis

efficiency, kernel trick, ability to deal with unstructured data, regularization features, high stability and performance rate, etc. make it popularly to be used in the classification of PD from normal subjects. ANN's capability to perform parallel processing, deal with incomplete data, high tolerance to a fault and gradual corruption also offer benefits in PD analysis. The best performance values such as accuracy, precision, recall, etc. depend on the type of gait data and the extracted gait parameters. Thus, considering the fusion of analysis techniques, sometimes the combination of SVM and ANN provides the best recall and precision and on the other side, the best values are obtained using the fusion of SVM, KNN, and NB.

The next section i.e. Section 6 discusses another important area that plays a major role in PD concern. The purpose was to find out what are the datasets available for PD, which datasets are publicly present and created by self, how many datasets were principally based on PD sensor gait data, and proceeding with them for further investigation. Thus, the final search concludes with six PD gait sensor datasets of which five are public and others are built by authors and are not public. Therefore, the critical analysis of considered articles from past years highlighted the use of self-created datasets by the authors in great number (almost 75.4%) as compared to others, as revealed by the graph given in Fig. 8. To achieve remarkable performance, the availability of a large amount of data is a necessary prerequisite. But determining the best dataset that fits into the model requirements (e.g. Severity levels data, real-time data, etc.) is sometimes a very challenging task. Therefore, most of the researchers preferred to build and use their self-made data by recruiting the

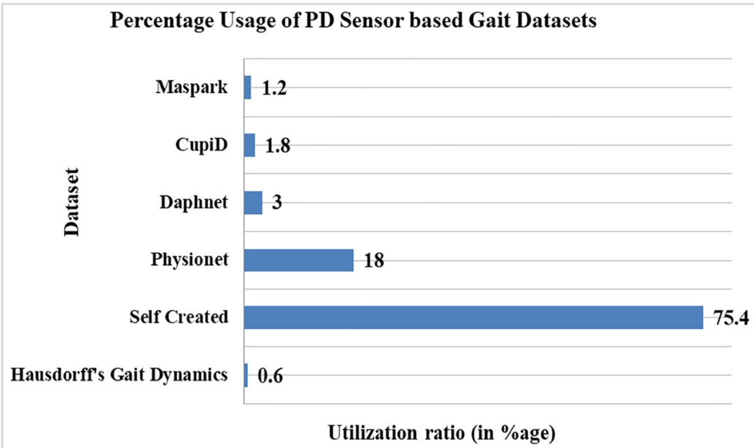

Fig. 8 The graphical presentation of %age usage of various sensor datasets preferred for PD investigation

PD and HC with proper consent from different areas to fulfill their study aim. However, using such a dataset can lead to a great performance but the unavailability of these datasets publicly is a major drawback. Moving to the publicly available datasets, Physionet has been significantly used (about 18%) due to its wide applications in biomedical research such as it provides free access- to the bulk of VGRF PD and comparable HC data (complex physiological signals), software libraries and also has assistance for its usage procedure. The entire data present has been properly reviewed and thus helping the clinicians to a large extent. Further, about 3% of work is analyzed to be based on Daphnet DS followed by CUPID (approx. 1.8%), MASPARK (almost 1.2%), and HGD (0.6%) datasets. Thus, both the self and publicly created datasets are contributing beneficially towards effective PD assessment. So once the data have been collected, and preprocessed, features are extracted, and then classifiers are used to classify abnormal and normal subjects. The literature has shown that certain parameters such as sensitivity, accuracy, specificity, F-score, etc. have been considered to validate the algorithm performance by comparing them with the others as presented in Table 2. Despite giving great efforts towards this area, several issues have been also confronted by the authors in their studies also highlighted in Table 2 which opens the new scopes for future research. The primary research problem to consider is the small sample size of PD patients and healthy controls i.e. small dataset size. Some researchers only considered PD patients and didn't compare their gait deviation measures with healthy ones while in other research studies; just the healthy subjects were considered just portraying the gait of diseased persons. Next is the issue of not considering PD severity levels into concern. As PD grows slowly and with its progression with time, its symptoms get worsen. So, it is necessary to consider all the severity levels for its early detection. In most of the works, the experiment is conducted only on one severity level of disease i.e. mild, moderate, or severe while ignoring the simultaneous comparison of all the severities. Thirdly is the bottleneck of the high cost of the sensor platform as well as the requirement of a heavy setup. Last is the problem of considering of few gait features for PD evaluation that can result in decreased accuracy of the system. Therefore, future work can be recommended and performed on such mentioned limitations of existing studies by enhancing the quality of the system by using more automated and highly collaborative techniques related to gait for more robust PD analysis. The use of a Vision-based framework (model-based approach) [78] and advanced deep learning for the purpose may be effective due to its high tolerance capability in several scenarios and may offer unique properties such as cost and time effectiveness, easy pre-processing, and background modeling, robust to noisy signal data, etc.

8 Conclusion

Parkinson's disease directly affects the functionality of the brain by degenerating dopamine neurons. Among all, gait biometrics can be seen as the effective mode for PD recognition due to its concealed and unobtrusive nature. The existing literature revealed various important aspects that need to be explored for better prediction of PD. Therefore, intending to explore the work and progress on PD via gait, this article comprehensively surveyed ten-year data from 2010 to 2020 focusing on Sensor-based (SB) technology. This survey article briefly summarized the basic concepts behind PD, its relation to a human gait, gait signal acquisition techniques, machine learning approaches used, and various gait datasets preferred over time.

The detailed analysis of state-of-art literature demonstrated a heavy inclination towards sensor technology for PD analysis. The majority of research works made use of wearable sensors in which inertial sensors (IS) have been in great demand due to their high-performance rate and other benefits including high flexibility. Further, this article extensively investigated the usage of various machine learning paradigms used in PD diagnosis and concluded that supervised MLP including SVM has been universally adopted covering 21.3%, and has achieved the highest performance in PD classification. Extending the previous studies, we surveyed all the gait datasets used in the research for PD inspection. Then the focus is diverted towards the utilization of only gait-based sensor signal DS and found about 75.4% of work surpassingly preferred the creation of self-made PD datasets to achieve the particular criteria of the framework proposed by the authors. Physionet DS, in publicly available datasets, is seemed to be given higher attention i.e. approx. 18% because of its easy accessibility feature.

With the intent to help researchers, academicians, and clinicians to make more effective PD recognition, this survey article provided a discussion to give insight on the outcome achieved in every section to analyze the uncovered areas in state-of-the-art. The analysis of work however shows the highest usage of IS but this technology is prone to certain drawbacks including high maintenance cost, wearing discomfort, mounting issues, heavy chances to get faulty results due to dust or any other blockage, harmful radiation effects, etc. that can cause major damage to a person's health. Therefore, an automated and sensor-free platform such as a vision-based (VB) approach needs to be applied in such analysis to diagnose PD effectively.

Further, the outcome of the survey revealed the non-availability of a robust VB PD gait dataset. This aspect can be focused on and fulfilled by creating cost-effective VB gait DS of PD subjects to perform such experimentation. Concerning MLP, SVM has been practiced the most but the amalgamation of the learning algorithms and use of advanced techniques such as DL, and ensemble learning is not taken into consideration. The diagnostic performance of the system can be improved significantly by combining multiple learning models. Another important analysis indicated that most of the studies lacked the evaluation of PD at different severity and also the comparison of PD subjects to NM gait and other such disorders is not focused. For an in-depth evaluation of a disease, it is worthwhile to measure gait deviations at each severity level. Further, different types of gait features in combination with robust body motion features can be extracted to improve the system's performance. So, the issues in past work performed on PD show several key points that should be focused on to carry out future work in this domain such as evaluating the VB paradigm, assessing PD using kinematic, spatiotemporal, and speeded up robust features despite just considering kinetic data, consideration of disease severities, increasing sample size of PD subject's, comparing multiple diseases also involving NM gait, implementing hybrid ML methods, etc. Thus, the results obtained and the suggestions made in this survey article can help researchers to build and extend the work by covering the highlighted aspects to perform reliable diagnosis and treatment of PD.

Appendix

The URLs for the images taken from the internet and used in this article are given as under.

Figure 2: http://theconversation.com/from-blood-letting-to-brain-stimulation-200-years-of-parkinsons-disease-treatment-75914 https://www.parkinsonsneurochallenge.org/sarasota-parkinsons-disease-resources/sarasota-what-is-parkinsons-disease.html https://en.wikipedia.org/wiki/Pathophysiology_of_Parkinson%27s_disease

Figure 5: https://www.tdk-electronics.tdk.com/en/2105790/company/press-center/press-releases/press-releases-tronics/inertial-sensors%2D%2Dminiaturized-mems-accelerometer-with-excellent-linearity/2105794 https://www.tekscan.com/applications/force-sensitive-insole https://commons.wikimedia.org/wiki/File:AMTI_OPT464508_force_plate.png http://www.

mobihealthnews.com/35705/athos-raises-12-2m-for-health-sensing-clothing https://www.aliexpress.com/i/32910049034.html https://www.openhardware.io/view/75/MyMultisensorCoinCell.

Also, all the acronyms used in the paper are given in Appendix Table 5.

Table 5 Glossary

Acronym	Meaning
ADL	Activities of Daily Living
AI	Artificial Intelligence
ANN	Artificial Neural Network
COFR	Coefficient of Friction
DS	Dataset
DT	Decision Tree
DL	Deep Learning
EMG	Electromyography
FI	Freezing Index
FOG	Freezing of Gait
GC	Gait Cycle
HC	Healthy Control
HMM	Hidden Markov Model
HNY	Hoehn and Yahr scale
HD	Huntington's Disease
IMU	Inertial Measurement Unit
IS	Inertial Sensor
KNN	K-nearest neighbor
LS	Lateral Sclerosis
LSTM	Long Short-Term Memory
ML	Machine Learning
MLP	Machine Learning Paradigm
MLT	Machine Learning Technique
MARG	Magnetic, Angular Rate, and Gravity
MRI	Medical Resonance Imaging
NB	Naïve Bayes
NN	Neural Network
ND	Neurological disorder
NWST	Non-Wearable Sensor Technology
PD	Parkinson's Disease
PPMI	Parkinson's Progression Markers Initiative
PSRN	Phase Space Reconstruction
PCA	Principal Component Analysis
PMLP	Probabilistic MLP
QOL	Quality of Life
RBF	Radial Basis Function
RF	Random Forest
RNN	Recurrent Neural Network
SSMLP	Semi-Supervised MLP
SB	Sensor-based
STFT	Short-Time Fourier Transform
SPT	Spatio-tempor
SIPL	Stepping in Place
SMLP	Supervised MLP
SVM	Support Vector Machine
UPDRS	Unified Parkinson's Disease Rating Scale
UMLP	Unsupervised MLP
VGRF	Vertical Ground Reaction Forces
WST	Wearable Sensor Technology

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

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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