A Survey of Artificial Intelligence in Gait-Based Neurodegenerative Disease Diagnosis

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Recent years have witnessed an increasing global population affected by neurodegenerative diseases (NDs), which traditionally require extensive healthcare resources and human effort for medical diagnosis and monitoring. As a crucial disease-related motor symptom, human gait can be exploited to characterize different NDs. The current advances in artificial intelligence (AI) models enable automatic gait analysis for NDs identification and classification, opening a new avenue to facilitate faster and more cost-effective diagnosis of NDs. In this paper, we provide a comprehensive survey on recent progress of machine learning and deep learning based AI techniques applied to diagnosis of five typical NDs through gait. We provide an overview of the process of AI-assisted NDs diagnosis, and present a systematic taxonomy of existing gait data and AI models. Through an extensive review and analysis of 164 studies, we identify and discuss the challenges, potential solutions, and future directions in this field. Finally, we envision the prospective utilization of 3D skeleton data for human gait representation and the development of more efficient AI models for NDs diagnosis. We provide a public resource repository to track and facilitate developments in this emerging field: https://github.com/Kali-Hac/AI4NDD-Survey.

CCS Concepts: • Computing methodologies \rightarrow Artificial intelligence; • Applied computing \rightarrow Health informatics; • General and reference \rightarrow Surveys and overviews.

Additional Key Words and Phrases: Artificial intelligence, Neurodegenerative diseases, Gait, Disease diagnosis

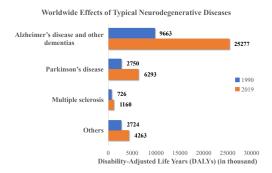
1 INTRODUCTION

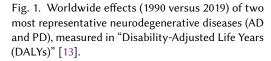
Neurodegenerative Diseases (NDs) such as Alzheimer's disease (AD) and Parkinson's disease (PD) are among the most widespread and devastating disorders affecting millions of people worldwide [1]. According to the Alzheimer's Disease Association [2] and the Parkinson's Foundation Report [3] in 2023, nearly 6.2 million people and 1 million people are diagnosed with AD and PD respectively in the United States. While in China, there are over 9.8 million AD patients [4], and it is estimated that Chinese PD patients will increase to 4.9 million by 2030, accounting for a half of the worldwide PD population [5]. From 1990 to 2019, the effected global population of AD, PD, and other neurodegenerative diseases (e.g., amyotrophic lateral sclerosis) has significantly increased (illustrated in Fig. 1), leading to a growing burden on global healthcare system. On the one hand, these diseases could result in pathological gaits and chronic pain in body joints, tissues, and nerves [6, 7], which severely reduce the flexibility, stability, mobility, and other functional capabilities of a human body. On the other hand, they also impose large psychological and financial burdens to patients and their family [8-10]. The treatment cost for these diseases has reached approximately USD 130 billion per year and further rise has been estimated [11, 12]. Therefore, it is essential to conduct an earlier and more reliable diagnosis of these diseases, so as to provide a timely proper treatment to mitigate the burden of societal and healthcare resources.

As one of the most essential motor symptoms associated with pathology, locomotion anomalies, especially observed in *human gait*, can reflect the incidence and progression of different NDs [14–16]. Taking AD, PD and **amyotrophic lateral sclerosis (ALS)** as an example, these diseases often cause patients to exhibit marked alterations and abnormalities in their walking patterns [17–26]. In general, compared with a normal gait (see Fig. 3), an impaired gait may display changes in speed,

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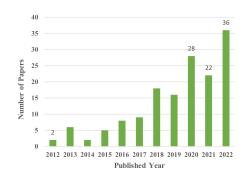


Fig. 2. The number of studies (from 2012 to 2022) relevant to gait-based neurodegenerative disease diagnosis using AI.

cadence, and limb moments within a gait cycle [19, 27, 28]. As shown in Fig. 4, the gait with a widened base, unsteadiness and irregularity of steps, and lateral veering (termed *Parkinsonian gait*) could suggest PD [19, 29]. In the case of advanced ALS, the patients may possess foot drop, where one foot flops down when lifting the leg, necessitating a higher lifting of the knee to prevent the toe from dragging on the ground (termed *neuropathic gait*) [30–32].

In recent years, driven by the widespread availability of body positioning technologies and economical portable devices to monitor human gait, gait-based NDs diagnosis (i.e., NDs classification, identification or prediction) has propelled a surge of attention across academic, industrial, and medical communities [33-45]. To perform NDs diagnosis from diverse gait data, the Artificial Intelligence (AI) technologies, especially Machine Learning (ML) and Deep Learning (DL) models, have been extensively explored and applied [34-37, 46, 47]. A common practice is to extract gait parameters (e.q., stride length, stance duration, gait cycle time) from sensor-based data such as vertical ground reaction force (vGRF) or vision-based data such as gait images, and leverage ML algorithms (e.g., support vector machine (SVM)) or deep neural networks to automatically recognize gait patterns associated with NDs to aid in their diagnosis [48-50]. These methods not only circumvent manual observation and assessment of NDs patterns in traditional diagnosis approaches, but also show immense potential in assisting healthcare professionals to diagnose and treat these diseases more efficiently [36, 37]. In this paper, we systematically review recent advancements of utilizing AI to help diagnose NDs from human gait. In particular, our work focuses on the diagnosis of *five* most prevalent and typical NDs (PD, AD, ALS, **Huntington's Disease (HD)**, Multiple Sclerosis (MS)) and all existing AI models that can help diagnose these diseases (i.e., identify, classify or predict NDs) from human gait data. A total of 2069 potentially relevant articles, including 14 survey papers, are found from three databases (PubMed, Web of Science (WoS), Google Scholar). We first screen these articles by titles and abstracts based on the pre-defined inclusion criteria, and then conduct a full-text assessment to exclude irrelevant papers. Finally, 164 of 2069 papers are selected to be included in our survey.

1.1 Objectives and Contributions

The objectives of this survey can be encapsulated in the following six key questions (Q): (Q1) How is human gait associated with NDs? (Q2) What is the process of AI-assisted NDs diagnosis from gait data? (Q3) What are various gait data types, gait collecting approaches, and AI model types for NDs diagnosis? (Q4) What are state-of-the-art AI models and their performance results (e.g., diagnostic





Fig. 3. Different phases of normal human gait with coordinated movements of legs and arms. Right: Examples for hemiplegic gait.

Fig. 4. Examples for hemiplegic gait (left), Parkinsonian gait (middle), and neuropathic gait (right) [51].

accuracy) in gait-based NDs diagnosis? (Q5) What are the main challenges and promising future directions of this field? (Q6) Is it feasible to exploit 3D skeleton data to represent human gait and build AI models for NDs diagnosis?

The contributions of this work are as follows. We provide a systematic literature review of existing AI technologies for gait-based diagnosis of five most widespread NDs (PD, AD, ALS, HD, MS). We formulate the general process of AI-assisted gait-based NDs diagnosis, and present a systematic taxonomy of used gait data and AI models. Our survey demonstrates how human gait features can be a crucial indicator for diagnosing various NDs, and highlights the significant role of current AI models in facilitating the automation of this diagnostic process. Moreover, we analyze the statistics of existing studies to reveal the current development and future trend of this area, and comprehensively discuss the key challenges in utilizing AI for gait-based NDs diagnosis, such as scarcity and imbalance of gait data, lack of multiple data modalities and sources, and unreliable AI model designs (e.q., limited generalizability, efficiency, and interpretability). We elaborate on these issues and delve further into their potential solutions, related technologies, and future research directions. To the best of our knowledge, this is the most elaborated survey on this topic, and it also provides a practical roadmap for future investigations of AI technologies for NDs diagnosis. As our research vision, 3D skeleton data, which is an emerging generic and scalable data modality, is for the first time explored to characterize gait patterns associated with NDs. We empirically present a 3D skeleton based framework for NDs diagnosis, paving the way for more efficient gait representations and AI model learning in this field.

1.2 Organization

Aligning with the above objectives, we organize the rest of this survey as follows. Sec. 2 provides the definitions of fundamental concepts related to gait, NDs, and gait-based NDs diagnosis (Q1). It also presents an overview for AI-assisted gait-based NDs diagnosis process (Q2), and a systematic taxonomy of gait data types, gait collection technologies, and AI model types (Q3). Sec. 3 elaborates on the literature screening result with a multi-faceted statistics analysis, and provide a content summary of included studies (Q4). In Sec. 5, we discuss the main challenges, potential solutions, and several promising directions in this area (Q5), while proposing our research vision on exploiting 3D skeleton data for NDs diagnosis (Q6). Finally, we conclude this survey in Sec. 6.

2 PRELIMINARIES

In this section, we first provide the definitions of frequently-used basic concepts related to our topic (see Sec. 2.1) and introduce abnormal gait types that are correlated to NDs (see Sec. 2.2). Then, we provide an overview of the AI-assisted diagnostic of NDs based on human gait, and display the

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workflow of AI learning in this process (see Sec. 2.3). A systematic taxonomy of gait data types, gait collecting technologies, and AI model types used in this area is also provided in Sec. 2.4 and 2.5.

2.1 Basic Concepts

- (1) **Gait**: It is defined as a mechanism of locomotion, which contains *rhythmic* and *coordinated* movements of different limbs to enable the forward progression of the body [52, 53] (as shown in Fig. 3). The gait of a person typically consists of the motion of lower extremities and their correlated posture in upper limbs or torso, which normally requires a synthesized coordination of nerves, skeletons, and muscles [54]. Owing to this reason, the abnormality or impairment of gait can serve as an effective indicator of potential body pains or diseases caused by physical injury, aging or related disorders [43, 55].
- (2) **Gait Assessment**: It is a broad observational assessment of the patients' gait patterns, which is typically performed by doctors or experts. This process mainly focuses on assessing patient's walking behaviors and analyzing their abnormalities in motion coordination and rhythms. The gait assessment data including sensor, vision, and their combined data are recorded and collected by professional medical instruments in hospitals or laboratories, and some other forms of data such as gait self-reports, medical history, and psychological examination to help better analyze the reason behind abnormal gait.
- (3) **Neurodegenerative Diseases (NDs)**: The diseases with progressive loss of nerve cells, neuron structure, or/and their functions in the brain or peripheral nervous system are collectively termed NDs. The focus of this study is on the five most common NDs, including AD, PD, ALS, HD, and MS.
- (4) **Diagnosing Diseases** (e.g., **NDs**) **from Gait**: It is a process of identifying, classifying or predicting a certain disease according to the assessment of gait. For traditional diagnostic methods, this process is executed based purely on physician's medical experience (e.g., using golden standards), assessment, and decision. For AI-based methods, we can input all gait-related data into the model to automatically learn, assess, and identify the abnormality of gait to predict or classify diseases.
- (5) **Disease Management**: General disease management methods consists of therapies using a combination of medications, physical therapies, psychological therapies, interventional procedures or surgeries. For NDs, the management is often disease-specific with focus on either the disease pathogenesis or symptoms experienced [56].

2.2 Pathological Gaits

- 2.2.1 Neurodegenerative Disease Related Gaits.
 - Neuropathic gait is characterized by foot drop, where one foot flops down when lifting the leg, necessitating a higher lifting of the knee to prevent the toe from dragging on the ground during walking (see Fig. 4). Neuropathic gait may be a symptom of amyotrophic lateral sclerosis (ALS), multiple sclerosis (MS) or peripheral neuropathy.
 - **Parkinsonian gait** can be identified by a forward stoop with the back and neck bent. This results in patients with Parkinson's disease tending to take smaller steps.
 - Choreiform gait is characterized by the irregular, jerky, involuntary movements in all extremities. This gait can be seen in certain basal ganglia disorders including Huntington's Disease (HD), Sydenham's chorea, and other forms of chorea, athetosis or dystonia.
- 2.2.2 Other Disease-Related Gaits. Apart from the above NDs-related gaits, there are many other pathological gaits reflecting different body injuries or diseases (detailed in appendices), such as myopathic gait (e.q., for muscular dystrophy, muscle disease, spinal muscle weakness), ataxic gait

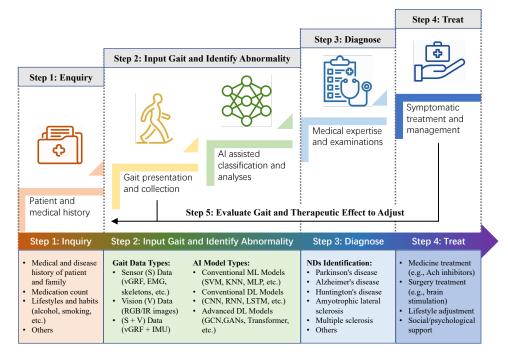


Fig. 5. Overview for the process of Al-assisted gait-based neurodegenerative disease diagnosis.

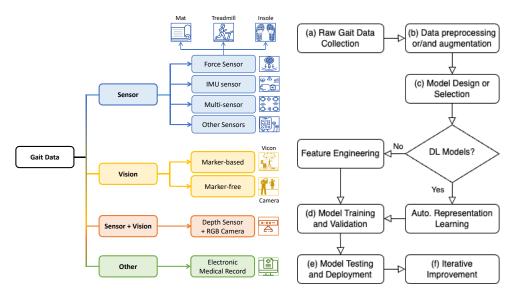


Fig. 6. The taxonomy of gait data types used for Al-assisted NDs diagnosis.

Fig. 7. Overview of AI model learning workflow.

(e.g., for alcohol intoxication, brain injury), hemiplegic gait (e.g., for stroke), diplegic gait (e.g., for cerebral palsy, stroke, head trauma), sensory gait (e.g., for tabes dorsalis, diabetes).

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2.3 Overview of Al-assisted Gait-Based Neurodegenerative Disease Diagnosis

The general process for AI-assisted NDs diagnosis based on human gait is presented in Fig. 5. It can be summarized as five steps: (1) Enquiry; (2) Input gait and identify abnormality; (3) Diagnose; (4) Treat; (5) Evaluate therapeutic effect for adjustment, which can be illustrated as follows:

- (1) **Enquiry**: Doctors enquiry the medical and disease history of a patient as diagnostic priors or clues for next-step disease risk assessment, disease diagnosis, and medication management.
- (2) **Input Gait and Identify Abnormality**: The gait data (*e.g.*, walking videos) of the patient are collected and inputted into a pre-trained AI model specifically designed for NDs diagnosis. In this process, the AI model assists doctors to automatically analyze the abnormal gait patterns to predict the most likely NDs (if present) in the patient.
- (3) **Diagnose**: Doctors and medical experts synergize their domain expertise and results of other physical or neurological examinations to clinically diagnose the disease.
- (4) **Treat**: Based on the diagnostic result, a symptomatic treatment is conducted on the patient to halt disease progression, reduce pain, and improve life quality.
- (5) **Evaluate Gait and Therapeutic Effect to Adjust**: The therapeutic effect is recorded into the medical history in step (1), and doctors perform the next-round assessment with step (2) and (3) to optimize the symptomatic treatment and disease management in step (4).

It is noteworthy that exploiting AI models for gait analyses and classification (*i.e.*, Step 2) is the main part of the gait-based NDs diagnosis process. It includes the workflow of designing, training, and validating AI models using pre-collected gait data. As shown in Fig. 7, the AI learning workflow can be divided into (a) raw gait data collection, (b) data preprocessing or/and augmentation, (c) model design or selection, (d) model training and validation, (e) model testing and deployment, and (f) iterative improvement (*e.g.*, model fine-tuning using more data). For conventional ML models, feature engineering is usually required after step (c) to manually extract discriminative feature such as gait descriptors. For DL models, the design of models (*e.g.*, neural network architectures) (step (c)) and the sufficiency of training data (step (a) and (b)) are often the two most essential determinants of model performance. Since more high-quality training data can better guide the model optimization, extend the learnable feature space, and improve the generalization ability (*i.e.*, higher performance on new testing data) of the model, it is feasible to collect more gait data while using effective data augmentation strategies (*i.e.*, generate more augmented training samples) to iteratively boost the model performance (detailed in Sec. 5.1).

2.4 Gait Data Taxonomy

We present the taxonomy of existing gait data types in Fig. 6 by categorizing them into four main classes based on their collection modalities. We elaborate on the common techniques used in each modality, along with their corresponding merits and demerits.

- **Sensor Modality**: Advancement in sensor technologies allows its application in various tasks such as gait analysis, action recognition, etc. The sensors explored among the collected papers offer various advantages and could be classified into these four types, including force, inertial, hybrid, and other less prevalent sensors [41, 57–60].
- (1) **Force Sensor (FS)**: There are mainly two types of force or pressure capturing approaches. The first is to use non-wearable floor-mounted devices (*e.g.*, force mats, treadmill) to measure **vertical Ground Reaction Force (vGRF)**, moments, or plantar pressure profiles [41]. In a laboratory setting, these stationary floor-mounted devices are sufficient for precise data collection. However, since those devices are often bulky, operating-costly, and expensive, it's not often clinically applicable. Therefore, researchers develop some small wearable devices (*e.g.*, insole) whose application in the field has became a popular choice and risen

- significantly in the past decade, due to its portable features and cheap installment, at the cost of less accuracy and reliability compare with the floor-mounted ones [61, 62].
- (2) **Inertial Sensor**: Also termed as **Inertial Measurement Unit (IMU)**, is often attached to limb segments (*e.g.*, foot) [63] or embedded in wearable devices (*e.g.*, smartwatch) to capture dynamic motion (*e.g.*, 3D-acceleration) of the subject [64, 65]. These sensors or devices record the repeating pattern of gait signals generated by the locomotion of the subjects. These signals will then be interpreted with various algorithms for the intended tasks, including gait event detection, kinetic or kinematic parameters estimation, and gait classification.
- (3) Multi-Sensor: These sensors typically combine various types of sensors for a more comprehensive data collection. Among the surveyed papers, studies such as [66–68] utilize both IMU sensors and Force Sensitive Resistors (FSRs), while [69] employs Electroencephalogram (EEG) sensors and FSRs. These combinations harvest the strengths of each sensor type hence help enhancing the reliability and accuracy of gait event detection and classification.
- (4) Other Sensors: Sensors included in this category are less prevalent and exploited among collected papers. However, these sensors still play an important role in providing a more full-sided understanding of the human gait. For instance, EEG sensor is used to measure the brain electrical activity signals data which can be used to analyze brain activity patterns that may correlate with specific gait abnormalities [69–71]. Electromyography (EMG) sensor is another useful sensor which is used to measure the electrical activity produced by muscles whose activities are controlled by the motor neurons [72]. Since NDs patients suffer from the degeneration of nerve cells, they manifest significantly different muscle electrical pattern from healthy subjects [36]. Therefore, their EMG data can be utilized to aid NDs diagnosis [72].
- Vision Modality: The vision modality employs optoelectronic Motion capture (Mocap) systems, including various types of cameras (e.g., Infrared (IR) Camera [73]), to capture the locomotion of subjects during walking. It's used to overcome the limitations of the traditional clinical examination which purely depends on the physicians' naked eyes. Depends on the precision requirement of the video data, the vision modality could be further divided into two sub-categories, namely marker-based and marker-less systems [47].
- (1) **Marker-based**: This approach is developed at an early stage when the cameras are not advanced enough for precise motion capture. Therefore, these Mocap systems (*e.g.*, Vicon) use *reflective* markers to help capture targets' movement in the images more precisely. The advantages of using the marker-based approach are that they're highly accurate and provides exact location of the body landmark. These advantages hence make this modality a gold standard in the field. However, this method requires attaching markers to the body, leading to additional expenses and the potential of alter the gait [74–76].
- (2) Marker-free: Due to the limitations of the marker-based approach and the development of the camera technology, the marker-free approach comes into appearance. This approach derives corresponding features from the target's gait video without using any markers. Another highlight is the emerging application of smartphones in this field, which, despite being in its infancy, offers new insights due to its advantages like compactness, portability, and affordability. However, it still faces challenges such as lower accuracy in tracking movements of body parts compared to the gold standard (*i.e.*, marker-based approaches).
- Sensor+Vision Modality: This modality could also be referred to as multi-modal modality. In comparison with single-modal approaches, although the latter ones have their own merits and show some promising results, this combined approach unleashes a bigger potential, such

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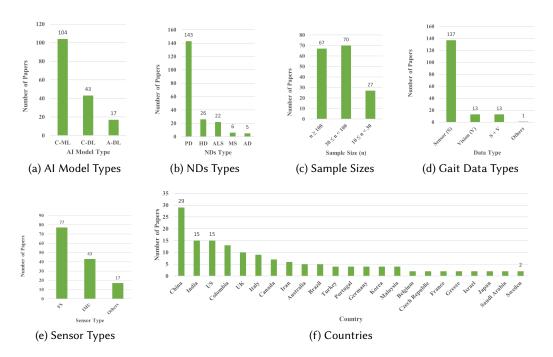


Fig. 8. Statistics of the included papers with different (a) Al model types, (b) NDs types, (c) experimental sample sizes, (d) gait data types, (e) sensor types, and (f) countries. We show the lowest and top three quantities in (f). Papers of different years are shown in Fig. 2. Detailed analyses are provided in Sec. 3.2.

as providing richer data and more comprehensive features, capturing more subtle changes in gait, improving recognition performance [71, 77, 78]. In particular, the application of Microsoft Kinect system has gain a tremendous amount of attention in the field due to its utilization of both depth sensor and RGB camera. This integration enables a more accurate estimation of the gait parameters without sacrificing the advantages mentioned in the marker-less vision modality. More specifically, using conventional cameras to estimate skeleton coordinates produces coarse results. However, when employing the depth sensor, the spatiotemporal features can be precisely derived from the skeleton joints' coordinates obtained using it. The precision and efficacy of using Kinect has been verified in many studies which compare the results with the gold standard (marker-based vision) approach. Nevertheless, one limitation of current Kinect system is that its precision reduces as the subject walks further away from the camera, resulting in a width and length-limited data collection space [79–82]. Besides the RGB-D camera approach, there are also other combinations of these two modalities. For example, Tahir et al. fused a marker-based IR camera and a force-sensitive platform [83], while Chatzaki et al. utilized a conventional camera, IMU, and a force platform [78]. Additionally, Zhao et al. merge some vGRF and IMU sensors with Kinect [77].

• Other Modalities: Trabassi *et al.* use Electronic Medical Record (EMR) which contains various patient-related features and medical history data that are indicative of early PD symptoms or risk factors as well as the first diagnosis of gait or tremor disorders to create prediction models [84].

2.5 Al Model Taxonomy

The AI models used in existing studies can be mainly classified into three types based on the their feature learning manners and model architectures:

- Conventional Machine Learning (C-ML) Models: C-ML models primarily use manual feature extraction and data-driven statistical techniques for pattern recognition. Examples include Decision Trees (DT) [85], Support Vector Machines (SVM) [86], Linear Regression (LR) [87], Naive Bayes (NB) [88], K-Nearest Neighbors (KNN) [89], Random Forest (RF) [90], etc. Artificial neural networks with very few layers such as 3-layer multilayer perceptrons (MLP) [91] are also viewed as C-ML models. It is noteworthy that deep learning is commonly viewed as an important branch of machine learning, thus we use "conventional machine learning" to denote *classic* machine learning models apart from deep learning models.
- Conventional Deep Learning (C-DL) Models: Defined as neural networks with deep layers (typically more than 3 layers) or commonly-used deep learning backbones for automatic feature extraction and representation learning from data. Examples include Convolutional Neural Networks (CNN) [92], Recurrent Neural Networks (RNN) [93], vanilla long short-term memory (LSTM) [94], ResNet [95], etc.
- Advanced Deep Learning (A-DL) Models: Incorporates more complex or novel architectures, advanced training techniques, and elements of other AI fields like reinforcement learning into classic deep networks. Examples include graph convolutional networks (GCN) [96], Transformers [97], Generative Adversarial Networks (GANs) [98], etc.

3 SURVEY STATISTICS AND ANALYSES

In this section, we showcase the results of our literature searching and screening, with a statistical analysis of selected papers to shed light on the current development and future trend of this field.

3.1 Study Selection

We adopt the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) [99] to conduct our survey, and the flow diagram of PRISMA is provided in the appendices. We summarize the literature selection process as follows: During the paper identification stage, we retrieve 840 records from PubMed, 895 records from WoS, and 596 records from Google Scholar. By comparing the collected records across these three databases, a total of 2069 records remain after 262 duplicate records are removed. In the paper screening stage, after screening the titles and abstracts of the remaining 2069 papers according to the inclusion criteria, 243 articles are further selected for the full-text assessment. Finally, after an in-depth review of the full texts of these selected papers, 103 articles are excluded and 140 regular articles are included in this survey for further information extraction and content summarization. The list of excluded papers from the full-text screening stage, along with the reasons for their exclusion, is detailed in our appendices. Moreover, 14 eligible survey papers [34–44, 46, 47, 100] are found in the screening stage. From these survey papers, we identify another 99 potentially-matched articles via screening their titles and abstracts. After the full-text assessment, we include 24 regular articles from those. In summary, we include a total of 164 eligible articles, comprising 140 from the academic databases and 24 from survey papers, in our survey.

3.2 Statistics of Selected Papers

To provide an intuitive overview for all 164 selected papers, we present the distribution of papers from different aspects: year of publication (see Fig. 2), country of publication, type of NDs studied, type of gait data, type of AI models, and size of samples (see Fig. 8).

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3.2.1 Distribution of Publication Years. As presented in Fig. 2, from 2012 to 2022, the AI-assisted NDs diagnosis from human gait has attracted growing attention in the research community. Especially in the last three years, the annual number of related research papers has exceeded 21, reaching a peak of 36 in 2022.

- 3.2.2 Distribution of Countries. The results in Fig. 8f suggest that China, India, and the United States (US) are the top 3 contributing countries to this research field, with 29 papers (17.7%), 15 papers (9.1%) each from India and the US, respectively. This approximately matches the real-world situation where Chinese and Indian NDs patients constitute the two largest groups globally, thus a broader research resources and efforts are put into this important topic. It is also observed that, within the top 10 countries with the most publications, the number of developed countries (US, UK, Italy, Canada, Australia) participated in this research field is equal to that of the developing countries (China, India, Colombia, Iran, Brazil). However, among these 10 countries, the total publications from developing countries constitutes 59.6% (68 publications), whereas that from developed countries accounts for only 40.4% (46 publications).
- 3.2.3 Distribution of ND Types. Fig. 8b shows the numbers of papers focused on different NDs types. Note that the studies containing diagnosis of multiple NDs (19 articles) are also included into each NDs type (e.g., a study simultaneously diagnosing PD, HD, and ALS are counted as one PD/HD/ALS study). The statistics show that PD receives the most research focus among all the NDs, including a total of 143 articles (87.2%). The second most studied ND's type is HD with 26 papers (15.9%), while there are 22 (13.4%), 6 (3.7%), 5 (3.0%) papers focused on ALS, MS, and AD respectively. Interestingly, although AD is the most populated diseases among all NDs (see Fig. 1), the study of its diagnosis based on gait has yet to receive much attention, possibly because other NDs patients, such as PD patients, may exhibit more evident abnormal gaits that can be exploited to perform more reliable diagnosis. Promisingly, more and more studies [48, 77, 101–106] have demonstrated the feasibility of leveraging gait data to identify HD, AD, ALS, and MS, therefore a deeper exploration of these research directions should be conducted.
- 3.2.4 Distribution of Gait Data Types. As reported in Fig. 8d, 137 studies (83.5%) utilize sensors including Inertial Measurement Units (IMUs) and force/pressure sensitive resistors (FSRs) to collect vertical Ground Reaction force (vGRF) data. These sensors can capture detailed and dynamic information about body movements and forces involved in walking to analyze gait cycles and parameters. There are 13 studies (7.9%) focused on vision-based devices such as RGB cameras and infrared cameras to extract gait patterns from videos. A same number of studies (13 articles) combine both sensor-based and vision-based devices to collect multi-modal gait data for learning.

Fig. 8e further shows the distribution of sensor types used in 137 sensor-based studies: The force sensors (FS) (e.g., force/pressure sensitive resistors) and IMUs are the two most widely-used sensor types, occupying 56.2% (77 studies) and 31.4% (43 studies) respectively. For other sensors (17 studies), there are 5 studies combining both FS and IMUs as gait data sources, while 5 studies utilize gait analysis system (GAS) (e.g., mats, walkways, treadmills). The low-cost and non-invasive motion capture device, Kinect [82, 107], is also used as both a sensor and a vision-based device for gait data collection (2 studies). We provide a further discussion on exploiting sensor-based (e.g., Kinect-based) 3D skeleton data for NDs diagnosis in Sec. 5.2.

3.2.5 Distribution of AI Models. As shown in Fig. 8a, in the past decade, only 17 articles (10.4%) propose novel A-DL models for NDs diagnosis from gait, while most of the studies use conventional AI methods such as C-ML and C-DL with 104 (63.4%) and 43 articles (26.2%) respectively. However, most conventional AI models possess limited performance on large-scale medical data, thereby underscoring the challenge and urgency of developing more advanced AI models in this field. Such

Table 1. Existing studies (P-1 to P-124) of Al-assisted PD diagnosis based on gait. We summarize the input data, main Al model, experimental sample size, and reported accuracy (range) of each study. Quality scores (S_Q) that evaluate the advancement of Al models, comprehensiveness of comparison, and sufficiency of samples are computed.

ID	Study	Year	NDs Types	Data Type	Device/Data	AI Model	Sample Size	Accuracy (%)	Quality (SQ)
P-1	[83]	2012	PD	Senosr+Vision	Infrared camera+Replective markers	NN, SVM	32	98.2	0.45
1-1	[03]	2012 115		Seliosi + v Isioii	+Force sensitive resistor	1414, 5 7 171	32	70.2	0.45
P-2	[72]	2013	PD	Sensor	EMG	SVM	10	90.0	0.33
P-3	[65]	2013	PD	Sensor	IMUs	AdaBoost	173	81.0	0.56
P-4	[108]	2013	PD	Senosr+Vision	Infrared camera+Replective markers +Force sensitive resistor	DT	32	100.0	0.45
P-5	[109]	2013	PD	Sensor	vGRF	SVM	62	81.5-83.4	0.56
P-6	[110]	2013	PD	Sensor	IMUs	RF, DT, NB	16	96.1	0.33
P-7	[111]	2014	PD	Sensor	Force sensitive resistor	LS-SVM, HMM	31	90.3	0.67
P-8	[64]	2014	PD	Sensor	IMUs	RF	20	98.0	0.33
P-9	[49]	2015	PD	Sensor	vGRF	KFD, BA, KNN, SVM, RF	49	82.0-92.6	0.44
P-10	[80]	2015	PD	Vision	RGB Camera	NN	51	97.2	0.67
P-11	[112]	2015	PD	Sensor	vGRF	KNN	166	83.0	0.56
P-12	[113]	2015	PD	Senosr+Vision	Kinect (Camera+Depth sensor)	Bayesian probability classification	51	94.1	0.44
P-13	[60]	2016	PD	Sensor	IMUs+Force sensitive resistor	LDA, SVM, ANN	166	83.3-90.0	0.56
P-14	[114]	2016	PD	Sensor	vGRF	Deterministic learning, RBF-NN	166	91.6-99.4	0.78
P-15	[115]	2016	PD	Sensor	Force sensitive resistor	Neural networks	165	87.9	1.00
P-16	[116]	2016	PD	Sensor	vGRF	BN, NB, MLP, LR, RF, FT, etc	166	87.6-88.9	0.78
P-17	[117]	2016	PD	Sensor	Force sensitive resistor	Q-BTDNN	166	90.9-92.2	1.00
P-18	[118]	2017	PD	Sensor	IMUs	KNN	580	80.8-90.2	0.56
P-19	[119]	2017	PD	Sensor	IMUs (Smartphone)	RF	50	87.0	0.44
P-20	[57]	2017	PD	Sensor	IMUs+vGRF	SVM, KNN, RF, DT	47	93.6	0.67
P-21	[120]	2017	PD	Sensor	vGRF	SVM	31	90.3-100	0.67
P-22	[121]	2017	PD	Sensor	Walkway system (GAITRite)	RF, RBF-SVM	80	85.0	0.44
P-23	[122]	2017	PD	Sensor	vGRF	Tensor decomposition	165	100.0	0.56
P-24	[123]	2017	PD	Sensor	vGRF	GLRA, SVM	58	82.8-84.5	0.44
P-25	[124]	2018	PD	Sensor	IMUs	MLP, DBNs	45	93.5-94.5	0.56
P-26	[125]	2018	PD	Sensor	Kinect	LR, NB, RF, DT	60	61.0-82.0	0.44
P-27	[50]	2018	PD	Sensor	vGRF	SVM	166	94.8	0.56
P-28	[126]	2018	PD	Sensor	IMUs	NB, LDA, k-NN, DT, SVM	50	68.9-75.6	0.44
P-29	[67]	2018	PD	Sensor	IMUs+Force sensitive resistor	Continuous Hidden Markov Model (cHMM)	26	0.98 (AUC)	0.44
P-30	[127]	2018	PD	Sensor	IMUs	SVM, RF, NB	90	78.0-96.7	0.67
P-31	[122]	2018	PD	Sensor	vGRF	Tensor model	165	86.2	0.78
P-32	[128]	2018	PD	Sensor	IMUs	SVM, KNN, DT, NB	51	89.1	0.67
P-33	[129]	2018	PD	Sensor	vGRF	LR, DT, RF, SVM, KNN	166	93.1	0.56
P-34	[130]	2018	PD	Sensor	vGRF	SVM, PSO	135	87.1-95.7	0.56
P-35	[75]	2018	PD	Vision	Camera+Reflective markers	Minimum redundancy maximum relevance	40	98.5	0.44
P-36	[131]	2018	PD	Sensor	Kinect	(MRMR), PCA Fisher's Score (FS)	40	75.0-85.0	0.33
P-37	[132]	2018	PD	Sensor	vGRF	Locally Weighting Random	165	99.0	0.89
D 20	[122]	2010	DD	Canaan	wCDE	Forest (LWRF)	6.4	00.6	0.67
P-38	[133]	2018	PD	Sensor	vGRF	RBF-SVM	64	90.6	0.67
P-39 P-40	[134] [79]	2018	PD PD	Sensor	vGRF Camera (Kinect)	LSTM, CNN	166 30	93.9-98.6	0.89
P-40	[/9]	2019	PD	Vision	Camera (Kinect)	SVM, ANN	30	89.4	0.44

development requires more efforts and cooperation from AI scientists and healthcare professionals in the future.

3.2.6 Distribution of Sample Sizes. As shown in Fig. 8c, 137 papers (83.5%) conduct their experiments with more than 30 samples (i.e., number of patients plus number of controls), and the number of papers that possess small-size samples ($10 \le n \le 30$) only occupies 16.5% (27 papers). This suggests that most AI models require a relatively larger size of samples and gait data to obtain satisfactory performance, otherwise it might be insufficient for obtaining reliable diagnosis. This also aligns with the recent advancements of medical deep learning based AI models that necessitate massive medical labeled data.

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Table 2. Continued table of Table 1 for Al-assisted PD diagnosis based on gait.

ID	Study	Year	NDs Types	Data Type	Device/Data	AI Model	Sample Size	Accuracy (%)	Quality (S _O)
P-41	[135]	2019	PD	Sensor	IMUs	SVM, RF	196	0.805-0.878 (AUC)	0.56
D 40	[127]	2010	PD	C	vGRF	KNN, DT, RF, NB,	1/5	445	
P-42	[136]	2019	PD	Sensor	VGRF	SVM, K-Means, GMM	165	69.0-90.0	0.78
P-43	[81]	2019	PD	Vision	Camera (Kinect)	Conv LSTM	182	64.0-83.0	0.67
P-44	[127]	2019	PD	Sensor	Dat	SVM, RF, AdaBoost,	30	92 6 06 7	0.44
r-44	[137]	2019	FD	Selisoi	IMUs	Bagging, NB	30	83.6-96.7	0.44
P-45	[69]	2019	PD	Sensor	EEG	RF, SVM, KNN	41	85.7	0.44
P-46	[138]	2019	PD	Sensor	IMUs	CNN	84	97.6	0.56
P-47	[139]	2019	PD	Sensor	Force sensitive resistor	SVM	166	88.9-100.0	0.78
P-48	[140]	2019	PD	Sensor	Walkway system (GAITRite)	RF, SVM, LR	303	97.0	0.56
P-49	[141]	2019	PD	Sensor+Vision	Optoelectronic cameras+	RF, GBM	46,	86.4	0.44
				Selisor - Vision	Dynamometric platform				
P-50	[142]	2019	PD	Sensor	vGRF	NN	166	98.8	0.78
P-51	[143]	2020	PD	Sensor	Force sensitive resistor	Extreme learning machine	31	93.5	0.56
						(ELM) neural network			
P-52	[144]	2020	PD	Sensor	vGRF	DNN	165	98.7	0.89
P-53	[66]	2020	PD	Sensor	IMUs+Force sensitive resistor	SVM	10	97.4-98.8	0.33
P-54	[145]	2020	PD	Sensor	vGRF	Discriminant analysis	47	95.0	0.44
P-55	[146]	2020	PD	Sensor	IMUs (Smart Phone)	RF	456	85.5-95.0	0.56
P-56	[147]	2020	PD	Sensor	vGRF	NN	166	97.4	0.89
						XGBoost, Artificial			
P-57	[148]	2020	PD	Sensor	Force sensitive resistor	Neural Network (ANN),	64	41.0	0.67
						Symbolic Regression (SR)			
P-58	[149]	2020	PD	Sensor	vGRF	CNN, LSTM	166	98.0	0.89
P-59	[66]	2020	PD	Sensor	IMUs+Force sensitive resistor	Adaptive Unsupervised	12	98.3	0.44
						Learning			
P-60	[150]	2020	PD	Sensor	IMUs	MLP, SVM	34	68.9	0.67
P-61	[151]	2020	PD	Sensor	IMUs	PLS-DA	93	97.9	0.44
P-62	[152]	2020	PD	Sensor	IMUs	LR	16	93.6	0.33
P-63	[153]	2020	PD	Sensor	vGRF	NN, SVM, KNN, DT, RF	567	49.0-61.0 (F1 score)	0.67
P-64	[154]	2020	PD	Vision	Camera	Mask R-CNN	301	97.3	0.67
P-65	[155]	2020	PD	Sensor	vGRF	SVM, DT	166	69.9-99.4	0.78
P-66	[156]	2020	PD	Sensor	IMUs	Bidirectional-LSTM	114	82.4	0.67
P-67	[157]	2020	PD	Sensor	IMUs	CNN	2804	0.86 (AUC)	0.67
P-68	[158]	2020	PD	Sensor	vGRF	ANN	166	98.3	0.89
P-69	[159]	2021	PD	Sensor	vGRF	LSTM	64	98.6	0.89
P-70	[160]	2021	PD	Sensor	vGRF	Bi-LSTM	116	91.2-100.0	0.89
P-71	[161]	2021	PD	Sensor	vGRF	KNN, NB, SVM	165	88.5-98.8	0.78
P-72	[162]	2021	PD	Sensor	IMUs	GMM	380	0.69 (AUC)	0.56
D 70	[1/2]	2021	DD	C	TA CIT-	Random under-sampling	420	0.74 0.00 (ALTO)	0.56
P-73	[163]	2021	PD	Sensor	IMUs	boosting (RUSBoost)	432	0.76-0.90 (AUC)	0.56
D 71	[174]	2021	DD	C	Pitii-t	classification	1//	07.2.00.4	0.78
P-74 P-75	[164]	2021	PD PD	Sensor Sensor	Force sensitive resistor vGRF	CNN, XGBoost CNN	166 166	97.3-98.4 92.7-98.3	0.78 1.00
	[165]		PD						
P-76	[84]	2021	rD	Others	Electronic medical record	LR, RNN	28216	0.874 (AUC)	0.78
P-77	[73]	2021	PD	Vision	Infrared camera+	LR, KNN, NB,	111	98.1	0.56
					Reflective marker	LDA, SVM, RF			
P-78	[74]	2021	PD	Vision	Infrared camera+ Reflective marker	CNN	42	98.7	0.67
P-79	[166]	2021	PD	Concon	vGRF	LSTM	11	94.5	0.67
P-79 P-80	[166]	2021	PD	Sensor Vision	Camera	CNN	22	84.5 94.9	0.67
1-90	[10/]	2021	rD	v iSIOII	Camera	CININ	44	74.9	0.44

4 OVERVIEW OF EXISTING STUDIES

In this section, we systematically review existing studies related to AI-assisted NDs diagnosis based on human gait. We categorize all studies by different NDs types (PD, HD, AD, ALS, MS) with a data summary for them (shown in Table 1, 2, 3, 4, and 5) and a discussion on representative studies.

Quality Evaluation of Studies. To comprehensively measure the quality of each study, we empirically grade the novelty of AI models, comprehensiveness of method comparison, and sufficiency of experimental samples at three levels with the score 1, 2, or 3. We sum their scores and divide them by the maximum score to get a normalized quality score S_Q ranging from 0 to 1. S_Q is computed for each study and the detailed evaluation criterion is provided in the appendices.

ID Study Year NDs Types Data Type Device/Data AI Model Sample Size Accuracy (%) Quality (SO) Sparse non-negative P-81 [168] 2021 97.2 0.67 least-squares (NNLS) P-82 PD vGRF 166 1.00 NN P-83 IMUs SVM 96.7 0.56 PD vGRF CNN P-84 2021 Sensor 166 97.0 0.67 PD KNN, Fuzzy neural network 97.6 P-85 2022 Sensor vGRF 165 1.00 Sensor P-86 [63] 2022 PD IMHs CNN, GRU 134 83 7-92 7 0.67 0.78 P-87 2022 PD vGRF RF 165 94 5-98 8 P-88 2022 Sensor vGRF LR, SVM, DT, KNN 306 81.0-85.0 0.56 P-89 PD IMUs 92.7-96.3 0.56 2022 SVM 115 Sensor P-90 IMUs SVM, RI 64.1-72.7 2022 Sensor 99 0.44 P-91 2022 PD Sensor IMHs SVM, DT, RF, KNN, MLP 128 74.0-86.0 0.56 81.8-84.5 P-92 PD Vision Camera (Kinect) LR. SVM. DT. NB. RF 0.44 2022 60 Sensor 2022 IMUs PD-ResNet 457 95.5 1.00 0.33 2022 Force sensitive resistor 22 99.6 Sensor P-95 PD IMUs (Smart phone) RF [180] 2022 Sensor 1397 73.0 0.56 Feature-weighted Minimum P-96 [181] 2022 Vision 28 0.56 Camera Distance Classifier Model P-97 [182] 2022 PD Sensor vGRF CNN. RF 166 99.5 1.00 Symmetric positive definite P-98 [183] PD 22 2022 Vision Camera 99.4 0.67 (SPD) Riemannian network IMUs P-99 2022 PD Sensor CNN, NN 17 91.0-92.0 0.56 Spatial-temporal graph convolutional P-100 [185] Sensor Retro-reflective markers 42 0.67 network (MS-GCN) XGBoost, SVM, RF P-101 2022 IMUs 134 81.0-88.3 0.56 Sensor+Vision Camera+Force sensitive resistor AdaBoost, Extra Trees, RF 0.44 NB. SVM. DT. RF. P-103 [76] 2022 PD Sensor+Vision Camera+Force sensitive resistor 126 76.9-84.6 0.56 LR, MLP P-104 [187] 2022 PD IMUs DCNN, LSTM 30 83.3 0.78 Sensor CNN. LR. RF. P-105 [188] 2022 PD IMUs (Smart phone) 99.0-100.0 Sensor 11 0.44 Gradient-Boosted Trees Correlative Memory P-106 [77] PD Sensor+Vision Camera (Kinect)+vGRF+IMUs 93 99.5-100.0 2022 1.00 Neural Network (CorrMNN) P-107 2022 PD Vision CNN, SVM 22 96.6 0.44 Camera Gaussian Naive Bayes, P-108 [190] 2022 PD Vision 22 99.0 0.33 LR. RF. SVM P-109 2022 PD Vision Camera (Smart phone) SlowFast GCN network 68 77.1-87.5 0.89 P-110 PD Force sensitive resistor+IMUs RF, LR, Gradient Boosting 0.33 [68] 2022 Senso 97.3 P-111 2022 Sensor vGRI SVM 166 98.2 0.78 PD SVM, ANN P-112 vGRF 93.0 [193] 2022 0.56 48318 Camera (DSLR)+ P-113 PD Sensor+Vision KNN 96 0.44 Passive market P-114 2022 PD Sensor IMUs MLP, KNN, RF, SVM 30 100.0 0.56 P-115 2022 PD vGRF ANN 64.4-86.8 0.67 vGRF 2D CNN 0.89 P-116 [196] 2023 98.0 Sensor 166 KNN, DT, SVM, P-117 [197] PD IMUs 30 94.0-96.0 0.44 ANN, RF IMUs PD 0.55 P-118 [198] 2023 Sensor CNN 90 82.8-86.4 0.55 IMUs PCA, SVM 88.0-90.0 P-119 2023 PD Senso 280 Radial basis function PD 87.6-100.0 0.88 P-120 [200] 2023 Sensor Force sensitive resistor 216

Table 3. Continued table of 2 for Al-assisted PD diagnosis based on gait.

4.1 Parkinson's Disease (PD)

PD

PD

PD

Vision

Sensor

Sensor

Sensor

Camera (Smart phone)

IMUs

IMUs

IMUs

P-121 [201] 2023

P-122 [202] 2023

P-123 [203] 2023

P-124 [204] 2023

As shown in Table 1, 2, 3, and 4, there are 124 studies that focus on PD diagnosis based on human gait. It is worth mentioning that there are 19 studies, each of which simultaneously includes the diagnosis of PD and other NDs, as shown in Table 4 (referred to as "Combinatorial Diagnosis of Different NDs". We separately discuss these studies in Sec. 4.2. Based on our survey, there are 77, 34, and 13 PD studies using C-ML, C-DL, and A-DL models respectively. It should be mentioned that there are a large number of PD studies (up to 124 studies), and since the studies with high-quality

neural network (RBFNN) Weighted adjacency matrix based

Static-Dynamic temporal

Non-linear model

Convolution Network (WM-STGCN)

Spatiotemporal Graph

SVM

networks

87.1

82.0

96.7

84.9

50

78

166

53

0.88

0.44

1.00

0.44

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Table 4. Existing studies (C-1 to C-19) that include combinatorial diagnosis of different NDs (PD, ALS, HD) based on gait. We summarize the input data, main AI model, experimental sample size, reported accuracy (range), and quality score of each study.

ID	Study	Year	NDs Types	Data Type	Device/Data	AI Model	Sample Size	Accuracy (%)	Quality (SQ)
C-1	[101]	2012	PD, ALS, HD	Sensor	Force sensitive resistor	SVM	64	90.6	0.44
C-2	[205]	2013	PD, ALS, HD	Sensor	vGRF	Elman's recurrent neural network (ERNN)	63	90.6	0.78
C-3	[102]	2015	PD, ALS, HD	Sensor	Force sensitive resistor	SVM, RF, MLP, KNN	64	96.6-100.0	0.44
C-4	[206]	2017	PD, ALS, HD	Sensor	vGRF	SVM, EC, DT, KNN	62	79.3	0.56
C-5	[207]	2017	PD, ALS, HD	Sensor	vGRF	Adaboost	64	87.3-92.3	0.67
C-6	[208]	2018	PD, ALS, HD	Sensor	vGRF	RF, SVM	64	90.6-96.9	0.44
C-7	[209]	2018	PD, ALS, HD	Sensor	Force sensitive resistor	fusszy KNN	64	98.4	0.44
C-8	[210]	2020	PD, ALS, HD	Sensor	Force sensitive resistor	Random forest	64	79.3-91.7	0.67
C-9	[211]	2020	PD, ALS, HD	Vision	Camera	Discriminant Analysis, RF, Multi-SVM, KNN	64	92.2	0.44
C-10	[212]	2020	PD, ALS, HD	Sensor	Force sensitive resistor	SVM, KNN	64	99.8-100.0	0.44
C-11	[213]	2020	PD, ALS, HD	Sensor	vGRF	CNN	64	98.4-100.0	0.56
C-12	[103]	2020	PD. ALS. HD	Sensor	vGRF	Sparse non-negative least squares (NNLS), SVM,	64	99.8-100.0	0.89
C-12	C-12 [103]	2020	FD, ALS, FID	Selisoi		multilayer feed forward neural network (MLFN)	04		
C-13	[214]	2020	PD, ALS, HD	Sensor	Force sensitive resistor	KNN	64	90.5	0.44
C-14	[215]	2021	PD, ALS, HD	Sensor	vGRF	CNN, SVM	64	97.4-100.0	0.78
C-15	[77]	2022	DD VIC FID	Sensor+Vision	Camera+IMUs	Correlative memory neural network (CorrMNN)) 64	99.7-100.0	0.89
C-13	[//]	2022	10, ALS, 110	Selisor+vision	+Force sensitive resistor	Correlative memory neural network (Corrivitivity)			
C-16	[216]	2022	PD, ALS, HD	Sensor	vGRF	AlextNet CNN	63	96.4	0.78
C-17	[217]	2022	PD, ALS, HD	Sensor	vGRF	RF, classification trees	64	69.6-95.1	0.67
C-18 [218]	[210]	2022	PD, ALS, HD	Sensor	Force sensitive resistor	Learning Algorithm for Multivariate	60	98.3	0.56
	[410]	2023	1 D, ALS, HD			Data Aalysis (LAMDA), Neural networks.	00		0.30
C-19	[219]	2023	PD, ALS, HD	Sensor	Force sensitive resistor	LSTM, GRU, ResNet, FCN, etc	64	75.4-83.3	0.56

Table 5. Existing studies of Al-assisted diagnosis of AD (A-1 to A-5), ALS (S-1 to S-3), HD (H-1 to H-7) or MS (M-1 to M-6) based on gait.

ID	Study	Year	NDs Type	Data Type	Device/Data	AI Model	Sample Size	Accuracy (%)	Quality (S_Q)
A-1	[220]	2016	AD	Sensor	IMUs	SVM, MLP, RBNs, DBSs	72	91.0-96.6	0.56
A-2	[71]	2020	AD	Sensor+Vision	Camera+EEG	SVM, RF, CNN, ST-GCN, etc	87	91.1-98.6	0.89
A-3	[221]	2020	AD	Sensor	Pressure sentsitive mat	SVM	78	78.0	0.44
A-4	[107]	2022	AD	Sensor+Vision	Kinect depth sensor + Camera	SVM	85	97.8	0.44
A-5	[222]	2023	AD	Sensor	IMUs	SVM, KNN, RF, MLP, etc	145	72.2	0.67
S-1	[104]	2016	ALS	Sensor	Force sensitive resistor	SVM	28	92.9	0.33
S-2	[223]	2020	ALS	Sensor	Force sensitive resistor	SVM, KNN. DT	29	86.2-96.6	0.33
S-3	[224]	2021	ALS	Sensor	Force sensitive resistor	SVM, KNN, NB, LDA, etc	29	89.7	0.44
H-1	[48]	2016	HD	Sensor	IMUs	HMM, SVM	42	88.2	0.44
H-2	[225]	2018	HD	Sensor	IMUs	DT, RF, Logitboost, Multiboost	14	78.6-92.9	0.56
H-3	[226]	2019	HD	Sensor	Walkway system	SVM, 3D CNN	12	82.0-86.9	0.56
H-4	[227]	2019	HD	Sensor	Force sensitive resistor	SVM, KNN, NB, LDA, etc	36	58.3-94.4	0.44
H-5	[228]	2019	HD	Sensor	Force sensitive resistor	SVM, KNN, NB, LDA, etc	36	100.0	0.67
H-6	[229]	2019	HD	Sensor	vGRF	SVM, NB, DT, RF, etc	35	85.7-97.1	0.44
H-7	[230]	2020	HD	Sensor	Magnetics and inertial measurement units	SVM	42	90.5	0.44
M-1	[105]	2019	MS	Sensor	Force sensitive sensor	SVM, MLP, KNN, ELM	945	89.8	0.67
M-2	[59]	2021	MS	Sensor	Treadmill	SVM, RF, AdaBoost, MLP, etc	40	94.3	0.44
M-3	[231]	2021	MS	Sensor	Force sensitive sensor	SVM, Gaussian Naive Bayes, DT, KNN, etc	60	74.5	0.44
M-4	[232]	2021	MS	Sensor	IMUs	TL DCNN HAR models	97	77.6-91.1	0.89
M-5	[106]	2021	MS	Sensor	IMUs	SVM, LR, RF	97	79.3-85.1	0.44
M-6	[58]	2022	MS	Sensor	Walkway system	SVM, LR, XGBoost	88	77.0-81.0	0.44

AI models and diagnostic results are the focus of our survey, we select representative studies from papers with quality score $S_O > 0.6$ for discussion.

[111] (Table 1, ID = P-7) utilizes Hidden Markov Models (HMM) with Gaussian Mixtures to classify gait data and differentiate Parkinson's disease (PD) patients from healthy subjects. Using stride interval as the distinguishing feature, the HMM method achieves an accuracy rate of 90.3%. [120] (ID = P-21) explores the use of wavelet analysis combined with SVM for the identification of PD based on spatio-temporal gait variables, achieving a classification accuracy of 90.32%. The study demonstrates the potential of using wavelet analysis as an efficient method for classifying PD and healthy subjects. In [128] (ID = P-32), the authors quantify gait parameters objectively

using wearable accelerometers, and compare them with a motion capture system to automatically discriminate patients with PD using machine learning models such as SVM, KNN, and DT. The proposed approach achieves an accuracy of approximately 89.1% and suggests that the wearable accelerometer-based system is suitable for assessing and monitoring PD and Freezing of gait (FOG) in real-life scenarios. [142] (ID = P-50) proposes a novel method for classifying gait patterns between patients with PD and healthy controls. This method reconstructs the phase space of vGRF and decomposes the gait dynamics using empirical mode decomposition, which are fed to neural networks (NN) for classification with accuracy of 98.8%. The study of [150] (ID = P-60) explores the use of single-sensor accelerometer data from healthy subjects to extract features relevant to multi-sensor accelerometer gait data for Parkinson's disease classification. They use a pre-trained convolutional autoencoder as the source model and a simple multi-layer perceptron as the target model to classify PD and achieve 68.92% accuracy. In [168] (ID = P-81), a time-varying singular value decomposition method is designed to extract the most useful and informative part of the vGRF signal data, and then sparse non-negative least squares (NNLS) approach is leveraged to classify PD and HCs, achieving 97.2% accuracy. The study of [81] (ID = P-43) leverages convolutional LSTM to identify PD patients from Kinect-based skeleton data and achieves up to 83% accuracy. It also suggests that the data preprocessing (e.g., cropped data) can help boost the classification performance. [144] (ID = P-52) devises a deep neural network (DNN) based model to identify Parkinsonian gait based on vGRF data and achieves 98.7% accuracy. This is also the first study to predict the Unified Parkinson's Disease Rating Scale (UPDRS) severity (i.e., Parkinsion severity rate) of a subject and achieve 85.3% accuracy. [63] (ID = P-86) combines CNN and gated recurrent units (GRUs) to perform classification between PD and health subjects from IMU signals, achieving 83.7-92.7% accuracy. The results suggest that the combination of temporal and spectral information is more effective in classifying gait patterns of PD patients. [165] (ID = P-75) uses deep CNN to classify gait deterioration in PD patients based on spatio-temporal vGRF signals and achieves 95.5% accuracy in average. The study suggests that the heel strike and body balance are the most indicative gait elements in PD classification. [172] (ID = P-85) proposes an interval type-2 fuzzy neural network with novel quasi-Levenberg-Marquardt (qLM) learning approach to identify PD patients from the gait cycle based vGRF signals. Based on the 10 clinical features extracted from 14 gait features, the model achieves 97.6% accuracy with a smaller size of parameters and a good interpretability (i.e., rules based on fuzzy logic). [201] (ID = P-121) proposes a novel model named WM-STGCN that leverages a Weighted adjacency matrix and Multi-scale temporal convolution in a spatio-temporal Graph Convolution Network to classify PD gaits from normal gaits and achieves up to 87.1% accuracy on 2D skeleton data. This method outperforms many existing methods including LSTM, KNN, DT, AdaBoost, and ST-GCN models [233]. [203] (ID = P-123) devises a static-dynamic temporal networks that consists of one-dimensional, two-dimensional convolutional networks, and attention mechanisms to classify PD patients based on foot force (vGRF time series) and achieves 96.7% accuracy.

4.2 Combinatorial Diagnosis of Different NDs

As shown in Table 4, there are 19 studies that simultaneously focus on diagnosis of PD, ALS, and HD based on human gait, and 11, 6, 2 studies use C-ML, C-DL, A-DL models, respectively. We provide a brief content summary and discussion for representative studies below.

[205] (ID = C-2) uses a cross-correlation method to extract features with recurrent neural networks to classify HC and people with neurodegenerative diseases (PD, HD, ALS), achieving highly-competitive performance with 90.6% accuracy. The study of [102] (ID = C-3) exploits 9 statistical features (mean, minimum, etc) of gait rhythm signals (*i.e.*, gait cycle parameters) to perform neurodegenerative disease (ND) diagnosis using different classic machine learning models

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(SVM, RF, MLP, KNN), and achieves 96.6-100% accuracy. Najafabadian etal. [207] (ID = C-5) present a nonlinear gait signal analysis approach to classify NDDs by extracting chaotic and fractal features from gait data and reach a classification accuracy of 92.34%. [208] (ID = C-6) introduces a technique called Statistical Energy Values and Peak Analysis (SEP) for detecting NDDs from signals obtained through force-sensitive resistors. The accuracy, sensitivity, and specificity values are best achieved using the Random Forest Classifier reported at 96.9%, 96.8%, and 96.7% respectively. [210] (ID = C-8) introduces a framework called Topological Motion Analysis (TMA) which embeds gait fluctuation time series into a phase space. In detail, persistent homology is used to extract topological signatures of barcodes, and a Random Forest classifier is employed for analysis. This study demonstrates the effectiveness of TMA in classifying diseases such as ALS, HD, and PD compared to HC, achieving high accuracy of 79.31%, 91.67%, and 87.10% respectively. [213] (ID = C-11) proposes a CNN model to differentiate gait of NDs patients and HC based on vGRF signal data (10-second signal) and achieves 95.95-100% accuracy. [103] (ID = C-12) introduces a non-invasive, cost-effective diagnostic tool for analysing gait signals obtained from vGRF sensors. The best classification results are obtained using SVM model and the achieved average accuracy rates are 100% for ALS, 99.78% for PD, and 99.90% for HD. A hybrid model that combines multiple sensor data is proposed in [77] (ID = C-15) to learn gait differences between ALS, HD, PD, and healthy individuals. The model includes a spatial feature extractor (SFE) and a correlative memory neural network (CorrMNN) for capturing representative features and temporal information, which outperforms many state-of-the-art techniques with 99.7-100.0% accuracy. [217] (ID = C-17) devise Petri net models of human gait with Rs and classification trees (CTs) to classify different neurodegenerative diseases (PD, HD, ALS) from Petri net features of vGRFs, and achieves 91.7-95.1% accuracy.

4.3 Huntington's Disease (HD)

As shown in Table 5, there are 7 studies that include AI-assisted HD diagnosis based on human gait (not including 19 combinatorial studies in Table 4). The majority of these studies (6 studies) leverage C-ML models, while other studies (1 study) use C-DL models.

[48] (Table 5, ID = H-1) proposes a method to classify gait between Huntinton's disease (HD) and health elderly based on IMU data using HMM derived features and SVM classifier, and achieves overall accuracy 90.5% by combining HMM-based features, time and frequency domain features. In [225] (ID = H-2), 11 gait features are extracted from accelerometer data to classify HD patients using different machine learning models (RF, DT, Logiboost, Multibooost) and achieves up to 92.86% accuracy. Two attribute selection algorithms are proposed to choose the most representative gait patterns of subjects. [226] uses pressure data collected during formation of individual footsteps to classify HD by 3D CNN. The experiments showed that using the basic deep learning backbone VGG16 and similar modules can achieve classification accuracy of 89%. Different machine learning models (KNN, SVM, NB, DT, LDA) are utilized in [227] to identify HD from foot force based gait dynamics parameters and achieves up to 100% accuracy with SVM and DT when considering the right foot stance interval. In [229], five machine learning models (SVM, DT, NV, RF, LR) are utilized to recognize HD from gait dynamics features and achieves 85.71-97.14% accuracy. [230] uses the IMU data and SVM model to classify HD gait and healthy gait of elderly, achieving 90.5% accuracy.

4.4 Multiple Sclerosis (MS)

As reported in Table 5, 6 studies that focus on MS diagnosis based on human gait, and there are 4, 1, and 1 using C-ML, C-DL, and A-DL models respectively.

In [105] (Table 5, ID = M-1), the authors uses Extreme Learning Machine (ELM), SVM, MLP, and KNN to classify multiple gait disorders including MS, stroke, and cerebral palsy from gait force data, achieving a accuracy result of 89.8%. The study of [232] (ID = M-4) devises a CNN-based transfer

learning framework to identify MS patients from wearable smartphone sensor data and achieves up to 91.1% accuracy. The interpretations of results also suggest that cadence-based measures, gait speed, and ambulation-related signal perturbations are distinct features for classification. [58] (ID = M-6) leverages gait parameters extracted from raw data of a walkway system to identify HD patients using different classic machine learning models (SVM, LR, XGBoost) and achieves up to 81% accuracy. The performance is shown to be further improved to 88% when augmenting standard parameters with other custom parameters and normalized subject characteristics.

4.5 Alzheimer's Disease (AD)

As presented in Table 5, there are 5 studies that focus on AD diagnosis based on human gait, in which 3, 1, 1 studies exploit C-ML, C-DL, and A-DL models.

In [220] (ID = A-1), the authors explore the use of machine learning classifiers including SVM, MLP, RBNs, and DBSs for diagnosing AD based on postural control kinematics. Four classifiers are compared, and the accuracy of AD diagnosis ranges from 91% to 96.6% when combining postural kinematics and Montreal Cognitive Assessment (MoCA) variable. This study suggests that machine learning models can aid in computer-aided diagnosis of AD using postural control kinematics. The study of [221] (ID = A-3) collects walking data and derives gait features from participants by using both the "single-tasking" and "dual-tasking' test. The features are then fed as input to the SVM model to classify HC and AD, achieving 78.0% accuracy. In [107] (ID = A-4), the authors explore the feasibility of using the Timed Up and Go (TUG) test, a simple balance and walking assessment, as a tool for detecting AD compared to HC. Joint position data was collected from subjects performing the TUG test using a Kinect camera. Through signal processing and statistical analyses, significant features were identified and used with a support vector machine classifier, achieving high accuracy (97.75%). Different ML models (SVM, KNN, RF, MLP, NB, MLP) [222] (ID = A-5) are assembled to diagnose AD using gait parameters extracted from IMU sensors signals, and achieves about 72.2% accuracy. This study totally proposes seven walking experiment paradigms and collects data using seven wearable devices.

4.6 Amyotrophic Lateral Sclerosis (ALS)

As reported in Table 5, there are 3 studies that focus on AI-assisted ALS diagnosis based on human gait (excluding 19 combinatorial studies in Table 4), and all studies employ C-ML models.

In [104] (Table 5, ID = S-1), the study focuses on analyzing gait variability in patients with amyotrophic lateral sclerosis (ALS) and extracting two key features, standard deviation statistics and permutation entropy. These features were inputted into a support vector machine classifier to classify ALS patients and healthy controls. The results demonstrated high accuracy (92.86%) in distinguishing ALS patients from controls, indicating the potential of gait variability analysis as a diagnostic or monitoring tool for ALS. [223] (ID = S-2) leverages one-minute gait series and parameters to classify between ALS patients and healthy subjects using machine learning models (SVM, KNN, DT) and achieves up to 96.6% accuracy with DT. [224] (ID = S-3) extracts metrics of fluctuation magnitude and fluctuation dynamics from gait time series, and leverages five classic machine learning models (SVM, KNN, NB, LDA, DT) to classify ALS and healthy subjects. Both SVM and KNN achieves the best performance with 89.7% accuracy on the GaitNDD database.

5 DISCUSSIONS

In this section, we first identify the key challenges in AI-assisted NDs diagnosis based on human gait. Then, with regard to these challenges, we correspondingly propose potential solutions and promising future directions. Finally, we provide a research vision on 3D skeleton based gait representations and AI models for more efficient NDs diagnosis.

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5.1 Challenges and Future Directions

5.1.1 Limited NDs Types and Studies. As shown in Sec. 3.2.3, most studies (87.2%) in this area focus on PD gait and related diagnosis, while the number of other NDs studies is very limited. For example, although AD is the most influential neurodegenerative disease around the world (see Fig. 1), only a few works (5 studies) focus on the AI-assisted diagnosis of AD from gait. On the other hand, apart from the five most representative NDs focused in this survey, there are also other rare NDs such as prion disease and motor neuron disease, which deserve more attention and effort to explore AI solutions for their gait-based diagnosis.

In the future, it is necessary to conduct a deeper investigation on abnormal gaits of more NDs, especially the rarely-explored NDs, and devise corresponding AI models to automatically assist their clinical diagnosis. Another important direction is to devise a general gait learning model that can identify common and different gait abnormality across various NDs, so as to improve the generalization capacity of gait analysis models to serve for more other diseases.

5.1.2 Scarcity and Imbalance of Data. The medical data including gait data collected for NDs diagnosis are highly limited, and in the selected 164 articles only several datasets are publicly available: The Gait in Neurodegenerative Disease Database and Gait in Parkinson's Disease from Physionet database [234] are two most frequently-used used datasets; Other datasets include SDUGait [235], Floodlight PoC dataset [236], UK Biobank Dataset [237], Ga, Ju, Si Groups [238–240]. However, these datasets are limited in both sample sizes and NDs types. Most of them contain less than 100 subjects (see Sec. 3.2.6), and the number of NDs types is typically less than 3, while PD gait data are much more than other NDs in terms of quantity and quality (i.e., unbalanced data size of different diseases). This could limit the learning performance of AI models especially deep learning models, which inherently require large-scale and class-balanced data to achieve more reliable prediction.

To address these challenges, more high-quality gait data of different NDs should be collected. First, it is feasible to cooperate with larger hospitals, medical institutes, or communities to involve more patients and health controls into the collection of gait and related data. Second, the number of patients in each disease and the data size of each patient should be controlled within a reasonable range, *e.g.*, enlarging the sample size of each disease to more than hundreds and keeping the total data size of each disease as similar as possible. Such balanced data could benefit the model to learn higher inter-class difference with better robustness against intra-class diversity [241]. To address the challenges of data scarcity and imbalance in this area and facilitate related research, we will collect and open a large-scale multi-modal gait dataset for NDs diagnosis in the future.

5.1.3 Lack of Multi-Source/Modal Gait Data. As reported in Sec. 3.2.4, most studies in this area typically collect either sensor-based or vision-based gait data with a single device. For sensor-based data, force sensitive resistor or IMU is the commonly-used device, while they are rarely combined in the same study for gait data collection. Nevertheless, as AI-assisted disease diagnosis is a vital task with high demand of model accuracy and reliability, utilizing only single-source or single-modality data might be insufficient to fully capture latent disease features from different dimensions. Taking PD as an example, the vision-based appearance features (e.g., unnatural facial expression) and sensor-based motion features (e.g., walking tremor) can be complementary to provide a full picture for PD diagnosis.

Therefore, an important future direction is to collect gait data from multiple sources and modalities. First, it is feasible to combine multiple devices as different sources of same-type data (*e.g.*, multi-view data with differently-positioned cameras), where all devices/sources can compensate each other to better reconstruct or depict the whole pattern with less information loss [242]. Second,

combining different modalities such as RGB images, depth images, 3D skeletons, and force data (vGRF) is valuable as they can provide gait information from different dimensions (*e.g.*, appearances, poses) to better predict NDs [77].

- 5.1.4 Challenges in AI Model Design. According to the analysis of existing AI methods in gait-based NDs diagnosis, there are several challenges in designing more reliable AI models as follows.
- (1) Accuracy: Existing studies report the model accuracy typically ranging from 60% to around 95%, with very few studies possessing accuracy less than 60%. Many studies using C-ML models report model performance with very high accuracy. For the low-accuracy methods, they cannot reach the requirement to assist in medical diagnosis, as the frequent wrong prediction might induce serious medical risk. However, for the methods with very high accuracy, careful evaluations with other indicators such as generalizability and interpretability are required. It is worth noting that these models with nearly 100% accuracy possibly overfit the training data while the the testing data may possess highly similar data distribution to training data (i.e., small domain shift [243]). In this case, these AI models are hard to get satisfactory performance on out-of-distribution data such as new real-world gait data.
- (2) Generalizability: Despite high accuracy of quite a few AI methods in this area, many of them are trained, validated, and tested on a single dataset or self-collected gait data, which usually contain limited data sizes, views, scenes or conditions. Therefore, these methods may only perform well on the scenarios that are similar to that of the training data, while they cannot generalize to more challenging data [244]. For example, if the training data contain only gait data of elderly patients, the trained AI model could possess lower accuracy when predicting NDs of young adults using corresponding gait data. In summary, the AI model trained on a single dataset or datasets with limited scenarios (e.g., single setting) typically possesses low generalization ability in real-world application.
- (3) Efficiency: As shown in Sec. 3.2.5, the majority of existing studies (104 papers, 63.4%) utilize C-ML models, which typically enjoy much fewer model parameters and less computational complexity than deep learning models. In general, C-ML models is more efficient than DL models (C-DL and A-DL) under the same accuracy, which makes C-ML more favorable to be deployed in real-world applications. However, compared with conventional ML models, the emerging DL models have stronger ability in mining effective patterns from large-scale medical data, which are more useful and popular in the big data era. For DL models, it is necessary to achieve a good trade-off between model efficiency (e.g., model parameter size, computational complexity) and model performance (e.g., accuracy, speed) [245], so as to better assist in disease diagnosis.
- (4) Interpretability: In high-stake fields like medical diagnosis, it is important for AI models to provide human-friendly reliable explanations to facilitate the medical decision [246–248]. In the surveyed area, there are only a few C-ML model based studies that have identified the important body parts or gait features in classification, while most DL models do not devise an effective mechanism such as feature disentangling and importance visualization [249] to provide interpretability. This may increase the risk of wrong diagnosis and discourage the users such as doctors from adopting the predicted result.
- (5) Fairness of Comparison: Since a unified model evaluation protocol (*e.g.*, metrics) is still unexplored in this area, the performance comparison between different studies/models might be unfair. For example, some studies adopt the area under the Receiver Operating Characteristic (ROC) curve for evaluation, while some others take accuracy as metric. Moreover, some studies evaluate their models on different testing sets of the same dataset, or use different datasets to train models, which they cannot be fairly compared even using the same evaluation metric. In our survey, we

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report the model accuracy as the main metric, while their comparison should be conducted under using the same metric, dataset, and testing set.

To address the aforementioned challenges, it is essential to improve not only the accuracy of an AI model but also its generalizability, efficiency, and interpretability. A potential future direction is to exploit more advanced deep learning models and larger-scale gait datasets with different scenario settings to learn both domain-specific (e.g., AD-specific) and domain-general (i.e., NDs-shared) gait features, so as to improve the model accuracy and enable it to be transferred/generalized to other scenarios. For efficiency, it is feasible to employ lighter network architecture (e.g., MobileNets [250]) or model compression techniques (e.q., knowledge distillation [251], network pruning [252]) to reduce the model size and computational complexity but retaining similar model accuracy. Another promising direction is to adopt smaller gait data such as the emerging 3D skeleton data, which can concisely represent human poses with key body joints and typically require lightweight AI models to learn discriminative gait patterns [253]. To improve model interpretability, different types of human-friendly explanation including text description and feature visualization can be considered. We can integrate model-specific explanation mechanisms into different AI architectures, e.q., visual class activation maps (CAM) [254] for CNN, knowledge graphs [255] for graph neural networks (GNN). Inspired by the recent success of ChatGPT, it can be used to provide insightful description for the importance of features if we transform gait features into text format. Moreover, ChatGPT can also act as an agent to lead and improve the AI model learning [256], in which we can add prompts to generate interpretable results. As there exist key body parts and poses for NDs diagnosis, we can try to disentangle the gait abnormality related semantics from normal motion semantics (e.g., daily actions) to identify the most important or unique component of NDs patients' features. Simultaneously improving the accuracy, generalizability, efficiency, and interpretability, it is hopefully to obtain a more reliable and practical AI model for gait-based NDs diagnosis. Meanwhile, a unified evaluation protocol, which synergizes different benchmark datasets, validation settings, and evaluation metrics, should be further devised to fairly compare different AI models to facilitate the development of this area.

5.2 Research Vision

Recently driven by economical, non-obtrusive and accurate skeleton-tracking devices like Kinect [262], 3D skeleton data has been a popular and generic data modality for many gait-related tasks such as gait recognition and person re-identification [253, 258, 259, 263–269]. A 3D skeleton is defined as 3D coordinates of key human joints (typically 20 or 25 key joints [262]) of a person, while 3D skeletons are defined as all joints' temporal series conveying motion dynamics of the person. In this concise way, 3D skeletons can provide both body structure and pose information for gait analysis. Encouraged by the promising results of 3D skeletons in many fields, we propose the research vision of exploiting 3D skeleton data to characterize NDs-related gait patterns to enhance the diagnosis performance. In this section, we first discuss the unique advantages of 3D skeleton data for gait representation and learning, which can potentially address challenges in AI-based NDs diagnosis in terms of efficiency and scalability (see Sec. 5.2.1). Then, we propose a generic 3D skeleton based framework to design AI models specifically for NDs diagnosis (see Sec. 5.2.2).

5.2.1 Skeletons as Efficient and Scalable Gait Representations. Unlike traditional methods that rely on visual appearance features (e.g., silhouettes) or force signals (e.g., vGRF) to capture gait, 3D skeletons can simultaneously model human body structure, poses, and gait patterns using only 3D positions of key body joints. They can not only offer detailed spatial 3D coordinates and their temporal dynamics for statistical gait analysis, but also provide intuitive body representations

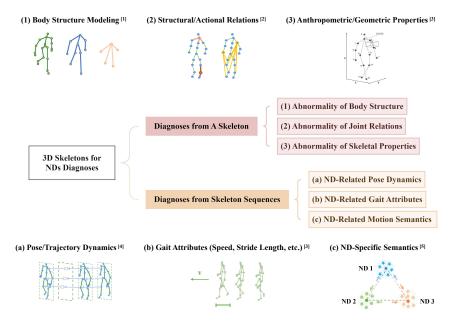


Fig. 9. Overview of 3D skeleton based NDs diagnosis framework. We visualize different directions of Al model design in terms of skeleton-level ((1)-(3)) and sequence-level NDs diagnosis ((a)-(c)), and also provide representative Al methods of this direction as an example solution ([1]: [257]; [2]: [258]; [3]: [259]; [4]: [260]); [5]: [261])

(e.g., pose visualization) that help illustrate variations in gait. Moreover, the 3D skeletons can be conveniently captured by a single contactless device such as Kinect.

Specifically, 3D skeleton data possess the following advantages to improve the efficiency of gait learning: (a) Smaller data inputs compared with appearance-based methods that typically require large-size (e.g., high-resolution) image/video data; (b) Lighter AI models than conventional image-based models to process and learn skeletons [261]; (c) Lower resource/device requirement compared with other sensor-based data that require multiple devices such as IMUs or expensive systems such as walkway systems; (d) Higher convenience of collection with unobtrusive and contactless detection compared with other sensor methods that usually require wearing devices (e.g., sensors) or body markers. These advantages enable them to be potentially applied to capturing and learning gait with higher efficiency in terms of real-world deployment and model design.

On the other hand, 3D skeletons can serve as scalable gait representations for different application scenarios: (a) For medical diagnosis and other privacy-sensitive areas, 3D skeletons can replace traditional vision data such as RGB images to *exclude* all visual appearance information (*e.g.*, faces of patients), so as to provide better privacy protection for downstream tasks such as gait classification; (b) Compared with other gait representations that rely on RGB or depth images, 3D skeleton based representations possess more robust performance under variations of scales, views or other external factors [270], which enables them to be flexibly used in more scenarios; (c) As 3D skeletons are general modality for many tasks including action recognition [271], gait recognition [264], and person re-identification [253], all these tasks could be flexibly transferred or combined to provide better abnormal gait classification for NDs diagnosis. For example, the most distinctive pose regions in action recognition tasks can be utilized to locate the gait abnormality of NDs patients, while the identity-specific gait patterns in person re-identification tasks can be

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exploited to recognize NDs patients and help decouple disease-specific gait patterns; (d) There are many successful practices to combine 3D skeleton data and other modalities such as RGB images, depth images, and 3D clouds [263, 265] to improve feature effectiveness for various tasks. It is feasible to combine 3D skeleton data with the above data modalities or other data such as IMUs signals and force signals to further boost the performance of gait learning and NDs diagnosis. It is worth noting that the most commonly used skeleton-tracking device, Kinect, can simultaneously capture RGB images, depth images, and 3D skeletons, which provides great benefit for multi-modal representations of gait.

5.2.2 3D Skeleton based NDs Diagnosis Framework. As presented in Fig. 9, by using 3D skeletons as gait representations, NDs can be diagnosed from two main aspects, a single skeleton and a skeleton sequence. For skeleton-level NDs diagnosis, the abnormalities in body structure, joint relations, and skeletal properties are key focus of AI models: (1) We can exploit multi-level or hierarchical body structure modeling [257] to help capture more discriminative features between NDs patients and healthy subjects; (2) The structural and actional relations between body joints or parts usually characterize unique walking patterns of a person [272], so we can combine them to learn both local and global motion correlations to better catch valuable patterns [258] (e.g., abnormal gait patterns); (3) There exist crucial skeletal properties including anthropometric and geometric attributes (e.g., joint distances and angles) that can help recognize different actions [271] or identify different persons [259]. These key skeletal properties incorporating domain-specific knowledge could be potentially used to identify different NDs.

For skeleton sequence level NDs diagnosis, learning NDs-related pose dynamics, gait attributes, and latent motion semantics is the key to AI model design (see Fig. 9): (a) For NDs patients, their poses might be unnatural or twisted, which could be reflected on their motion dynamics such as body-joint trajectory. Therefore, it is feasible to capture pose or trajectory dynamics from 3D skeletons [260] and extract the NDs-related parts for diagnosis; (b) Considering that NDs patients typically possess abnormal gait attributes such as lower speed and uncertain stride length, we can compute these gait features from 3D skeletons [259] as important discriminators of different diseases; (c) Advanced AI models such as deep learning models can learn latent high-level semantics in high-dimensional feature space to help better classify abnormal gaits. For example, we may devise self-supervised tasks such as skeleton sequence reconstruction, sorting, prediction [253], or contrasting [261] to learn high-level semantics in terms of motion continuity and consistency, which can be used to detect gait abnormality by comparing with normal samples for NDs diagnosis. We can also leverage unsupervised clustering algorithms to find latent gait semantics (e.g., gait prototypes [261]) related to different NDs for diagnosis.

6 CONCLUSION

In this paper, we provide an overview of the recent advancements of Artificial Intelligence (AI) models for diagnosing neurodegenerative diseases (NDs) through human gait. Our survey showcases a general process of gait-based NDs diagnosis using AI with focus on five representative NDs: PD, AD, HD, ALS, MS, and systematically reviews all existing studies with an elaboration on their used gait data, AI models, and overall performance. We outline and discuss the current challenges, potential solutions, and promising future directions in this field. Furthermore, we propose a novel research vision on the utilization of emerging 3D skeleton data for human gait representation and AI model development for more efficient NDs diagnosis.

As an important interdisciplinary topic, utilizing AI technologies for gait-based NDs diagnosis requires expertise in gait analysis, medical science, and AI. Therefore, it may necessitate a significant amount of time and effort to conduct an in-depth understanding and exploration of this topic. By

systematically reviewing existing technologies, revealing their key challenges, and identifying future research directions, our survey aims to provide a quick view of this topic to researchers especially those with knowledge in gait, medicine, or AI alone. We hope that this survey can provide valuable insights for researchers from diverse backgrounds and facilitate the future innovation of this interdisciplinary realm.

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A Survey of Artificial Intelligence in Gait-Based Neurodegenerative Disease Diagnosis - Appendix

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APPENDIX OUTLINE

The overview for this appendix is presented as follows.

- In Sec. 1, we detail the survey strategy and process, including the inclusion and exclusion criteria (see Sec. 1.1), query phrases (see Sec. 1.2), screening and data abstraction (see Sec. 1.3).
- In Sec. 2, we provide a full description for potential disease-related gaits.
- In Sec. 3, we present the computing formula for quality evaluation scores of studies.
- In Sec. 4, we conduct a complementary elaboration on existing gait data types and their collecting technologies.
- In Sec. 5, we offer the lists of all included papers and representative excluded papers.

1 SURVEY STRATEGY AND PROCESS

1.1 Inclusion and Exclusion Criteria

For the definition of NDs and related concepts, we follow the standard in "International Classification of Diseases 11th Revision (ICD-11)" released by the World Health Organization (WHO)¹. We search and gather papers information from three well-established literature sources, namely *PubMed*, *Web of Science (WoS)*, and *Google Scholar*.

We provide the detailed inclusion and exclusion criteria in Table 1. From the papers surveyed, we include those containing keywords associated with: "pathological gaits", "neurodegenerative disease diagnosis", and "artificial intelligence". Meanwhile, we exclude papers that focus on other topics such as "therapy", "treatment", "intervention", and "prevention". To provide a comprehensive review of recent advances in this field, we restrict the publication time range of the papers to between Jan 1, 2012, and September 1, 2023. The language and the studied species of the papers are restricted to English and human, respectively. The example search keywords of PubMed is presented in Table 2, and we provide the concrete query phrases for PubMed and WoS searching in Sec. 1.2.

 $^{^{1}}$ International Classification of Diseases 11^{th} Revision (ICD-11)

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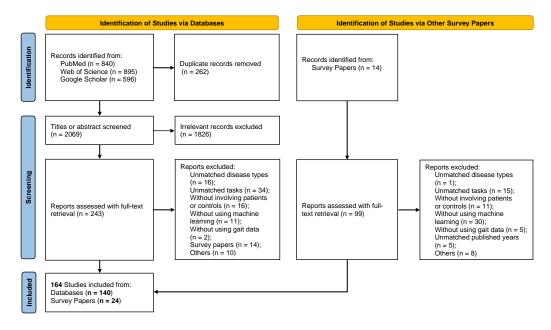


Fig. 1. Overview of the literature selection process based on Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagrams.

Table 1. Inclusion and exclusion criteria for the survey.

No.	Category of Criteria	Inclusion Criteria	Exclusion Criteria
1	Types of Diseases		Studies focused on other diseases instead of five NDs, or NDs unrelated to
		PD, ALS, HD, MS) associated with gaits	gaits

3	Task of the Study Artificial Intelligence (AI) Techniques	Studies focused on the diagnosis (including prediction, classification or identification) of gait-related NDs 1. Conventional Machine Learning (C-ML) Models: Decision Trees, Support Vector Machines, Linear Regression, Naive Bayes, K-Nearest Neighbors, Random Forest, 3-layer multilayer percep-	Studies focused on the classification and identification of gait-related information rather than the diagnosis of diseases. Some excluded examples as shown as follows: gait recognition/gait identification; (focused on identities, ages, genders, etc.); gait prediction (focused on motion prediction); gait simulation/estimation/detection; gait collection techniques; gait abnormality assessment (without health controls); gait phase/cycle classification/identification; gait-based fall detection; gait-based fatigue detection; Freezing of gait (FoG) detection (focused on FoG in Parkinson's patients without healthy controls); development/treatments/therapy for diseases; disease severity assessment; disease management/intervention/prevention; disease related operation Not use artificial intelligence approaches, or only use pure statistical methods, such as: Rule-based systems, Linear mixed-effect model, ANOVA
4	Experimental Sample	trons, etc; 2. Conventional Deep Learning (C-DL) Models: Convolutional Neural Networks, Recurrent Neural Networks, vanilla long short-term memory, ResNet, etc; 3. Advanced Deep Learning (A-DL) Models: Graph Convolutional Networks, Transformers, Generative Adversarial Networks, etc. The size of samples (including health	Sample size less than 10, or only contain
4	Size	controls and patients) is not less than 10	patients without health controls
5	Performance Metrics	Studies reporting accuracy-related per- formance metrics (e.g., precision, AUC)	Did not report accuracy-related performance metrics, or only report hypothesis testing results (e.g.,significance)
6	Article Type	Published peer-reviewed articles: Original research or Structured reviews of the literature reported in accordance with PRISMA guidelines	Unpublished articles, articles without formal peer reviews, or not published in the English language
7	Species of Samples	Human	Different animals except human
8	Publication Year	Articles published between 2012 to 2023	Articles published before 2012

1.2 Query Phrases

PubMed Query Phrases Using Advanced Search: ("pathological gaits" OR "gait impairment" OR "abnormal gait" OR "diplegic gait" OR "hemiplegic gait" OR "neuropathic gait" OR "Parkinsonian gait" OR "gait abnormality" OR "gait disorders" OR "gait diagnosis" OR "Gait/classification" [Mesh] OR "gait classification" OR "gait abnormality classification" OR "pathological gait classification" OR "gait disease diagnosis" OR "gait disease prediction" OR "gait disease classification" OR "gait disease identification" OR "gait disease assessment") AND ("deep learning" [Mesh] OR "artificial

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Table 2. Search strategy and main inclusion/exclusion criteria used in the literature search from PubMed. We manually filter and screen the searched articles according the disease and time range domains. The concrete query phrases for PubMed and WoS databases are shown in Sec. 1.1.

Domain	Search Keywords
Gait	("pathological gaits" OR "gait impairment" OR "abnormal gait" OR "diplegic gait" OR "hemiplegic gait" OR "neuropathic gait" OR "Parkinsonian gait" OR "gait abnormality" OR "gait disorders" OR "gait diagnosis" OR "Gait/classification" [Mesh] OR "gait classification" OR "gait abnormality classification" OR "pathological gait classification" OR "gait disease diagnosis" OR "gait disease prediction" OR "gait disease classification" OR "gait disease assessment") AND
Technology	("deep learning" [Mesh] OR "artificial intelligence" [Mesh] OR "machine learning" [Mesh] OR "artificial intelligence" OR "deep learning" OR "machine learning" OR "Support Vector Machine" OR "Transformer" OR "Graph Neural Network" OR "Bayesian" OR "Decision Trees" OR "Fuzzy Logic" OR "Gradient Boosting" OR "k-means Clustering" OR "Nearest Neighbors" OR "Neural Networks" OR "random forests" OR "reinforcement learning")
Excluded Type	NOT ((Therapy[Title]) OR (Treatment[Title]) OR (Intervention[Title]) OR (Prevention[Title])))
Disease	$(Manually \ filter) \ Include \ "Parkinson's \ disease" \ OR \ "Alzheimer's \ disease" \ OR \ "Amyotrophic lateral sclerosis" \ OR \ "Huntington's \ disease" \ OR \ "Anticological sclerosis" \ OR $
Time range	(Manually filter) Published from January 1, 2012 to September 1, 2023

intelligence" [Mesh] OR "machine learning" [Mesh] OR "artificial intelligence" OR "deep learning" OR "machine learning" OR "Support Vector Machine" OR "Transformer" OR "Graph Neural Network" OR "Bayesian" OR "Decision Trees" OR "Fuzzy Logic" OR "Gradient Boosting" OR "k-means Clustering" OR "Nearest Neighbors" OR "Neural Networks" OR "random forests" OR "reinforcement learning") NOT ((Therapy[Title]) OR (Treatment[Title]) OR (Intervention[Title]) OR (Prevention[Title])))

WoS Query Phrases Using Advanced Search: TI = (((pathological gaits) OR (gait impairment) OR (abnormal gait) OR (diplegic gait) OR (hemiplegic gait) OR (neuropathic gait) OR (Parkinsonian gait) OR (gait abnormality) OR (gait disorders) OR (gait diagnosis) OR (gait classification) OR (gait abnormality classification) OR (pathological gait classification) OR (gait disease diagnosis) OR (gait disease prediction) OR (gait disease classification) OR (gait disease identification) OR (gait disease assessment)) AND ((deep learning) OR (artificial intelligence) OR (machine learning))) OR AB = (((pathological gaits) OR (gait impairment) OR (abnormal gait) OR (diplegic gait) OR (hemiplegic gait) OR (neuropathic gait) OR (Parkinsonian gait) OR (gait abnormality) OR (gait disorders) OR (gait diagnosis) OR (gait classification) OR (gait disease predict ion) OR (gait disease classification) OR (gait disease diagnosis) OR (gait disease predict ion) OR (gait disease classification) OR (gait disease assessment)) AND ((deep learning) OR (artificial intelligence) OR (machine learning))) NOT TI = ((therapy) OR (treatment) OR (intervention) OR (prevention)) NOT SO=CLINICAL REHABILITATION NOT WC= Rehabilitation AND PY=(2012-2023)

With the aforementioned search, inclusion, and exclusion strategies, we first select the articles via screening their titles and abstracts, and then perform full-text assessment on the selected articles to ensure that they match the requirement of this review. It is worth noting that we adopt different inclusion and exclusion guidelines and several quality evaluation constraints as shown in Appendix B. For example, the included papers are limited to those using ML/DL models for NDs diagnosis, excluding those using only rule-based or mathematical analysis method. All included papers conduct experiments with both healthy controls and NDs patients. Papers are excluded if the sample size is less than 10. For included papers, we report the experimental results of the best-performing AI models, using commonly-used evaluation metrics (e.g., accuracy, area under the curve (AUC)).

1.3 Screening and Data Abstraction

The systematic literature selection process is conducted according to the criteria of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), as shown in Fig. 1. The three phases of PRISMA can be summarized as follows:

- **Identification:** Firstly, different authors conduct the preliminary literature search from PubMed, WoS, and Google Scholar independently, and identify all potentially-matched articles (2069 articles) after discarding duplicate papers.
- Screening: Then, we select relevant papers via screening their titles and abstracts according
 to the pre-defined inclusion and exclusion criteria. The selected articles (243 articles), whose
 titles and abstracts matched the inclusion criteria, are further reviewed through a full-text
 assessment.
- Inclusion: Finally, we review the full text of the screened articles and exclude the unmatched articles. We record the key contents of all included articles (164 articles), including title, authors, year, country, organization, journal/book, name of disease, data type, AI model, number of samples, etc., which are summarized in our paper.

2 POTENTIAL DISEASE-RELATED GAITS

- Myopathic gait is sometimes called a waddling gait and characterized by a side-to-side movement. It is often a result of the weakness in the pelvic area. Myopathic gait may be a symptom of muscular dystrophy, muscle disease, or spinal muscle weakness.
- Ataxic gait is known for staggering movements during walking. A person with such gait tends to wobble from side to side and is unable to walk in a straight line. Additionally, their balance while standing could be affected as well, leading to a swaying motion. Ataxic gait can be a symptom of alcohol intoxication or a sign of brain injury.
- **Hemiplegic gait** is an abnormal gait that affects one side of the body, *i.e.*, one side of the arm does not move and the leg on the same side needs to be dragged in a semi-circle to be brought forward during walking. A hemiplegic gait is often the result of a stroke.
- **Diplegic gait** affects both sides of the body and is characterized by stiff, slightly flexed hips and knees, with ankles turned inward. The gait often involves a scissor-like movement of the legs and tiptoe walking, resulting in shorter steps. A diplegic gait can be a result of cerebral palsy, stroke, or head trauma.
- **Sensory gait** occurs when a person is unable to receive proprioceptive information, which is necessary to discern the position of their legs. As a result, individuals often lift their feet higher than usual and then slam them down hard onto the ground to sense their location. This gait can be seen in disorders with damaged dorsal columns (*e.g.*, B12 deficiency or tabes dorsalis) or in diseases affecting the peripheral nerves (*e.g.*, uncontrolled diabetes).

3 QUALITY EVALUATION CRITERION

To provide a comprehensive quality score for each study, we empirically grade the novelty of AI models, comprehensiveness of method comparison, or sufficiency of experimental samples at three levels with the score 1, 2, or 3, which are defined as below:

- Score (S_n) for Novelty of AI Models
- (1) Score $S_n = 1$: The main proposed method belongs to or contains only C-ML models.
- (2) Score $S_n = 2$: The main proposed method belongs to or contains C-DL models.
- (3) Score $S_n = 3$: The main proposed method belongs to or contains A-DL models.
- Score (S_c) for Comprehensiveness of Method Comparison
- (1) Score $S_c = 1$: The study only compares different settings of the proposed method, without comparing with any other existing methods or studies.
- (2) Score $S_c = 2$: The study compares the proposed method with one published method or study.

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Table 3. Number of studies related to different NDs (PD, HD, MS, AD, ALS) and different model types (C-ML, C-DL, A-DL). "Combinatorial" denotes studies that simultaneously focus on diagnosis of multiple NDs including PD, ALS, and HD.

ND / Model	C-ML	C-DL	A-DL	Total
PD	77	34	13	124
Combinatorial (PD, ALS, HD)	11	6	2	19
HD	6	1	0	7
MS	4	1	1	6
AD	3	1	1	5
ALS	3	0	0	3
Total	104	43	17	164

- (3) Score $S_c = 3$: The study compares the proposed method with more than one published methods or studies.
- Score (S_s) for Sufficiency of Experimental Samples
- (1) Score $S_s = 1$: The size of experimental samples (*i.e.*, number of patients plus number of controls) is less than 30.
- (2) Score $S_s = 2$: The size of experimental samples is equal to or more than 30, and less than 100.
- (3) Score $S_s = 3$: The size of experimental samples is equal to or more than 100.

To normalize the final quality score S_Q to the value range from 0 to 1, we sum the scores from all three aspects and divide them by the maximum score:

$$S_Q = \frac{S_n + S_c + S_s}{9} \tag{1}$$

The quality score S_Q is computed for each study and presented in the tables of our paper.

4 GAIT DATA TAXONOMY

We present the taxonomy of all collected gait data types in Fig. ?? by categorizing them into four main classes based on their collection modalities. We elaborate on the common techniques used in each modality, along with their corresponding merits and demerits. At the end, we summarize by discussing the benefits and limitations of using these four different modalities in various applications.

- Sensor Modality: Advancement in sensor technologies allows its application in various tasks such as action recognition, event detection, kinematic and kinetic parameter estimation, gait classification, *ect*. The sensors explored in the collected papers include force sensors[1–4], inertial sensors, some hybrid sensors comprise of different kinds of sensors[5–8] as well as other less prevalent sensors. Depending on the specific sensor type, they offer various advantages, including portability, low cost, and miniaturization.[9].
- (1) **Force Sensor**: There are mainly two types of force or pressure capturing approaches, in the filed of NDs classification based on gait, that are used to collect the foot-ground interaction data during locomotion. The first is to use non-wearable floor-mounted devices (*e.g.*, force plates, pressure platform) with either load cells or force sensitive resistors (FSRs) where one measures the ground reaction force (GRF) and moments in three dimensions: vertical, anteroposterior (forward-backward), and mediolateral (side-to-side), and the other obtains detailed plantar pressure profiles, respectively[9]. In a laboratory setting, either load cells or FSRs would be sufficient for precise data collection when integrated into some stationary floor-mounted devices. However, since those devices are often bulky,

- operating-costly, and expensive, it's not often clinically applicable. Aiming at solving these constrains, researchers develop the second approach by merging the load cells and/or FSRs into some small wearable devices (e.g., insole) [10, 11]. Although these wearable sensors have less accuracy and reliability compare with the floor-mounted ones, due to its portable features and cheap installment, its application in the field has became a popular choice and risen significantly in the past 2 decades.
- (2) **Inertial Sensor**: Also termed as Inertial Measurement Unit (IMU), is an amalgamation of a triaxial accelerometer, gyroscope, or magnetometer, each providing critical data on three-dimensional acceleration, angular velocity, and the ambient magnetic field's magnitude and direction, respectively[9, 12]. It is often attached to limb segments (*e.g.*, foot, shank, hip)[13–15] or embedded in wearable devices (*e.g.*, shoes, smartphone, smartwatch) to capture dynamic motion of the subject[16–21]. These sensors or devices, depending on their placement locations, record the repeating pattern of gait signals generated by the locomotion of the subjects. These signals will then be interpreted with various algorithms for the intended tasks, including gait event detection, kinetic or kinematic parameters estimation, and gait classification.
- (3) **Multi-Sensor**: These sensors typically combine various types of sensors for a more comprehensive data collection. Among the surveyed papers, studies such as [22–24] utilize both IMU sensors and FSRs for gait data collection, while [25] employs both EEG sensors and FSRs. These combinations harvest the strengths of each sensor type for a more comprehensive understanding of gait characteristic hence help enhancing the reliability and accuracy of gait event detection and classification.
- (4) Other Sensors: Sensors included in this category are less prevalent and exploited among collected papers. However, these sensors still play an important role in providing a more comprehensive understanding of the human gait. For instance, *EEG (electroencephalogram) Sensor* is a type of sensor used to measure the electrical activity of the brain using small, flat metal discs attached to the scalp. Its signals contain opulent information regarding brain's functional process[26]. In the context of gait disorder detection, EEG data can be used to analyze brain activity patterns that may correlate with specific gait abnormalities[25, 27]. Researchers have been using EEG data to aid the diagnosis, early detection, and classification of NDs (*e.g.*, AD) in several studies[28, 29]. Besides, *EMG (Electromyography) Sensor* is used to measure the electrical activity produced by muscles during contraction and rest[30]. These muscle cells activity is controlled by the nerve cells called motor neurons. Since NDs patients (*e.g.*, PD) suffer from the degeneration of nerve cells, they manifest significantly different muscle electrical pattern with various disease severity as well as from healthy subjects[12]. Therefore, their EMG data can be utilized to analyze muscle activation patterns during walking and hence aid in the diagnostic of various NDs such as PD[30].
- Vision Modality: The vision modality employs optoelectronic motion capture (Mocap) systems to capture the locomotion of subjects during walking. It's used to mimic the clinical examination which purely depends on the physicians' naked eyes. However, due to the constrains of human eyes, using a more robust camera-based system for gait diagnosis is more practical. The vision modality uses various types of cameras (e.g., Analog, Smartphone[31, 32], Digital Single Lens Reflex (DSLR) [33], and Infrared (IR) Camera[34]) to estimate human gait. Depends on the precision requirement of the video data, the vision modality could be further divided into two sub-categories namely marker-based and marker-less Mocap systems[35].
- (1) **Marker-Based**: This approach is developed in an early stage when the motion capture (Mocap) system are not advanced enough for precise motion capturing. Therefore, these Mocap systems (*e.g.*, Vicon, IR Cameras, etc) use reflective markers which can be placed

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on the body landmarks and used as a guide for the camera to precisely capture target's movement. The model of human body is constructed after for feature extraction. The advantages of using the marker-based approach are that is highly accurate and provides exact location of the body landmark. These advantages hence make this modality as a gold standard in the field for collecting the most precise gait data. However, this method requires attaching markers to the body, leading to additional expenses and the potential to alter the gait, high setup costs, a lack of clinical friendliness. [36–38].

- (2) Marker-Free: Due to the limitation of the marker-based approach mentioned above and the development of the camera technology, the marker-free approach comes into appearance in the mid-ninety. This approach capture the gait video of the target without attaching nay markers on the subject's body. Then the vision related statistical information and other biomechanical features (e.g., GEIs (Gait Energy Images)[39] or Optical Flow[40]) are derived from the video clips. Moreover, The application of smartphone technology, although still in its infancy, has also given a new insight towards this field since it's has all the benefits of this modality (e.g., highly compact, portable, no requirement of lab environment, becoming cheaper, fast advancement, etc). However, since it's still in its early developing stage, it also suffers from disadvantages such as lower accuracy, etc.
- Sensor+Vision Modality: This modality could also be referred to as multi-modal modality. In comparison with single-modal approaches, although the latter ones have their own merits and show some promising results, combining sensor and vision modality unleashes a bigger potential, such as providing richer data and more comprehensive features, capturing more subtle changes in gait, improving recognition performance [27, 41, 42]. In recent years, the application of Microsoft Kinect system has gain a tremendous amount of attention from many authors in the field due to its utilization of both depth sensor, which contains an infrared laser projector and an infrared camera, and RGB camera. This integration enables a more accurate estimation and calculations for the gait parameters while not sacrificing the advantages mentioned in the marker-less vision modality. More specifically, using only the conventional camera to estimate skeleton coordinates usually produce coarse results. However, when employing the depth sensor, the spatiotemporal features of subjects can be derived from the precise coordinates of skeleton joints obtained using it. This additional spatial information, which is not available in the marker-less vision approach, provides a more comprehensive description of the gait. In addition, the precision and efficacy of using Kinect has been verified in many studies which compares the result with the data obtained using gold standard (Marker-Based vision) approach. Nevertheless, one of the short comings of using the depth sensor is that its precision reduces as the subject walks further away from the camera, resulting in a width and length-limited data collection space [43-46]. Besides the RGB-D camera approach, there are also other combinations of these two modalities. For example, You et al. combined vision techniques with EEG sensors in their study [27]. Similarly, Tahir et al. fused a marker-based IF camera and a force-sensitive platform [47], while Chatzaki et al. utilized a conventional camera, IMU, and a force platform [42]. Additionally, Zhao et al. merge some vGRF and IMU sensors with Kinect[41].
- Other Modalities: Trabassi et al. use electronic medical record (EMR) which contains various
 patient-related features and medical history data that are indicative of early PD symptoms
 or risk factors as well as the first diagnosis of gait or tremor disorders to create prediction
 models.[48]

In a nutshell, despite having so many benefits of using sensor technology to directly obtain NDs gait, it still suffers from certain limitations such as high cost, time, power, and personnel for the

non-wearable stationary sensors and wearing discomfort, drifting effect, and potential gait altering problem for the wearable ones. These limitations thus make it unsuitable for obtaining rich gait parameters in a precise and clinic-friendly manner. On the other hand, the vision based modality involved using highly-precise Mocap systems and is considered as the gold standard for data collection. However, it too has some flaws such as costly to operate, necessity of lab environment, requirement of high proficiency, *ect*. However, the combined sensor and vision approach utilizes both modalities' merits without sacrificing its performance too much. It also provides a more comprehensive view of the human gait data by considering both the spatiotemporal data and the overall skeleton joints correlations of the whole body. Thanks to these advantages, we further highlighted the benefit of using skeleton data to aid in NDs diagnosis in the research vision section.

5 SUPPLEMENTARY LISTS OF INCLUDED AND EXCLUDED PAPERS

Table 4. List of included survey papers (N = 14).

No.	First Author	Title	Organization	Journal /Conference	Year	Country	Database	DOI
1	Navleen Kour	[33]	Shri Mata Vaishno Devi University	EXPERT SYSTEMS	2022	India	Web of Science	10.1111/exsy.12955
2	Preeti Khera	[49]	Academy of Scientific & Innovative Research (AcSIR)	ENGINEERING SCIENCE AND TECHNOLOGY-AN INTERNATIONAL JOURNAL-JESTECH	2022	India	Web of Science	10.1016/j.jestch .2021.05.009
3	Luay Fraiwan	[50]	Abu Dhabi University	PLOS ONE	2021	Abu Dhabi	Web of Science	10.1371/journal .pone.0252380
4	NAVLEEN KOUR	[35]	Shri Mata Vaishno Devi University	IEEE ACCESS	2019	India	Web of Science	10.1109/ACCESS. 2019.2949744
5	Navleen Kour	[12]	Shri Mata Vaishno Devi University	MULTIMEDIA TOOLS AND APPLICATIONS	2022	India	Web of Science	10.1007/s11042 -022-13398-7
6	di Biase L	[51]	Università Campus Bio- Medico di Roma	Sensors (Basel)	2020	Italy	PubMed	10.3390/s20123529
7	Pardoel S	[52]	University of Waterloo	Sensors (Basel)	2019	Canada	PubMed	10.3390/s19235141
8	Gupta R	[53]	Delhi Technological, University	Ageing Res Rev	2023	USA	PubMed	10.1016/j.arr. 2023.102013
9	Figueiredo J	[54]	University of Minho	Med Eng Phys	2018	Portugal	Google Scholar	10.1016/j.medeng phy.2017.12.006
10	Vienne A	[55]	Université Paris Descartes	Front Psychol	2017	France	Google Scholar	10.3389/fpsyg .2017.00817
11	Das R	[9]	North-Eastern Hill University	Frontier in Neuro- science	2022	India	Google Scholar	10.3389/fnins. 2022.859298
12	Salchow- Hömmen	[56]	Charite University	Frontiers in Human Neuroscience	2022	German	Google Scholar	10.3389/fnhum .2022.768575
13	Hui Wen Loh	[57]	Singapore University of Social Sciences (SUSS)	SENSORS	2021	Singapore	Web of Science	10.3390/s21217034
14	Zainab Ayaz	[58]	University of Peshawar	NEURAL COMPUTING & APPLICATIONS	2021	Pakistan	Web of Science	10.1007/s00521 -021-06626-y

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Table 5. List of all included papers (N=164).

No.	First Author	Title	Organization	Journal /Conference	Year	Country	Database	DOI	Disease	:
1	Abir Alharbi	[59]	King Saud University	INTERNATIONAL JOURNAL OF COM- PUTER MATHEMAT- ICS	2020	Saudi Ara- bia	Web of Science	10.1080/002071 60.2019.1607842	PD	
2	Domenico Buon- giorno	[43]	Politecnico di Bari	BMC MEDICAL INFOR- MATICS AND DECI- SION MAKING	2019	Italy	Web of Science	10.1186/s12911 -019-0987-5	PD	
3	Andrea Mannini	[15]	Scuola Superiore Sant'Anna	SENSORS	2016	Italy	Web of Science	10.3390/s 16010134	HD (a Post Stroke)	and
4	Armin Salimi- Badr	[60]	Shahid Beheshti University	APPLIED INTELLI- GENCE	2022	Iran	Web of Sci- ence	10.1007/s10489 -022-04276-8	PD	
5	Juliana Paula Fe- lix	[61]	Universidade Federal de Goias	2019 IEEE 31ST INTERNATIONAL CONFERENCE ON TOOLS WITH ARTIFI- CIAL INTELLIGENCE (ICTAI 2019)	2019	Brazil	Web of Science	10.1109/ICTAI. 2019.00243	HD	
6	Juliana Paula Fe- lix	[62]	Universidade Federal de Goias	2020 IEEE INTERNA- TIONAL CONFER- ENCE ON BIOIN- FORMATICS AND BIOMEDICINE	2020	Brazil	Web of Science	10.1109/BIBM 49941.2020. 9313308	ALS	
7	Carlos Fernandes	[63]	Universidade do Minho	PROCEEDINGS 2018 IEEE INTERNA- TIONAL CONFER- ENCE ON BIOIN- FORMATICS AND BIOMEDICINE (BIBM)	2018	Portugal	Web of Science	10.1109/BIBM .2018.8621466	PD	
8	Balaji, E	[64]	PSG College Tech- nology	APPLIED SOFT COM- PUTING	2021	India	Web of Science	10.1016/j .asoc.2021 .107463	PD	
9	Felix, Juliana Paula	[65]	Universidade Federal de Goias	2021 IEEE 45TH AN- NUAL COMPUTERS, SOFTWARE, AND APPLICATIONS CON- FERENCE (COMPSAC 2021)	2021	Brazil	Web of Science	10.1109/COMP SAC51774.20 21.00295	ALS	
10	Tuan D. Pham	[66]	Prince Mohammad Bin Fahd University	INTERNATIONAL CONFERENCE ON ELECTRICAL, COM- PUTER AND ENERGY TECHNOLOGIES (ICECET 2021)	2021	Saudi Arabia	Web of Science	10.1109/IC ECET52533. 2021.9698524	PD	
11	Yi Xia	[1]	Anhui University	BIOMEDICAL SIGNAL PROCESSING AND CONTROL	2015	China	Web of Science	10.1016/j.bspc .2015.02.002	ALS, HD	PD
12	Ferdous Wahid	[67]	University of Mel- bourne	IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMAT- ICS	2015	Australia	Web of Science	10.1109/JBHI .2015.2450232	PD	
13	Helber Andrés Carvajal-Castaño	[13]	Universidad de Antioquia	ELECTRONICS	2022	Colombia	Web of Sci- ence	10.3390/elec tronics11172684	PD	
14	Rehman, Rana Zia Ur	[68]	Newcastle Uni- versity	SENSORS	2019	UK	Web of Science	10.3390/s 19245363	PD	
15	Khoury, Nicolas	[69]	Universite Paris-Est-Creteil- Val-de-Marne (UPEC)	SENSORS	2019	France	Web of Science	10.3390/s 19020242	PD	
16	Balaji E	[70]	PSG College Tech- nology	MEDICAL ENGINEER- ING & PHYSICS	2021	India	Web of Science	10.1016/j. medengphy.2021 .03.005	PD	
17	Imanne El Maachi	[71]	Universite de Montreal	EXPERT SYSTEMS WITH APPLICATIONS	2020	Canada	Web of Sci- ence	10.1016/j.eswa .2019.113075	PD	

18	Navita Mehra	[72]	Maharshi Dayanand University	INTERNATIONAL JOURNAL OF AD- VANCED COMPUTER SCIENCE AND APPLI- CATIONS	2022	India	Web of Science		PD	
19	James R. Williamson	[73]	Lincoln Lab- oratory; Mas- sachusetts Institute of Technology (MIT)	SENSORS	2021	USA	Web of Science	10.3390/s 21062047	PD	
20	Alex Li	[74]	Stanford University	DIAGNOSTICS	2022	USA	Web of Science	10.3390/diagnostics 12102404	PD	
21	Mirelman, Anat	[75]	Teva Pharmaceu- tical Industries	MOVEMENT DISOR- DERS	2021	Israel	Web of Sci- ence	10.1002/mds.28631	PD	
22	Nguyen, Quoc Duy Nam	[76]	National Cheng Kung University	ENTROPY	2020	Taiwan, China	Web of Sci- ence	10.3390/e 22121340	PD, ALS	HD,
23	Juliana Paula Fe- lix	[61]	Universidade Fed- eral de Goias	ADVANCES IN VISUAL COMPUTING, ISVC 2019, PT II	2019	Brazil	Web of Science	10.1007/978 -3-030-337 23-0_41	HD	
24	Che-Wei Lin	[77]	National Cheng Kung University	SENSORS	2020	Taiwan, China	Web of Sci- ence	10.3390/s 20143857	PD, ALS	HD,
25	Yi-Wei Ma	[78]	National Taiwan University of Sci- ence & Technol- ogy	SOFT COMPUTING	2021	Taiwan, China	Web of Science	10.1007/s 00500-021 -06170-w	PD	
26	Taiki Ogata	[79]	Tokyo Institute of Technology	FRONTIERS IN PHYSI- OLOGY	2022	Japan	Web of Sci- ence	10.3389/fphys .2022.726677	PD	
27	Christian Ur- cuqui	[80]	Universidad ICESI	2018 14TH INTER- NATIONAL CONFER- ENCE ON SEMANTICS, KNOWLEDGE AND GRIDS (SKG)	2018	Colombia	Web of Science	10.1109/SKG .2018.00029	PD	
28	Shyam V. Peru- mal	[8]	State University System of Florida	ICT EXPRESS	2016	USA	Web of Sci- ence	10.1016/j.icte .2016.10.005	PD	
29	Enas Abdulhay	[81]	Jordan University of Science & Tech- nology	FUTURE GENERA- TION COMPUTER SYSTEMS-THE INTER- NATIONAL JOURNAL OF ESCIENCE	2018	Jordan	Web of Science	10.1016/j .future.2018 .02.009	PD	
30	Abdullah S. Al- harthi	[59]	University of Manchester	IEEE SENSORS JOUR- NAL	2021	UK	Web of Sci- ence	10.1109/JSEN .2020.3018262	PD	
31	Juan C. Pérez- Ibarra	[22]	Universidade de Sao Paulo	IEEE SENSORS JOUR- NAL	2020	USA	Web of Sci- ence	10.1109/JSEN .2020.3011627	PD	
32	Febryan Setiawan	[82]	National Cheng Kung University	BRAIN SCIENCES	2021	Taiwan, China	Web of Sci- ence	10.3390/brainsci 11070902	PD, ALS	HD,
33	Carlotta Caramia	[14]	Roma Tre University	IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMAT- ICS	2018	Italy	Web of Science	10.1109/JBHI .2018.2865218	PD	
34	Andrew P. Creagh	[83]	University of Oxford	SCIENTIFIC REPORTS	2021	UK	Web of Sci- ence	10.1038/s41598 -021-92776-x	MS	
35	Rana Zia Ur Rehman	[84]	Newcastle University	FRONTIERS IN AGING NEUROSCIENCE	2022	UK	Web of Sci- ence	10.3389/fnagi .2022.808518	PD	
36	Juan Felipe Reyes	[45]	Universidad ICESI	2019 IEEE COLOM- BIAN CONFERENCE ON COMMUNICA- TIONS AND COM- PUTING (COLCOM 2019)	2019	Colombia	Web of Science		PD	
37	Rami Alkhatib	[85]	Rafik Hariri Uni- versity	IEEE SENSORS LETTERS	2020	Lebanon	Web of Sci- ence	10.1109/LSENS .2020.2994938	PD	
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Women's University Women's University File International Conference on Intelligent Computing And Control SYSTEMS (ICICCS 2020)											
Saperma Lunverse SebSORS 2022 Endy Web of Sci. 22103730 PD	38	Elham Rastegari	[86]		THE 52ND ANNUAL HAWAII INTERNA- TIONAL CONFER- ENCE ON SYSTEM	2019	USA			PD	
19	39	Dante Trabassi	[87]		SENSORS	2022	Italy		22103700	PD	
Wenting Hu [6] Memorial University MISARKO KUNNE 2022 Canada Web of Sci- 0.1186/s12938 MS Manor-Ospina, [6] Fundacion Valle Add Lili FRONTIERS IN HU- MORENO KUNNE 2022 28/3076 MS 2022 28/307	40	Xiuyu Huang	[88]	, ,	TION PROCESSING	2019	Australia		8-3-030-368	HD	
	41	Wenting Hu	[6]	sity Newfound-	BIOMEDICAL ENGI-	2022	Canada			MS	
Hamza Abujirda 189 Worcester Poly BloMEDICAL 2020 U.S. Web of Science -1976/ab39a8 PD	42		[46]			2022	Colombia			PD	
Francisco Display Universidad Lieb Al-CESS 2018 Mesico Web of Sci 2018,2840327 HD	43	Hamza Abujrida	[89]		PHYSICS & ENGI-	2020	USA			PD	
1	44		[90]	Juarez Autonoma	IEEE ACCESS	2018	Mexico			HD	
According Pabio Cuzzolin Pabio Pabio Cuzzolin Pabio Pabio Cuzzolin Pabio P	45	Yajing Guo	[25]	0	2019 IEEE 8TH JOINT INTERNATIONAL INFORMATION TECHNOLOGY AND ARTIFICIAL INTELLI- GENCE CONFERENCE	2019	China			PD	
Camilo Vasquez- Correa P2 Oniversidad of Reference Correa Antioquia Reference Correa Antioquia Reference	46	Fabio Cuzzolin	[91]		GAIT & POSTURE	2017	UK		gaitpost.2017	PD	
Alexandra- Georgiana Geo	47		[92]		BIOMEDICAL AND HEALTH INFORMAT-	2019	Colombia			PD	
STIVATION Very stranger	48	Georgiana	[93]	University of	BIOENGINEERING	2019	Romania		47216.2019	PD	
Solution	49		[94]			2020	Malaysia			PD	
Sachneet Kaur 7	50	Yang xiaoli	[95]	versity of Tech-	TRANSLATIONAL ENGINEERING IN HEALTH AND	2022	China			PD	
DURNAL OF MEDI- CAL AND BIOLOGI- CAL AND BIOL	51	Rachneet Kaur	[7]	,	ON BIOMEDICAL EN-	2021	USA			MS	
S.A.Vajiha Begum [97] Mother Teresa PROCEEDINGS OF 2020 India Web of Science 48265.2020 PD,	52	Luis C. Guayacan	[96]	Industrial de	CAL AND BIOLOGI-	2022	Colombia		40846-022-	PD	
Newcastle University SCIENTIFIC REPORTS 2019 UK Web of Science 10.1038/s41598 PD	53	S.A.Vajiha Begum	[97]	Women's Univer-	THE INTERNATIONAL CONFERENCE ON IN- TELLIGENT COMPUT- ING AND CONTROL SYSTEMS (ICICCS	2020	India		48265.2020		ALS,
55 A.P. Creagh [83] University of Ox- IEEE JOURNAL OF 2021 UK Web of Sci- 2020.2998187 MS BIOMEDICAL AND HEALTH INFORMATICS 56 MARÍA GOÑI [20] Helmholtz Asso- IEEE ACCESS 2022 Germany Web of Sci- 2022 3156659 PD	54		[98]			2019	UK			PD	
56 MARÍA GOŇI [20] Helmholtz Asso- IEEE ACCESS 2022 Germany Web of Sci- 2022 3156659 PD	55		[83]	University of Ox-	BIOMEDICAL AND HEALTH INFORMAT-	2021	UK	Web of Sci-	10.1109/JBHI	MS	
Catton	56	MARÍA GOÑI	[20]	Helmholtz Asso- ciation		2022	Germany	Web of Science		PD	

57	Hamza Abujrida	[21]	Worcester Poly- technic Institute	2017 IEEE-NIH HEALTHCARE IN- NOVATIONS AND POINT OF CARE TECHNOLOGIES (HI-POCT)	2017	China	Web of Science	10.1109/HIC. 2017.8227621	PD
58	Trentzsch, Katrin	[99]	Technische Uni- versitat Dresden	BRAIN SCIENCES	2021	Germany	Web of Sci- ence	10.3390/brain sci11081049	MS
59	Md Nafiul Alam	[5]	University of North Dakota Grand Forks	PLOS ONE	2017	USA	Web of Science	10.1371/journal .pone.0175951	PD
60	Sathya Bama, B	[100]	Sathyabama Insti- tute of Science & Technology	HEALTH SYSTEMS	2022	India	Web of Sci- ence	10.1080/204 76965.2022 .2125838	PD
61	Younghoon Jeon	[101]	Korea National University of Transportation	IEEE SENSORS JOUR- NAL	2023	Korea	Web of Science	10.1109/JSEN .2023.3259034	AD
62	P Divyashree	[102]	Indian Institute of Information Tech- nology	IEEE TRANSACTIONS ON COMPUTA- TIONAL SOCIAL SYSTEMS	2023	India	Web of Science	10.1109/TCSS .2022.3224046	PD
63	Tunç Aşuroğlu	[103]	Tampere Univer- sity	HEALTH AND TECH- NOLOGY	2022	Finland	Web of Sci- ence	10.1007/s12553 -022-00698-z	PD
64	Olmos J	[104]	Biomedical Imag- ing, Vision and Learning Labora- tory	Annu Int Conf IEEE Eng Med Biol Soc	2022	Colombia	PubMed	10.1109/EMBC 48229.2022 .9871206	PD
65	Yuan W	[48]	Harvard Medical School	BMC Neurol	2021	USA	PubMed	10.1186/s 12883-021 -02226-4	PD
66	Zhao A	[41]	Qingdao Univer- sity	IEEE Trans Cybern	2022	China	PubMed	10.1109/TCYB .2021.3056104	ALS, HD, and PD
67	You Z	[27]	Shenzhen Peo- ple's Hospital	Front Public Health	2020	China	PubMed	10.3389/fpubh .2020.584387	ALS
68	Zhang S	[105]	The University of Sydney	Stud Health Technol Inform	2019	Australia	PubMed	10.3233/SH TI190267	HD
69	Hughes JA	[106]	St. Francis Xavier University	IEEE J Biomed Health Inform	2020	Canada	PubMed	10.1109/JBHI .2019.2961808	PD
70	Ingelse L	[107]	Universidade de Lisboa	Sensors (Basel)	2022	Portugal	PubMed	10.3390/s 22113980	PS, PD
71	Xia Y	[108]	Anhui University	IEEE Trans Neural Syst Rehabil Eng	2020	China	PubMed	10.1109/TNS .2019.2946194	PD
72	Filtjens B	[109]	KU Leuven	J Neuroeng Rehabil	2022	Belgium	PubMed	10.1186/s 12984-022 -01025-3	PD
73	Mileti I	[23]	Sapienza Univer- sity of Rome	Sensors (Basel)	2018	Italy	PubMed	10.3390/s 18030919	PD
74	Zeng W	[110]	Longyan Univer- sity	Neurosci Lett	2016	China	PubMed	10.1016/j.neulet .2016.09.043	PD
75	Carvajal-Castaño HA	[111]	Universidad de Antioquia	Hum Mov Sci	2022	Colombia	PubMed	10.1016/j .humov.2021 .102891	PD
76	Park H	[34]	Dong-A University	J Neuroeng Rehabil	2021	Korea	PubMed	10.1186/s 12984-021 -00975-4	PD
77	Rovini E	[112]	Viale Rinaldo Piaggio	Ann Biomed Eng	2018	Italy	PubMed	10.1007/s 10439-018 -2104-9	PD (and Idiopathic Hyposmia (IH))
78	Seifallahi M	[113]	Florida Atlantic University	IEEE Trans Neural Syst Rehabil Eng	2022	USA	PubMed	10.1109/TNSRE .2022.3181252	AD
79	Pham TD	[114]	Linkoping Uni- versity	IEEE Trans Biomed Eng	2018	Sweden	PubMed	10.1109/TBME .2017.2779884	PD
80	Filtjens B	[36]	KU Leuven	BMC Med Inform Decis Mak	2021	Belgium	PubMed	10.1186/s12 911-021- 01699-0	PD

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81	Ťupa O	[44]	University of Chemistry and Technology in Prague	Biomed Eng Online	2015	Czech Republic	PubMed	10.1186/s 12938-015 -0092-7	PD
82	Shalin G	[115]	University of Waterloo	J Neuroeng Rehabil	2021	Canada	PubMed	10.1186/s 12984-021 -00958-5	PD
83	Costa L	[116]	University of Minho	Comput Intell Neurosci	2016	Portugal	PubMed	10.1155/2016 /3891253	AD
84	Perez-Ibarra JC	[22]	University of São Paulo	IEEE Trans Neural Syst Rehabil Eng	2020	Brazil	PubMed	10.1109/TNSRE .2020.3039999	PD
85	Ricciardi C	[117]	University Hospi- tal of Naples	Comput Methods Programs Biomed	2019	Italy	PubMed	10.1016/j.cmpb .2019.105033	PD
86	Som A	[118]	Arizona State University	Annu Int Conf IEEE Eng Med Biol Soc	2020	USA	PubMed	10.1109/EMBC 44109.2020. 9176572	PD
87	Khorasani A	[119]	Iran University ofScience and Technology	J Med Syst	2014	Iran	PubMed	10.1007/s 10916-014 -0147-5	PD
88	Rehman RZU	[120]	Newcastle University	Sensors (Basel)	2020	UK	PubMed	10.3390/s 20185377	PD
89	Aich S	[121]	Inje Universit	Sensors (Basel)	2018	Korea	PubMed	10.3390/s 18103287	PD
90	Zeng W	[122]	Longyan Univer- sity	Neural Netw	2019	China	PubMed	10.1016/j. neunet.2018 .12.012	PD
91	Joshi D	[123]	Indian Institute of Technology	Comput Methods Programs Biomed	2017	Indian	PubMed	10.1016/j .cmpb.2017 .04.007	PD
92	Nair P	[124]	IITB-Monash Re- search Academy and IIT Bombay	Annu Int Conf IEEE Eng Med Biol Soc	2020	India	PubMed	10.1109/EMBC 44109.2020 .9175343	PD (Drug induced)
93	Xia Y	[125]	Anhui University	Med Biol Eng Comput	2016	China	PubMed	10.1007/s11517 -015-1413-5	ALS
94	Kugler P	[30]	Friedrich Alexan- der University of Erlangen- Nuremberg	Annu Int Conf IEEE Eng Med Biol Soc	2013	Germany	PubMed	10.1109/EMBC .2013.6610865	PD
95	Omid Mohamad Beigi	[126]	Brock University	Biosystems	2023	Canada	PubMed	10.1016/j. biosystems.20 23.105006	PD
96	Hirotaka Uchit- omi	[127]	Tokyo Institute of Technology	Scientific Reports	2023	Japan	PubMed	10.1038/s 41598-023- 39862-4	PD
97	Guoen Cai	[128]	Fujian Medical University Union Hospital	The Journals of Geron- tology, Series A: Biolog- ical Sciences and Medi- cal Sciences,	2023	China	PubMed	10.1093/ger ona/glad101	PD
98	Yubo Sun	[129]	Nankai Univer- sity	Mathematical Bio- sciences and Engineer- ing	2023	China	PubMed	10.3934/mbe .2023601	PD
99	Zhang J	[31]	Sungkyunkwan University	Sensors (Basel)	2023	Korea	PubMed	10.3390/s 23104980	PD
100	Dobromir Dotova	[130]	McMaster Univer- sity	Journal of Motor Behavior	2023	Canada	PubMed	10.1080/00 222895.2023 .2217100	PD
101	Chenhui Dong	[131]	Changzhou University	IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITA- TION ENGINEERING	2023	China	PubMed	10.1109/TNSRE .2023.3269569	PD
102	Chatzaki C	[42]	Hellenic Mediter- ranean Univer- sity	Sensors (Basel)	2022	Greece	PubMed	10.3390/s 22249937	PD
103	Marta Isabel A. S. N. Ferreira	[38]	Universidade do Porto	Gait Posture	2022	Portugal	PubMed	10.1016/j.gait post.2022 .08.014	PD

105	Roozbeh Atri	[18]	Cohen Veterans Bioscience	Sensors (Basel)	2022	USA	PubMed	10.3390/s 22186831	PD
106	Cristian Tobar	[133]	Campus de Tul- cán	Biomedical Physics & Engineering Express	2022	Colombia	PubMed	10.1088/2057 -1976/ac8c9a	PD, ALS, HD
107	Aite Zhao,	[41]	Qingdao Univer- sity	IEEE Transactions on Cybernetics	2022	China	PubMed	10.1109/TCYB .2021.3056104	PD
108	Y. Yan	[134]	Shenzhen Insti- tutes of Advanced Technology, Chi- nese Academy of Sciences China	IEEE Access	2020	China	Google Scholar	10.1109/ACCESS .2020.2996667	ALS, HD, PD
109	Mannini, A	[15]	University of Sassari	Sensor 2016	2020	Italy	Google Scholar	10.1186/s12984 -020-00728-9	HD (and post- stroke)
110	Y. Mittra	[135]	Guru Gob- ind Singh Indraprastha University	2018 International Con- ference on Automation and Computational En- gineering (ICACE)	2018	India	Google Scholar	10.1109/ICACE .2018.8687022	PD
111	Moon S	[136]	Department of Physical Therapy, Ithaca College	J Neuroeng Rehabil	2020	USA	Google Scholar	10.1186/s12984 -020-00756-5	PD (and essential tremor)
112	Tianben Wang	[137]	Northwestern Polytechnical University	ACM Trans.	2016	China	Google Scholar	10.1145/2890511	PD
113	Luis C. Guayacan	[40]	Universidad Industrial de Santander	Journal of Biomedical Informatics 123 (2021) 103935	2021	Colombia	Google Scholar	10.1016/j.jbi .2021.103935	PD
114	Klomsae A	[138]	Chiang Mai University	Comput Intell Neurosci	2018	Thailand	Google Scholar	10.1155/2018 /1869565	PD, HD, and ALS
115	Behnaz Ghoraani	[139]	Florida Atlantic University	Biomedical Signal Processing and Control 64 (2021) 102249	2020	USA	Google Scholar	10.1016/j .bspc.2020 .102249	AD (and mild cog- nitive impair- ment (MCI))
116	FEBRYAN SETI- AWAN	[140]	National Cheng Kung University	IEEE Access	2022	Chinese Taiwan	Google Scholar	10.1109/ACCESS .2022.3158961	ALS, HD, and PD
117	Mendoza Oscar	[141]	National Institute of Technology, Srinagar	Multimedia Tools and Applications	2022	Colombia	Google Scholar	10.1007/s11042 -022-12280-w	PD
118	L. Gong	[39]	University of Lin- coln	2020 IEEE Intl Conf on Dependable, Auto- nomic and Secure Com- puting, Intl Conf on Per- vasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/ PiCom/ CBD- Com/ CyberSciTech)	2020	UK	Google Scholar	10.1109/DASC -PICom-CBDCom -CyberSciTech 49142.2020.00045	PD
119	Peyvand Ghaderyan	[142]	Sahand Univer- sity of Technol- ogy	Measurement 177 (2021) 109249	2021	Iran	Google Scholar	10.1016/j. measurement. 2021.109249	PD
120	Patil Prithvi	[2]	National Institute of Technology, Srinagar	2019 1st international conference on advances in science, engineering and robotics technology (ICASERT)	2019	India	Google Scholar	10.1109/ICASERT .2019.8934463	MS (and stroke, cere- bral palsy (children))
121	YILMAZ DERYA	[143]	Başkent Univer- sity	EJONS International Journal on Mathe- matic, Engineering and Natural Sciences	2020	Turkey	Google Scholar	10.38063/ ejons.255	PD, HD, or ALS
122	Khang Nguyen	[76]	Institute of Science and Information Technology	Research in Intelligent and Computing in En- gineering. Advances in Intelligent Systems and Computing, vol 1254	2021	Vietnam	Google Scholar	10.1007/978 -981-15- 7527-3_56	PD

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123	Dutta Saibal	[144]	Heritage Institute of Technology	Advances in Heuristic Signal Processing and Applications	2013	India	Google Scholar	10.1007/97 8-3-642-378 80-5_12	PD, ALS	HD,
124	Klucken J	[17]	University Hospi- tal Erlangen	PLoS ONE 8(2): e56956.	2013	Germany	Google Scholar	10.1371/journa .pone.0056956	PD	
125	Tahir Nooritawati Md	[47]	Universiti teknologi MARA	2012 Asain Network for Scientific Information	2012	Malaysia	Google Scholar	10.3923/jas .2012	PD	
126	Manap Hany Haz- fiza	[145]	Universiti teknologi MARA	2013 European Mod- elling Symposium	2013	Malaysia	Google Scholar	10.1109/EMS .2013.36	PD	
127	Niño Santiago	[146]	Universidad Industrial de Santander	Pattern Analysis and Applications	2022	Colombia	Google Scholar	10.1007/s10044 -022-01115-x	PD	
128	Y. Zheng	[147]	Guangdong University of Technology	2021 15th International Symposium on Medical Information and Com- munication Technology (ISMICT)	2021	China	Google Scholar	10.1109/ISMICT 51748.2021. 9434916	PD	
129	Zeng Qingyi	[32]	Nankai University	2022 12th International Conference on CYBER Technology in Automa- tion, Control, and Intel- ligent Systems (CYBER)	2022	China	Google Scholar	10.1109/CYBER 55403.2022. 9907308	PD	
130	Ahamed Musthaq	[148]	The Open University of Sri Lanka	arXiv preprint arXiv:2102.00628	2021	Nugegoda	Google Scholar	10.48550/arXiv .2102.00628	PD	
131	Balaji E	[149]	PSG College of Technology	Applied Soft Comput- ing	2020	India	Google Scholar	10.1016/j .asoc.2020 .106494	PD	
132	Pratiher Sawon	[150]	Indian Institute of Technology	Automated Visual Inspection and Machine Vision II	2017	India	Google Scholar	10.1117/12 .2278894	PD, I ALS	ID and
133	Li, Yan	[24]	University of Science and Technology of China	2022 15th International Congress on Image and Signal Processing, BioMedical Engineer- ing and Informatics (CISP-BMEI)	2022	China	Google Scholar	10.1109/CISP- BMEI56279.2022 .9980005	PD	
134	Wang, Qinghui	[151]	Longyan University	Cognitive Neurody- namics	2022	China	Google Scholar	10.1007/s 11571-022 -09925-9	PD	
135	Torres, An- drés Mauricio Cárdenas	[152]	University of San Buenaventura	Ingenierías USBMed	2023	Colombia	Google Scholar	10.1007/s11571 -022-09925-9	PD, HD	ALS,
136	Goh, Choon-Hian	[153]	Universiti Tunku Abdul Rahman	2022 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)	2022	Malaysia	Google Scholar	10.1109/IECBES 54088.2022. 10079640	PD	
137	Yi han	[154]	Zhejiang Univer- sity	Sensors	2023	China	Google Scholar	10.3390/s 23042104	PD	
138	Kour, Navleen	[33]	Shri Mata Vaishno Devi University	Expert Systems	2022	India	Google Scholar	10.1111/exsy .12955	PD knee osteo thriti (KOA	oar- is
139	Zhou, Zeyang	[155]	University of Technology Sydney	Proceedings of the 2023 International Con- ference on Robotics, Control and Vision Engineering	2023	Australia	Google Scholar	10.1145/360 8143.3608154	PD, HD	ALS,
140	Beigi, Omid Mo- hamad	[156]	Brock University	2022 IEEE Conference on Computational Intel- ligence in Bioinformat- ics and Computational Biology (CIBCB)	2022	Canada	Google Scholar	10.1109/CIBCB 55180.2022 .9863050	PD	

141	Xu Chen	[157]	Hefei University of Technology	Applications in Health, Assistance, and Enter- tainment: 4th Interna- tional Conference	2018	China	Google Scholar	10.1007/978 -3-319- 92037-5_20	PD	
142	Yuyao Zhang	[158]	Intelligent Polymer Research Institute	2013 International Conference on Digital Image Computing: Techniques and Appli- cations (DICTA)	2013	Australia	Google Scholar	10.1109/DI CTA.2013 .6691510	PD	
143	Rami Alkhatib	[159]	Université Jean- Monnet	Journal of Computer and Communications	2015	France	Google Scholar	10.4236/jcc .2015.33003	PD	
144	Ömer Faruk Er- tuğrul	[160]	Batman University	Expert Systems With Applications	2016	Turkey	Google Scholar	10.1016/j .eswa.2016 .03.018	PD	
145	Y. Nancy Jane	[4]	Anna University	Journal of Biomedical Informatics	2016	India	Google Scholar	10.1016/j .jbi.2016 .01.014	PD	
146	Yunfeng Wu	[161]	Xiamen Univer- sity	Biomedical Signal Pro- cessing and Control	2017	China	Google Scholar	10.1016/j .bspc.2016 .08.022	PD	
147	Seyede Marziyeh Ghoreshi Beyrami	[162]	Sahand Univer- sity of Technol- ogy	Measurement	2020	Iran	Google Scholar	10.1016/j .measurement .2020.107579	PD, ALS	HD,
148	A.Athisakthi	[163]	Mother Teresa Women's Univer- sity	International Journal Of Modern Engineering Research (IJMER)	2018	India	Google Scholar	10.1109/WCCCT .2016.66	PD, ALS	HD,
149	Bashir Najafaba- dian	[164]	Islamic Azad University	26th Iranian Confer- ence on Electrical Engi- neering (ICEE2018)	2017	Iran	Google Scholar	10.1109/ICEE. 2018.8472503	PD, ALS	HD,
150	Satyabrata Aich	[37]	Inje University	International Journal of Engineering & Technol- ogy	2018	South Korea	Google Scholar	10.14419/ ijet.v7i3 .29.18547	PD	
151	Anna Krajushk- ina	[165]	Tallinn Univer- sity of Technol- ogy	2018 IEEE International Conference on Systems, Man, and Cybernetics	2018	Estonia	Google Scholar	10.1109/SMC .2018.00630	PD	
152	Tunç Aşuroğlu	[166]	Başkent Univer- sity	Biocybernetics and Biomedical Engineer- ing	2018	Turkey	Google Scholar	10.1016/j.bbe .2018.06.002	PD	
153	Rana Hossam Elden	[167]	Helwan University	2018 IEEE 4th Middle East Conference on Biomedical Engineer- ing (MECBME	2018	Egypt	Google Scholar	10.1109/MECBME .2018.8402417	PD	
154	Siddharth Arora	[16]	Aston University	2014 IEEE International Conference on Acous- tic, Speech and Signal Processing (ICASSP)	2014	UK	Google Scholar	10.1109/ICASSP .2014.6854280	PD	
155	A Procházk	[168]	Institute of Chemical Technology in Prague	Digital Signal Processing	2015	Czech Republic	Google Scholar	10.1016/j.dsp .2015.05.011	PD	
156	Milica Djurić- Jovičić	[169]	University of Bel- grade	Neurological Research	2017	Serbia	Google Scholar	10.1080/01616412 .2017.1348690	PD	
157	Tuan D. Pham	[114]	Linkoping Uni- versity	IEEE Transactions on Biomedical Engineer- ing	2017	Sweden	Google Scholar	10.1109/TBME .2017.2779884	PD	
158	Tripoliti, Evan- thia E	[170]	University of Ioannina	Computer methods and programs in biomedicine	2013	Greece	Google Scholar	10.1016/j .cmpb.2012 .10.016	PD	
159	Mohammad Reza Daliri	[3]	Iran University of Science and Tech- nology	Measurement	2012	Iran	Google Scholar	10.1016/j .measurement. 2012.04.013	PD, ALS	HD,
160	Zhao, Aite	[171]	Ocean University of China	Neurocomputing	2018	China	Google Scholar	10.1016/j. neucom.2018 .03.032	PD	

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								10.1109/EMBC	
161	Butt, Abdul Haleem	[172]	University of Florence	2020 42nd Annual Inter- national Conference of the IEEE Engineering in Medicine & Biology So- ciety (EMBC)	2020	Italy	Google Scholar	44109.2020 .9176051	PD
162	Zhang, Hanrui	[173]	University of Michigan Medi- cal School	Patterns	2020	USA	Google Scholar	10.1016/j .patter.2020 .100042	PD
163	Yurdakul, Oğul Can	[174]	Middle East Tech- nical University	Biomedical Signal Pro- cessing and Control	2020	Turkey	Google Scholar	10.1016/j.bspc .2020.102070	PD
164	M. Sneha Baby	[175]	Rajiv Gandhi Institute of Technology	2017 International Conference on Circuits Power and Computing Technologies [ICCPCT]	2022	India	Google Scholar	10.1109/ICCPCT .2017.8074230	PD

Table 6. List of Representative Excluded Papers and Reasons.

No.	Title	Excluded Reason			
1	Accuracy of the Microsoft Kinect sensor for measuring movement in people with Parkinson's disease.	*Without using machine learning			
2	Gait analysis comparing Parkinson's disease with healthy elderly subjects	*Without using machine learning			
3	$ Arm\ swing\ magnitude\ and\ asymmetry\ during\ gait\ in\ the\ early\ stages\ of\ Parkinson's\ disease. $	*Without using machine learning			
4	$\label{lem:approx} A\ vision-based\ analysis\ system\ for\ gait\ recognition\ in\ patients\ with\ Parkinson's\ disease.$	*others			
5	Using Kinect to classify Parkinson's disease stages related to severity of gait impairment	*Without involving patients or controls			
6	Postural control deficit during sit-to-walk in patients with Parkinson's disease and freezing of gait	*Without using machine learning			
7	Decomposition of complex movements into primitives for Parkinson's disease assessment	*Without involving patients or controls			
8	A validation study of freezing of gait (FoG) detection and machinelearning-based FoG prediction using estimated gait characteristics with a wearable accelerometer,	*Without involving patients or controls			
9	Using transfer learning for classification of gait pathologies,	*Unmatched tasks			
10	Classification of pathologies using a vision based feature extraction	*Without involving patients or controls			
11	A vision-based system for movement analysis in medical applications: The example of Parkinson disease	*Without involving patients or controls			
12	Principal component analysis of gait in Parkinson's disease: Relevance of gait velocity	*Without using machine learning			
13	A vision-based regression model to evaluate Parkinsonian gait from monocular image sequences	*Without using machine learning			
14	Quantification and recognition of Parkinsonian gait from monocular video imaging using kernel-based principal component analysis,	*Others			
15	Video analysis of human gait and posture to determine neurological disorders	*Others			
16	A novel single-sensor-based method for the detection of gaitcycle breakdown and freezing of gait in Parkinson's disease	*Unmatched tasks			
17	Feature-Set-Engineering for Detecting Freezing of Gait in Parkinson's Disease using Deep Recurrent Neural Networks	*Unmatched tasks			
18	A non-invasive medical device for parkinson's patients with episodes of freezing of gait	*Others			
19	Home monitoring of motor fluctuations in Parkinson's disease patients	*Without involving patients or controls			

20	Gait analysis with wearables predicts conversion to parkinson disease.	*Without involving patients or controls
21	Automatic detection system for freezing of gait in Parkinson's Disease based on the clustering algorithm	*Unmatched tasks
22	Deep learning for freezing of gait detection in Parkinson's disease patients in their homes using a waistworn inertial measurement unit	*Unmatched tasks
23	Determining the optimal features in freezing of gait detection through a single waist accelerometer in home environments	*Unmatched tasks
24	Smart gait-aid glasses for Parkinson's disease patients.	*Unmatched tasks
25	Freezing of gait detection in parkinson's disease: a subject-independent detector using anomaly scores	*Unmatched tasks
26	A smartphone-based architecture to detect and quantify freezing of gait in Parkinson's disease.	*Unmatched tasks
27	Development and clinical validation of inertial sensor-based gait-clustering methods in Parkinson's disease.	*Without involving patients or controls
28	Gait anomaly detection of subjects with Parkinson's disease using a deep time series-based approach	*Others
29	The reliability of gait variability measures for individuals with Parkinson's disease and healthy older adults—the effect of gait speed.	*Without using machine learning
30	Effects of exercise on gait and motor imagery in people with Parkinson disease and freezing of gait	*Without using machine learning
31	The coefficient of friction in Parkinson's disease gait.	*Without using machine learning
32	Postural sensory correlates of freezing of gait in Parkinson's disease	*Unmatched tasks
33	Detection and quantification of freezing of gait and falls in Parkinson's disease patients using a body-worn sensor	*Unmatched tasks
34	Freezing of Gait detection in Parkinson's disease using accelerometer based smart clothes	*Unmatched tasks
35	Electromyography gait test for Parkinson disease recognition using artificial neural network classification in Indonesia.	*Without involving patients or controls
36	Home-based monitoring of falls using wearable sensors in Parkinson's disease.	*Without using machine learning
37	An in–laboratory validity and reliability tested system for quantifying hand–arm tremor in motions	*Without using machine learning
38	Fallers with Parkinson's disease exhibit restrictive trunk control during walking	*Others
39	Characterization of gait abnormalities in Parkinson's disease using a wireless inertial sensor system	*Without involving patients or controls
40	Diagnosing health problems from gait patterns of elderly	*Others
41	Biometric and mobile gait analysis for early diagnosis and therapy monitoring in Parkinson's disease	*Others
42	Accelerometry-based gait analysis and its application to parkinson's disease assessment-Part 2: A new measure for quantifying walking behavior.	*Without using machine learning
43	Automatic recognition of Parkinson's disease using surface electromyography during standardized gait tests	*Without using gait data
44	Detecting freezing-of-gait during unscripted and unconstrained activity	*Others
45	Objective detection of subtle freezing of gait episodes in Parkinson's disease	*Others
46	On assessing motor disorders in parkinson's disease	*Others
47	Smart Gait-Aid Glasses for Parkinson's Disease Patients	*Unmatched tasks
48	Gait and balance analysis for patients with Alzheimer's disease using an inertial-sensor-based wearable instrument	*Without using machine learning
49	A validated smartphone-based assessment of gait and gait variability in Parkinson's disease	*Without using machine learning
49		
50	Comparative gait analysis in progressive supranuclear palsy and Parkinson's disease	*Without using machine learning

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52	Contribution of a trunk accelerometer system to the characterization of gait in patients with mild-to-moderate Parkinson's disease	*Without using machine learning
53	Disability and fatigue can be objectively measured in multiple sclerosis	*Without using machine learning
54	Free-living gait characteristics in ageing and Parkinson's disease: impact of environment and ambulatory bout length	*Without using machine learning
55	Insights into gait disorders: walking variability using phase plot analysis, Huntington's disease	*Without using machine learning
56	Quantitative evaluation of gait ataxia by accelerometers	*Without using machine learning
57	The parkinsonian gait spatiotemporal parameters quantified by a single inertial sensor before and after automated mechanical peripheral stimulation treatment	*Without using machine learning
58	Uncontrolled head oscillations in people with Parkinson's disease may reflect an inability to respond to perturbations while walking	*Without using machine learning
59	Validity and reliability of an IMU-based method to detect APAs prior to gait initiation	*Without using machine learning
60	Clinical assessment of standing and gait in ataxic	*Unmatched disease type
61	Validation of an Accelerometer to Quantify a Comprehensive Battery of Gait Characteristics in Healthy Older Adults and Parkinson's Disease: Toward Clinical and at Home Use	*Without using machine learning
62	Wearable Sensors in Huntington Disease A Pilot Study	*Without using machine learning
63	A comprehensive assessment of gait accelerometry signals in time, frequency and time-frequency domains	*Without using machine learning
64	A mobile Kalman-filter based solution for the real-time estimation of spatio-temporal gait parameters	*Without using machine learning
65	A novel approach to reducing number of sensing units for wearable gait analysis systems	*Without using machine learning
66	Accurate and reliable gait cycle detection in Parkinson's disease	*Without using machine learning
67	An inertial sensor based balance and gait analysis system	*Without using machine learning
68	Levodopa Is a Double-Edged Sword for Balance and Gait in People With Parkinson's Disease	*Unmatched tasks
69	Prolonged walking with a wearable system providing intelligent auditory input in people with Parkinson's disease	*Unmatched tasks

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