REVIEW ARTICLE

Recent use of deep learning techniques in clinical applications based on gait: a survey

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Abstract

Gait analysis has been studied for a long time and applied to fields such as security, sport, and medicine. In particular, clinical gait analysis has played a significant role in improving the quality of healthcare. With the growth of machine learning technology in recent years, deep learning-based approaches to gait analysis have become popular. However, a large number of samples are required for training models when using deep learning, where the amount of available gait-related data may be limited for several reasons. This paper discusses certain techniques that can be applied to enable the use of deep learning for gait analysis in case of limited availability of data. Recent studies on the clinical applications of deep learning for gait analysis are also reviewed, and the compatibility between these applications and sensing modalities is determined. This article also provides a broad overview of publicly available gait databases for different sensing modalities.

Keywords: gait abnormality; gait disorders; gait analysis; deep learning; clinical applications

1 Introduction

Gait refers to the manner of locomotion achieved through the movement of the limbs by humans and other animals. Hereinafter, human gait is called “gait” in this study. Gait is affected by various organ systems, such as the central nervous system, musculoskeletal, and cardiorespiratory systems (Abu-Faraj et al., 2015). Gait analysis is the systematic study of dynamic posture and coordination during movement. Research on such analysis began in the 19th century. Since then, a large number of researchers have provided quantitative measurements of the human gait and applied them to such fields as security, sport, and medicine. The individual gait pattern is influenced by various factors such as age, sex (Kobayashi et al., 2016), muscle fatigue (García-Pinillos et al., 2020), and pathological conditions (Kaufman et al., 2001), due to its association with the majority of organ systems. Therefore, gait analysis can be a promising approach to provide practical information in diverse fields. In the context of security, gait has been used as a biometric feature to recognize an individual when it is difficult to obtain other biometric characteristics, such as fingerprints, veins of the palm, and facial or iris-related information. This is called gait recognition, human gait identification, or gait authentication (Kale et al., 2003; Gafurov et al., 2007; Wan et al., 2018). It is assumed that surveillance applications based on gait can be used in airports, hospitals, and metro stations because it is possible to identify targets remotely without physical contact and proximal sensing (Singh et al., 2019). In sports, gait analysis has been applied to recognize fatigue and faulty performance patterns in athletes, and to efficiently improve performance in a variety of sports, such as running and golf (Lynn & Noffal, 2010; Benson et al., 2018). The feedback obtained from gait analysis can help determine biomechanical faults and imbalances that may cause injuries. Therefore, such analysis can reduce the risk of sports-related injuries among athletes, such as those incurred through excessive use of a certain muscle or joint (Springer et al., 2016). Gait analysis that encompasses locomotive abnormalities...
is called “clinical gait analysis” (Ewins & Collins, 2014). This type of analysis has been mainly used as a clinical diagnostic tool and an assessment tool to evaluate the effectiveness of training and rehabilitation programs for patients (Baker, 2006; Barth et al., 2011).

Machine learning-based approaches are more effective in this context than classical mathematical and statistical methods in terms of learning from the available data, and extracting and discovering knowledge. Therefore, such machine learning techniques as neural networks have been employed in the 21st century to represent gait-related data, classify gait patterns, and estimate gait-related variables (Simon, 2004). With the growth in this technology, deep learning approaches have become popular in recent years. Because deep learning models can deal with high-dimensional and complex data, and provide accurate results, they have become popular in gait analysis as well.

This survey article provides a comprehensive summary of research on gait analysis for health and medical care that has used deep learning techniques. Despite the success of the use of deep learning for gait analysis in several contexts, an overview of research on clinical gait analysis using deep learning has not yet been provided in the literature. This survey is the first article that systematically provides the fundamental knowledge of such analysis with machine learning and the future directions for the research. To further develop work in the area, it is crucial for researchers from medicine and information science to cooperate with each other. Therefore, this survey fills this research gap with a thorough summary of technologies associated with clinical applications of gait analysis. The major contributions of this study are as follows:

(i) It provides a systematic survey of the literature on the use of deep learning in gait analysis for health and medical care.
(ii) It introduces data acquisition modalities for clinical applications, where this will help determine suitable sensors for use in future research.
(iii) It highlights novel techniques used to apply deep learning to gait analysis.
(iv) It provides a brief description of the available gait databases that can be useful for further clinical research on gait.
(v) The reader can find here research and subjects associated with the development of applications related to gait in the future.

The remainder of this paper is organized as follows: Section 2 provides an overview of the basics of gait. Section 3 summarizes abnormal gait patterns, and Section 4 provides a systematic introduction to gait-related applications in health and medical care. Section 5 provides a brief overview of sensing measurements used for such applications, and examines the trend of the use of sensing modalities corresponding to each application. Section 6 presents the general framework of gait analysis and several techniques for applying deep learning models to it. Section 7 provides a concise overview of public gait databases. Section 8 raises some current issues of the use of gait analysis in clinical practice and provides the future direction, and Section 9 describes the conclusion of this survey article. Table 1 summarizes all the abbreviations used in this article.

### 2 Human Gait

Human gait refers to a manner of limb movements made during locomotion. When a person is walking in an abnormal, uncoordinated, or unsteady pattern, this indicates at least one health issue. In some cases, multiple health problems are evidenced by one type of gait abnormality owing to the complex correlation between gait and systems of the human body. Thus, understanding normal gait patterns is essential for detecting alterations in gait associated with pathological conditions.

#### 2.1 Gait cycle

During normal walking, both limbs work in an analogous way, where the left arm advances as the right foot takes a step, and...
Figure 1: Typical normal gait cycle according to Sutherland, 1994.

Table 2: Gait cycle: periods and functions (adapted from Sutherland, 1994).

| Period                          | %Cycle | Function                                         | Contralateral                    |
|--------------------------------|--------|--------------------------------------------------|----------------------------------|
| Initial double-limb support    | 0–12   | Loading, weight transfer                         | Unloading and preparing for swing |
| Single-limb stance             | 12–50  | Support of entire body weight; center of mass moving forward | Swing                           |
| Second double-limb support     | 50–62  | Unloading and preparing for swing (preswing)     | Loading, weight transfer         |
| Initial swing                  | 62–75  | Foot clearance                                   | Single-limb stance               |
| Mid-swing                      | 75–85  | Limb advances in front of body                   | Single-limb stance               |
| Terminal swing                 | 85–100 | Limb deceleration, preparation for weight transfer | Single-limb stance               |

A single gait cycle can be divided into two primary phases: a stance phase and a swing phase (Perry et al., 1992). As shown in Fig. 1, the stance phase begins with a foot strike and ends with a toe-off of the same foot. The foot is in contact with the ground, and the limb is bearing weight over the phase. The duration of a stance phase generally accounts for approximately 62% of the normal gait cycle. The swing phase begins with the toe-off and ends with the strike of the same foot. The foot is in the air and moving forward without weight bearing over the phase. The duration of a swing phase generally accounts for approximately 38% of the normal gait cycle.

From the point of view of functional phases, the stance and swing phases can be further segmented into three periods as shown in Fig. 1. Each period in a normal gait cycle has a certain duration represented by normalized percentages, as shown in Table 2. The stance phase consists of initial double-limb support (loading response), single-limb stance (mid-stance), and second double-limb support (preswing). Initial double-limb support period starts after initial contact and ends with contralateral toe-off, when the opposite foot leaves the ground. During the period, body weight is transferred onto the supporting limb. Single-limb stance period occurs when one foot contacts the ground while the other limb is swinging. The ankle plays a role of a rocker in advancing the limb over the stationary foot. Second double-limb support period begins when contralateral limb contacts the ground and ends just before ipsilateral limb elevates. This is the transition period between stance and swing phases. The swing phase consists of initial swing, mid-swing, and terminal swing. Initial swing period starts at toe-off and continues until the swinging limb achieves its maximum knee flexion. Mid-swing period occurs when the swinging limb is aligned with the stance limb. During the period, the limb continues advancing, and its tibia achieves a vertical position. Terminal swing period ends upon initial heel strike, where the entire
series of muscles assists with stabilizing the knee joint. Apart from the aforementioned two-phase gait segmentation, gait-partitioning methods have been proposed consisting of three, four, five, six, seven, and eight phases (Taborri et al., 2016).

### 2.2 Parameters for clinical gait analysis

In clinical gait analysis, physicians use quantitative gait-related parameters to understand their patients’ gait-related pathologies (Whittle, 2014). These parameters can be categorized into four groups: spatio-temporal, kinematic, kinetic, and physiological and anthropometric parameters.

#### 2.2.1 Spatio-temporal parameters

Spatio-temporal parameters refer to the variables of time and distance in a gait cycle: step and stride width, cadence, walking speed, and phases and events (foot strike and toe-off; Kharb et al., 2011). Step length is the distance between the point of initial contact of one foot and the point of initial contact of the opposite foot. Stride length is the distance between successive points of initial contact of the same foot. Stride width (base of support) represents the distance between the heels of the two feet during double stance. Cadence is defined as the total number of steps in a given time. Walking speed (gait velocity) is the time taken to walk a specified distance. The phases and events of a gait are represented as percentages of the gait cycle or the duration of a stage (Cimolin & Galli, 2014; Yu et al., 2019).

#### 2.2.2 Kinematic parameters

Kinematic parameters are the measured values of angular rotations of the joints as well as translations of segments and the entire body mass (Sutherland, 2002). These parameters consist of joint angles (e.g. angles of the trunk, hip, knee, and ankle), and the corresponding linear acceleration and angular velocities (Abbass & Abdulrahman, 2013). In gait analysis, geometric calibration may be required to ensure that the local coordinate axis of the sensor is aligned with the anatomical axis of the given joint (Chinmilli et al., 2017).

#### 2.2.3 Kinetic parameters

Gait is an alternation between the loss of balance and its recovery while constantly shifting the center of mass of the body (Chambers & Sutherland, 2002). Therefore, kinetic parameters in this context refer to the ground reaction force (GRF), (Note that we provide a list of abbreviations used in the survey as 1.) foot plantar center of pressure (COP), joint torque, and joint loading (joint forces). The GRF is the force of equal magnitude exerted in the opposite direction from the ground up to the foot (DeLee et al., 2010). It has three components: its point of application, its magnitude, and its line of action (Meadows & Bowers, 2019). Foot plantar pressure is the pressure field that acts between the foot and the support surface during activities of daily living (ADLs; Abdul Razak et al., 2012). In gait analysis, the distributions of foot plantar pressure are monitored to determine pressure and the interface of the foot plantar surface and the shoe sole/surface of the mat platform.

#### 2.2.4 Physiological parameters

Physiological parameters are an indicator of energy expenditure: energy consumption, energy cost, heart rate, and electromyography (EMG; Sagawa et al., 2011). EMG is a technique in electrodiagnostic medicine to measure the muscular or electrical response to the stimulation of a nerve of the muscle (Türker, 1993). Dynamic EMG data are used to identify muscle weakness, deformity, or pain (Brunner & Romkes, 2008). Other physiological parameters are often used to measure levels of activity, prosthesis comfort, and/or functionality during rehabilitation (Wehman & Nikolic, 2005; Gams et al., 2013).

#### 2.2.5 Anthropometric parameters

Anthropometric parameters are often extracted from patient profiles, such as age, gender, weight, height, limblength, and the body mass index. They are used to compare gait parameters against age and distributions of sex-matched normal gait populations to determine whether the patient’s gait is within a normal range (Prakash et al., 2016). This is because previous work has shown gender-based and age-based differences in gait parameters, even between healthy subjects (Grabiner et al., 2001; Yu et al., 2009). Hence, gait data normalization methods are needed to eliminate fluctuations due to physical factors such as leg length and weight. (Pinzone et al., 2016).

### 3 Gait Abnormality

With advancing age, gait and postural abnormalities emerge that have detrimental effects on the individual’s life. Gait disorders are categorized into three groups in terms of causes: neurological diseases, musculoskeletal diseases, and combined diseases. Diagnoses and planning treatments for these disorders are implemented based on the patient’s medical history, and the results of physical, neurological, and orthopedic examinations. In these examinations, gait analysis is often employed as it can help assess motor function and identify factors associated with dysfunctional gait. Thus, it is essential to understand correlations between gait parameters and the cause of gait impairment. In the next section, three types of typical gait abnormalities are explained: gait disorders caused by aging, neurological gait disorders, and musculoskeletal gait disorders.

#### 3.1 Idiopathic gait disorders caused by aging

A large percentage of the world’s population is aging, and the number of elderly persons continues to grow. Older adults are more likely to face a number of health-related problems. Gait disorders caused by aging are mainly categorized into two types: cautious gait and senile gait.

##### 3.1.1 Cautious gait

Falling is among the most major health concerns among the elderly. The consequences of a fall range from nonfatal injuries (e.g. fractures, contusion, abrasions, and lacerations on the leg/foot, arm/hand, and lower trunk; Stevens & Sogolow, 2005) to fatal injuries (e.g. head injuries, such as subdural hematomas or subarachnoid hemorrhages as well as nonhead injuries such as hip fractures and cervical fractures; Chisholm & Harruff, 2010). Falls, regardless of the injury sustained, can degrade the quality of life (QOL) as elderly adults who have experienced falls are prone to become fearful. The resulting gait is called “cautious gait”; the term was coined by Nutt et al. (1993). It is a higher level gait disorder in old age. Cautious gait is typically marked by a mild to moderate decline in walking speed, reduction of stride length, a normal to mildly widened base of support, and shorter swing phase without any hesitation when initiating gait (Nutt, 2001). This psychogenic gait disorder is likely to limit ADL among the elderly and reduce their social engagement.
3.1.2 Senile gait
Gait disorders are the most common health problems among the aging population. The older people become, the higher is the prevalence of disorders among them (Mahlknecht et al., 2013). Gait impairments among the elderly are mostly caused by disorders of the musculoskeletal system or neurological diseases (Sudarsky, 1990). By contrast, one type of gait disturbance cannot be explained by any distinct disease. It is called “senile gait” and the term was coined by Koller et al. (1985). Stooped posture, a decrease in stride, cadence, and arm swing, an increase in the time for double-limb support, a reduction in gait rhythmicity, loss of normal heel–toe sequencing, less foot–floor clearance, and a reduction in hip and knee rotations are characteristic of senile gait (Wolfson et al., 1990).

3.2 Neurological and musculoskeletal gait disorders
Diagnosis tests for neurological disorders are often conducted with a combination of several devices such as CT scan, electroencephalogram (EEG), magnetic resonance imaging, electrodiagnostic tests, and positron emission tomography (Paldino et al., 2017). These devices are used to make a diagnosis based on a range of symptoms caused by structural, biochemical, or electrical abnormalities in the brain, spinal cord, or other nerves (Joy, 2021). Moreover, several observations have suggested that neurological diseases are likely to cause gait impairments (Stolze et al., 2005). A given neurological disease can cause several types of gait disorders. On the contrary, musculoskeletal gait disorders, such as osteoarthritis (OA) and deformities of the lower extremity, are the most common nonneurological gait disorders (Mahlknecht et al., 2013). The elderly people are also likely to have pathological gait disorders for a combination of neurological and musculoskeletal causes (Lim et al., 2007).

For most patients with a neurological disease, a broadened base of support may often be seen as one of the noticeable symptoms while walking (Nonnekes et al., 2018). However, the presence of this symptom does not provide enough clues to make a definite diagnosis since it can be observed in a wide range of neurological disorders. Therefore, some physical and neurological examinations are often required to discover more specific gait disorders. For example, waddling gait can be observed in patients with a myopathy, such as muscular dystrophies, spinal muscular atrophy, or congenital hip dysplasia, having muscular weakness on one side of the hip. If patients have bilateral weakness on the hip muscles, they drop the pelvis on both sides during walking (a waddling gait). The gait pattern shows short steps and a broad walking base, combined with lateral movements of the trunk and rotation in the knees (Van Iersel & Mulley, 2004).

For musculoskeletal disorders, the gait impairments are divided into different kinds of gait disorders depending on the painful part of the body. For instance, antalgic gait is caused by painful conditions in the lower back or lower extremity such as knee OA, ankle sprains (Myrick, 2014), and foot pain caused by Rheumatoid arthritis (Carroll et al., 2015). The individuals with pain in any part of the lower body attempt to walk with as short the stance phase as possible on the affected limb to avoid pain while walking.

Other basic pathological gait attributed to neurological and musculoskeletal conditions are described in Table 5, and are taken from Pirker and Katzenschlager (2017).

4 Clinical Applications of Gait Data
Gait data have been used for a variety of applications in different areas. In this paper, we focus on studies on gait for health and medical care. A review of related studies shows that the proposed systems can be categorized according to purpose. We propose such a taxonomy of clinical applications based on gait, as shown in Fig. 2. This section provides details of these applications.

4.1 Remote monitoring
As the number of elderly people and those with chronic disorders increases worldwide, there is a growing demand for innovative approaches to healthcare to improve our QOL. State-of-the-art healthcare systems are expected to support such people. One such service is remote patient monitoring (RPM), which is...
also referred to as remote health monitoring (Malasinghe et al., 2019). This service utilizes Internet of Things (IoT) technologies to collect a variety of medical data from individuals in one location, and sends this information to healthcare providers at a different location for assistance whenever required. This service is often used in hospitals, nursing facilities, and private homes where the elderly and patients cannot reach out for help. Recent work has focused on utilizing gait data for RPM (Lilien et al., 2019). Figure 2 shows applications based on gait for RPM, such as fall risk assessment, fall detection, fall prediction, and detecting and predicting the freezing of gait (FoG).

4.1.1 Fall risk assessment, detection, and prediction
Fall risk assessment systems are used to predict the risk of fall and target appropriate fall prevention strategies (Liang et al., 2019). Conventionally, retrospective fall history, medication reviews, and fall-focused physical examinations are used as criteria to determine the risk of fall (Phelan et al., 2015). For example, a patient who has experienced at least one fall within a certain period is marked as a faller or high risk, and otherwise as a non-faller or low risk. Recent studies have discovered several differences in gait-related biomechanics between fallers and nonfallers (Hausdorff et al., 1997; Mbourou et al., 2003). All measures of gait variability are considerably higher in elderly fallers than in elderly nonfallers: stride-to-stride variation in stride time, stance time, swing time, and percentage of stance time as measured during a six-minute walk (Hausdorff et al., 1997). Moreover, elderly fallers have a much smaller first step and a longer duration of the period of double support than elderly nonfallers (Mbourou et al., 2003). Thus, gait analysis through long-term monitoring can provide objective indicators of the risk of fall (Verghese et al., 2009).

Fall detection (postfall detection) systems are used to detect the occurrence of a fall in real time and notify the patient’s caretakers that he/she is in need of immediate attention. Because falling causes significant changes in a variety of gait parameters, such as speed and stride length, several gait data acquisition modalities have been used to detect falls and monitor the patient’s state (Chen & Lin, 2010; Nukala et al., 2014; Shibuya et al., 2015).

The tools for fall risk assessment and fall intervention programs are expected to predict and reduce the risk of falling and serious injuries over a long period (Murray et al., 2016); however, sudden falls are beyond the scope of such applications. To overcome this limitation, fall prediction (preimpact fall detection) systems are used to detect a fall before the body hits the ground (De Venuto & Mezzina, 2020; Yu et al., 2020). Preimpact fall is defined as a stage after the initiation of fall, but before body-ground impact (Hu & Qu, 2016). Some researchers have developed inflatable hip protectors to cushion a fall prior to impact (Davidson, 2004; Lockhart, 2006). Thus, if the occurrence of a fall can be predicted at a certain time before it happens, serious injuries may be preventable.

4.1.2 Detecting and predicting FoG
The FoG is an episodic gait pattern that is likely to occur on initiating the gait, turning, and approaching narrowed or cluttered spaces (Cohen et al., 2011). The frequency, duration, and intensity of FoG episodes should be considered to adjust doses of medication. The appropriate dosage prevents or reduces the severity of FoG (Nonnnes et al., 2015). Therefore, FoG detection while monitoring patients has a high priority.

Some clinical studies suggest that a rhythmically played sound, referred to as a cue, can help break a freeze and enable the person to resume walking (Nieuwboer et al., 2007; Donovan et al., 2011). Suppose that the FoG can be accurately predicted and the patient can notice its occurrence. This might help introduce preemptive cues or provide time for postural adjustment (Nieuwboer et al., 2007; Delval et al., 2014; Lu et al., 2017). Therefore, cooperation between the prediction and the cues helps reduce a major risk factor for falls and fall-related injuries in patients. However, FoG prediction has not been as extensively treated in research as FoG detection. Reasons for this may be associated with the difficulty of defining a “pre-FoG” episode. Detecting FoG is typically treated as a binary classification problem, where the data are divided into FoG and non-FoG classes (El-ziaat et al., 2019). On the contrary, FoG prediction has been treated as a binary or multiple classification problem, with a pre-FoG class added. When labeling a pre-FoG segment, it is difficult to visually identify its beginning owing to the ambiguous transition from normal walking to FoG (Pardoe et al., 2019). Thus, the pre-FoG class is mostly defined as a segment lasting 1–6 seconds prior to the onset of freezing with a fixed-size window (Pardoe et al., 2019).

4.2 Supporting physicians with quantitative gait analysis
Numerous analyses of patients with gait disorders have been conducted. The system proposed in the related studies can be categorized into four types of applications; diagnosis systems, disease state assessments, medication adherence assessments, and clinical gait assessments. The common aim of these applications is to help physicians provide quality patient care. Gait analysis using multivariate statistics and machine learning can provide a quantitative point of view on these disorders when making clinical decisions (Simon, 2004).

4.2.1 Diagnosis systems based on gait
Abnormal gait has been analysed to distinguish patients from healthy people, especially in early stages of diseases that cause abnormal gait. In general, patients are not aware of symptoms in early stages of the disease, and they are difficult for physicians to identify as well. However, some studies have shown that the gait data of patients in early stage of the onset of neurological diseases are different from those of healthy controls (Yang et al., 2008; Lord et al., 2013). A number of studies have thus proposed sensor-based systems that help doctors make diagnoses using gait analysis (Tao et al., 2012; Muro-De-La-Herran et al., 2014). These systems can be categorized into two groups: binary classification-based and multiclass classification-based systems. In the class of binary classification systems, people with abnormal gait are distinguished from those with normal gait (Tahir & Manap, 2012; Yang et al., 2012). In multiclass classification, several abnormal gait patterns (or gait disorders) are classified in addition to the normal gait (Aalaqtash et al., 2011; Zhao et al., 2018a; Aversano et al., 2020b). Therefore, the multiclass classification problem is more complex than the binary problem, and requires more focus on higher dimensional features when analysing gait. To overcome this difficulty, a number of studies have employed machine learning, especially deep learning, for analysis (Rehman et al., 2019).

4.2.2 Disease state assessment based on gait
The clinical evaluation of patients with Huntington’s disease (HD), Parkinson’s disease (PD), and Alzheimer’s disease (AD) is vital as physicians develop their treatment plans according to the results. The Unified Huntington’s Disease Rating Scale
(UHDRS) for HD and the Unified Parkinson’s Disease Rating Scale (UPDRS) (Fahn, 1987) for PD have been the gold standard used to measure the severity of motor diseases. For AD, the Global Deterioration Scale has been used to identify the stages of diseases in patients through standardized interviewing tools (Reisberg et al., 1982). The UHDRS was developed to assess four domains of clinical performance and capacity in HD: motor function, cognitive function, behavioral abnormalities, and functional capacity. The MDS-UPDRS, which is the latest version of the UPDRS (Goetz et al., 2008), consists of four subscales: (i) nonmotor experiences of daily living, (ii) motor experiences of daily living, (iii) motor examination, and (iv) motor complications. These scales require medical specialists to assess, and use descriptive symptoms that cannot provide a quantified diagnostic basis (Zhao et al., 2018b). To overcome this limitation, automatic and quantitative systems for the assessment of the progression of HD, PD, and AD have been developed using machine learning (Zhang et al., 2019; Alharthi et al., 2020; Brinas et al., 2020; Lu et al., 2020). Such systems can identify the state of the disease through machine learning-based gait analysis. Moreover, a majority of items in these scales reflect different aspects of gait performance related to speed, articular range of motion of the lower limb, and postural stability. Therefore, several types of gait features — related to its kinetics, kinematics, and spatio-temporal features — are often combined and used as a set of data inputs for training the models (Zhan et al., 2018; Balaji et al., 2020).

4.2.3 Medication state assessment based on gait

The medicine used for PD treatment has an important role in symptom control and the maximization of the efficacy of the available therapies. This is because late, extra, or missed doses may cause motor fluctuations (Stocchi et al., 2005). However, older patients with PD tend to have difficulty in achieving optimal adherence (Groset et al., 2005). Furthermore, existing approaches to medication adherence assessment, such as self-reporting, family reminder, and pill counts (Lehmann et al., 2014), rely on patients reporting their own medicine-taking behavior. They may not report their medication adherence correctly (Groset et al., 2006). To overcome this problem, medication adherence assessment using gait analysis has been examined. The FoG and action tremors worsen when patients are in a state where medication is not beneficial, compared with a state where the optimum benefit can be obtained from it (Brown et al., 1997; Fasano et al., 2011). Some studies have proposed systems that analyze the gait data of PD patients and identify their medication status as “taking” (“ON”) medication or “not taking” (“OFF”) it (Hssayeni et al., 2018).

4.2.4 Clinical gait assessment

Clinical gait assessment aims to detect gait abnormalities corresponding to a given health condition, and to quantitatively evaluate the gait of patients for clinical diagnosis and rehabilitation management. People who tend to develop chronic diseases, such as the elderly, are the subjects of such analyses, as are athletes. For example, Kondragunta et al. (2019) proposed a system to estimate gait parameters, such as step length, stride length, swing time, stance time, stride time, and cadence, for elderly care. Golami et al. (2020) and Johnson et al. (2020) proposed monitoring systems of gait parameters (e.g., joint angles of the lower extremities and multidimensional ground reaction forces and moments (GRF and GRM)) to prevent acute and chronic injuries to athletes. As mentioned above, a variety of gait parameters are predicted for clinical gait assessment. They can be divided into three groups: as spatio-temporal, kinematic, and kinetic gait parameters. Some studies have also proposed systems to estimate gait normality (Nguyen et al., 2018b, c; Nguyen & Meunier, 2019a, b) or gait symmetry (Steinmetzer et al., 2020).

4.3 Gait phase recognition for assistive exoskeleton control and rehabilitation

Gait phase recognition (gait event detection) is mainly used for two purposes in healthcare: (i) to help physicians provide effective treatments to patients with PD, stroke, brain trauma, and other diseases (Esquenazi et al., 2013; Buckley et al., 2020), and (ii) to develop and improve control strategies for orthoses, prostheses, and exoskeletons (Collins et al., 2015; Maqbool et al., 2016; Farah et al., 2019).

Gait phase recognition is generally divided into two groups: discrete and continuous methods. Discrete methods are designed to first segment the human gait as a series of discrete states in time, and to identify discrete subphases (Ding et al., 2018; Rubio-Solis et al., 2020). A robot controller then implements the encoded assistive function phase by phase. Discrete motion detection is treated as a classification problem to identify the discrete gait event. The advantage of such systems is that they are easy to implement through finite-state classifiers (Yan et al., 2017). As shown in Table 2, from Taborri et al. (2016), there are several ways to partition gait cycles corresponding to the intended use of the system. Each such phase model has been used for different assistive robots. For example, the two-phase model was applied to active orthoses of the lower limbs because it is adequate to control the knee module in case of orthosis (Taborri et al., 2015). The four-phase model was successfully used to control robots for ankle–foot orthosis (Bolus et al., 2017).

On the contrary, continuous methods involve estimating gait parameters (e.g., joint angles of the lower body; Ngeo et al., 2013) or the percentage of time taken by each gait phase (Kang et al., 2019). When the gait phase is considered a continuous variable representing the gait cycle, it is defined as a linearly increasing value from 0 to 100 (or from 0 to 1), where both values represent the heel strike of a leg during locomotion (Kang et al., 2019). Continuous motion detection is considered a prediction problem involving the estimation of specific values. Such systems help achieve smooth motion control for assistive robots (Yan et al., 2017).

5 Gait Acquisition Modalities for Clinical Gait Analysis

Although some methods of gait analysis can be generalized to all sensing modalities, most of them are specific to certain types. Based on related studies, we classify such modalities into three categories: wearable sensors, nonwearable sensors, and hybrid sensors. Each category can be further divided into subcategories. The proposed taxonomical graph for the sensing modalities of gait analysis is shown in Fig. 3. Note that all the studies listed in 3 applied deep learning to their proposed systems.

5.1 Nonwearable sensors

Nonwearable sensors are used in controlled research facilities. In the controlled environment, gait data are ambiently captured while the subject walks on a treadmill, floor sensor mat, or a clearly marked walkway. As shown in Fig. 3, these sensors are classified into three subgroups: vision-based measurement, impact force measurement, and radio frequency measurement.
Vision-based modality refers to the use of optoelectronic motion capture (Mocap) systems. Vision-based sensors consist of different types of cameras (e.g., analog, digital, and depth cameras) to track the movement of humans as they walk (Muro-De-La-Herran et al., 2014). This modality is further categorized into two groups: marker-based (MB) and marker-less (ML) sensors (Ceseracciu et al., 2014). Typical Mocap systems used for MB sensors are the 3D Mocap system, Vicon motion systems (Vicon, Oxford, UK), and IR cameras. These systems are used along with retroreflective markers to acquire the gait more accurately (Baker, 2006). A model of the human body is constructed manually; therefore, the MB modality is also known as a model-based approach in vision-based modality (Moeslund & Granum, 2001). Based on the model, such gait parameters as joint angles can be extracted. The ML modality uses camera systems, such as Microsoft Kinect sensors, camcorders, and smartphones, to capture the gaits of subjects (Abid et al., 2019; Chakraborty et al., 2020). The difference between the MB and ML modalities is that the latter does not require building a model of the human body to obtain the gait parameters. Instead, silhouettes are extracted using preprocessing techniques (e.g., background subtraction and 3D pose estimation from 2D image data; Li et al., 2019b; Kidziński et al., 2020; Moro et al., 2020).

Floor sensors are nonwearable sensors used to measure the impact force. They are placed along the floor to measure the static and dynamic pressure or force under the foot. They are also called force-pressure platforms or measurements. Such platforms can serve as instrumented walkways (McDonough et al., 2003) or instrumented treadmills (Dierick et al., 2004) in which force/pressure sensors are embedded.

Radar is an active sensing system to remotely determine the range, angle, or velocity of objects. The system consists of a transmitter producing radio waves, a transmitting antenna, a receiving antenna, and a receiver capturing returned signals modulated by illuminated targets. Radar can extract the Doppler frequency shift of the echo produced by a moving target by measuring how much the frequency of the received signal differs from the frequency of the signal that was transmitted (Camuffo, 2014). As a result, the radical velocity of the target at a distance by the Doppler shift can be measured (Tran et al., 2019). Since all radio frequency measuring instruments are noninvasive, non-contact, and insensitive to light, some works have applied them to in-home monitoring of elderly people, such as fall detection and FoG identification (Wang et al., 2017; Li et al., 2018; Alizadeh et al., 2019). However, the installation cost is significantly expensive compared with other sensing devices. Moreover, radio signals travel through air and space where it can be combined with other radio signals from other frequencies. If the signals are not properly directed, they can be interrupted by other signals and alter the information being transmitted. Considering the above-mentioned discussion, the review about radio frequency-based sensors is not conducted hereafter. The most common advantages of nonwearable sensors are the absence of power constraints and little physical obstruction. In other words, once all equipment for gait analysis has been installed, physicians and patients are much less involved with mechanical devices compared with wearable sensors. This reduces the time needed for gait monitoring.

## 5.2 Wearable sensors

Wearable sensors are the preferred modality for gait analysis. They are worn by users, whereas the location of the sensor varies depending on its type. As shown in Fig. 3, wearable sensors are classified into three subgroups: those used to measure the impact force, motion, and biosignals.

Wearable sensors to measure the impact force are called insole sensors. This measurement system uses force/pressure sensors embedded into shoes or socks to measure continuous gait during motion. They are also called instrumented shoes or smart insoles.

Inertial sensors are widely used for motion measurement. They consist of accelerometers and gyroscopes that sense linear acceleration along one or several directions and measure angular motion about one or several axes, respectively. The so-called inertial measurement unit (IMU) is a set of sensors consisting of three mutually orthogonal accelerometers and three mutually orthogonal gyroscopes. Microcontrollers are usually embedded into the IMU to process its measurements and Bluetooth modules are used for system communication.
In general, a biosignal is any signal that can be recorded from the human body. The signal can be either electrical [e.g. EEG and electromyogram (EMG)] or nonelectrical (e.g. breathing and movement; Naït-Ali, 2009). In studies on clinical gait analysis, surface EMG and dry EEG have been used most often owing to their noninvasive means of measurement. EMG is an electrodiagnostic technique to measure muscle response or electrical activity in response to the stimulation of a nerve of the muscle (Türker, 1993). Surface EMG refers to the electromyographic signal detected on the surface of the skin. EEG can be used to record and interpret the electrical activity of the brain (Subha et al., 2010). In dry EEG systems, dry electrodes are directly applied to the skin on the head without any gel or paste (Teplan et al., 2002).

Although the characteristics of the data collected by such sensors are different, the benefit of being wearable is common to them. In particular, for the evaluation of the gaits of patients, gait monitoring in everyday life may be required as it enables the detection of subtle changes in gait in different environmental conditions. For instance, according to Nonnekes et al. (2015), FoG events cannot be provoked during neurological assessment owing to their episodic nature. Thus, the presence of physicians may cause the patients to focus more on their gait and temporarily suppress freezing. However, wearable sensors can help overcome this problem.

5.3 Hybrid sensors

Several studies have used different types of sensors for clinical applications of gait data. The systems proposed in these studies differ in terms of the type of application and combination of sensors used. However, in most of them, performance is improved through sensor fusion, compared with the case when only one type of sensor is used. For example, Zhang et al. (2020b) developed PDLenS that uses different sensors embedded in a smartphone. It is a system to detect the effectiveness of drugs, and features the assessment of the voice, gait, and balance of PD patients. A microphone at the bottom of the smartphone is used to record voice data for the evaluation. A built-in accelerometer and gyroscope are used to record data on walking and standing for the other evaluations.

Apart from the above, multiple sensing modalities can be used in another way. In clinical gait assessment and gait phase detection, two types of sensors are used to simultaneously measure the same activity, and one of the databases is used as the ground truth. When evaluating the gait analysis systems, the results are compared with the corresponding ground truth data. Sharifi Renani et al. (2020) proposed a system to predict gait parameters that uses acceleration and angular velocity data from the IMUs as input. The IMU data for each stride segment were labeled with 12 gait characteristics, calculated using the Mocap data. Su et al. (2020) developed a gait phase recognition system that uses acceleration, angular velocity, and magnetic field intensity from IMUs as input. Foot switches placed under the sole of a participant’s feet were used to detect the gait phases as the ground truth.

5.4 Compatibility between clinical applications and sensing modalities for gait

This survey has reviewed work on deep learning-based methods of gait analysis for health and medical care published from 2018 to 2020. Tables 5 and 6 show a list of the papers reviewed for this survey. Based on them, we see that each application is more compatible with certain types of sensors than others. Compatibility here is associated with the benefits (+) and drawbacks (−) of each sensor, which are described in Table 3. This section provides details of the compatibility of each application.

5.4.1 Applications of remote monitoring

The applications of remote monitoring are associated with falling and FoG, such as fall risk assessment, and predicting and detecting a fall or FoG. The assessment of fall risk requires long-term gait monitoring (Vergheese et al., 2009). The occurrences of falls and FoG should be detected or predicted over 24 hours. Wearable inertial sensors are the most popular data acquisition tool for remote monitoring because they enable the noninvasive collection of gait data regardless of time and place. Radio frequency-based approaches have also been developed for fall and FoG detection. In such systems, radio frequency measuring instruments are employed to monitor a variety of ADLs incurring the risk of fall or FoG (Khan et al., 2020; Shrestha et al., 2020). The relevant measurements are contactless, insensitive to light, and effective even beyond obstacles such as walls. However, radar systems are not mobile, and thus, are more suitable for in-home monitoring. On the contrary, wearable sensors are a feasible solution for outdoor monitoring.

5.4.2 Applications for a specific disease/gait disorder

Many studies have developed clinical applications for a variety of diseases using the patients’ gait data. Table 5 lists some studies that have developed applications for PD and other diseases that incur gait disorders. The listed studies are only a part of the work that applied gait analysis to PD-related applications. It suggests that gait analysis in the context of PD has been studied more than for any other disease. PD patients suffer from severe motor impairment and disability (Jankovic, 2005).

Changes in locomotive functions can be an early sign of PD (Carpinella et al., 2007). Motor fluctuations, such as FoG and tremors, increase in the medication OFF condition than in the medication ON condition (Weiner, 2006). Moreover, the motor symptoms of PD affect a majority of the parts of the body (Sveinbjörnsdóttir, 2016). Inertial sensors are suitable sensing modalities for clinical applications for PD patients because they are small and light, and thus, can be placed in any required position on the body.

For PD diagnosis, some studies have used other resources, such as EEG signals (Sivaranjini & Sujatha, 2019) and magnetic resonance imaging (Sivaranjini & Sujatha, 2019). This is because PD is characterized by the gradual degradation of motor function in the brain, and sensing the relevant data can provide insights into the cause of the motor deterioration from the perspective of neural mechanisms (Wu & Hallett, 2005; Han et al., 2013). Compared with such data acquisition methods, wearable inertial sensors and insole sensors are easier to install, mobile, and less expensive.

As shown in Table 5, several studies have explored the use of deep learning for specific diseases or gait disorders. They cover a wide range of health conditions, such as neurological, neurodegenerative, and musculoskeletal diseases. Moreover, according to Jung et al. (2020b), frailty and cognitive dysfunction among the elderly can be identified by their gait patterns because idiopathic senile gait disorders may be signs of subclinical diseases, and indicate a high risk of developing dementia (Bloem et al. 2000; Newman et al., 2001). The suitable sensor modality is likely to depend on the symptoms of the target disease. For example, Bringas et al. (2019, 2020) used inertial sensors to identify the severity of AD using gait. This disease manifests as a progressive decline in
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Clinical gait assessment is mainly implemented using vision-based systems or wearable inertial sensor systems. According to Sharifi Renani et al. (2020) and Kondragunta et al. (2019), both sensing modalities can be used to estimate spatio-temporal gait parameters. González et al. (2016) compared two systems for quantitative gait analysis: a wearable inertial system that relies on two wireless acceleration sensors mounted on the ankles, and a passive vision-based system that externally estimates measurements through a structured light sensor and 3D point cloud processing. The wearable inertial system accomplished the estimation with slightly lower absolute and relative errors, but the difference between errors of the systems was subtle. Thus, the sensor modality for clinical gait assessment should be chosen in accordance with the installation location. When gait analysis is implemented in a crowded place where occlusions can occur, wearable inertial sensors are more suitable than vision-based sensors. On the contrary, vision-based systems may be more suitable in a controlled environment, such as a laboratory.

5.4.4 Gait phase detection/estimation systems
Systems of gait phase detection/estimation are generalized to almost all sensing modalities. However, wearable sensors are mainly used for systems that control wearable assistive devices, such as those for prostheses, orthoses, and exoskeletons (Chen et al., 2018; Prado et al., 2019; Nakagome et al., 2020). This is because wearable sensors can be attached to certain body parts or be used as part of the assistive device even while wearing it (Huang et al., 2019b; Nagashima et al., 2019; Wang et al., 2019). On the contrary, vision-based sensors, especially those employed in ML methods, are used for systems that provide gait rehabilitation with robotic assistance (Kidziński et al., 2019). Such rehabilitation is known as robot-assisted gait training (RAGT), and is expected to optimize gait training and reduce physical exhaustion for therapists (Holanda et al., 2017). Vision-based sensors are the preferred modality for RAGT because they can simultaneously extract comprehensive gait information from all parts of the body (Zago et al., 2020). This allows therapists to thoroughly analyse the gait parameters of their patients while training the system.

6 Clinical Gait Analysis with Machine Learning
The fundamental aim of clinical applications based on gait is to provide quantitative and objective feedback and to reduce the burden on the user. Conventional methods for these applications are observation, questionnaires, and functional tests of mobility, such as the timed-up-and-go test (Panel on Prevention

| Modality      | A&D of modality                               | Sensor type          | A&D of sensor                                                                 | Measurable characteristics                                      |
|---------------|-----------------------------------------------|----------------------|-------------------------------------------------------------------------------|------------------------------------------------------------------|
| Nonwearable   | (+) A range of spatio-temporal parameters can be obtained | Vision-based MB     | (+) High accuracy and precision of kinematics. (-) Takes time to attach markers | Skeleton: the position and orientations of joints                 |
|               | (+) Unintrusive system. (+) No power constraint | Vision-based ML     | (+) Easily obtains skeleton-related info using software. (-) High risk of posture deformation with pathological gait. (-) Limited range for detecting skeletons of moving subjects | Skeleton: the positions and orientations of joints               |
|               | (-) Limited area of measurement (-) Not suitable for outdoor applications | Floor sensors       | (+) Track foot plantar pressure without intrusion. (-) Signal corruption due to the presence of assistive devices. (-) Provide no details about the swing phase | GRFs and/or COP                                                  |
| Wearable      | (+) Mobile and inexpensive                    | Insole sensors      | (+) Easy to wear. (-) Provide no details about the swing phase               | GRFs and/or COP                                                  |
|               | (+) Allows for long-term gait analysis         | Inertial sensors    | (+) Allow for focusing the analysis at different locations of the human body. (-) Susceptible to linear drift | Acceleration, angular velocity                                   |
|               | (-) Power consumption limitations              | EEG                 | (+) Able to detect gait or intention to stand. (-) Susceptible to physiological artifacts | Frequency band: theta, alpha, beta, and gamma                    |
|               |                                               | EMG                 | (+) Able to detect gait or intention to stand. (-) Susceptible to factors such as sweat | Frequency range: 0–500 Hz, Amplitude range: 0–10 mV              |
of Falls in Older Persons & Society, 2011), Tinetti Performance-Oriented Mobility Assessment (Tinetti, 1986), and the 6-minute walk test (Enright, 2003). However, these methods require clinical expertise to analyse the data, and tend to provide subjective results (Craig et al., 2017). Therefore, classical statistical methods, such as null-hypothesis testing using the t-test and analysis of variance (ANOVA), and manually defined thresholds have been used to identify pathological gaits in previous studies (Alvarez et al., 2007; Huynh et al., 2015).

6.1 Machine learning techniques used for clinical gait analysis

Although classical methods can objectively analyse gait, they have some limitations. For example, when multiple biomechanical and clinical variables are correlated with each other and combined as risk factors associated with gait-related musculoskeletal injury, it is difficult to capture the complexity of these relationships using a statistical hypothesis test (Phinyomark et al., 2018). Kangas et al. (2008) proposed a fall detection system using three accelerometers attached to the waist, wrist, and head of the subject. When a value related to changes in the magnitude of acceleration exceeded a specific threshold, falls could be detected. However, such threshold-based systems struggle to identify falls from other activities that have similar characteristics in terms of acceleration (Vallejo et al., 2013).

In response to these shortcomings, multivariate analysis and machine learning methods have been employed to gait analysis. In particular, for FoG and gait phase detection, the most remarkable advantage of using these methods is the ability to accurately and efficiently extract multiple FoG episodes or gait cycles from a trial. Compared to visual detection methods, machine learning-based methods require less time for annotation, allow for the identification of more FoG episodes/gait cycles, and generate more data for further analysis (Hu et al., 2019; Filtjens et al., 2020).

The typical framework of machine learning-based gait analysis systems is shown in Fig. 4. The procedures for analysis are mainly divided into three: data acquisition, data preprocessing, and classification. Data acquisition is the process of sampling signals that measure gait in the real world by sensors as mentioned in chapter 5. The resulting samples are converted into digital numeric values that can be manipulated by a computer. Through data preprocessing pipelines, the collected raw data are converted into a format suitable for machine learning models. Data transformation is the process of turning into data from one format into another format that is more usable by the target system or application. Data cleaning is the process of preparing data for gait analysis by removing or modifying data that are incorrect, incomplete, irrelevant, duplicated, or improperly formatted. For example, Zhang et al. (2019) used footstep pressure data measured from some pressure-sensitive floor plates as the input to identify the severity level for HD patients. In the data preprocessing, the footprint data were converted into grayscale images. Moreover, the pixel value below 50 was set to 255 in order to eliminate background noise. The preprocessed images were fed into CNN to rate the severity of HD.

![Figure 4: The typical framework of gait analysis with machine learning.](image)
raw data for the target system. The extracted features are new features created by reformatting, combining, or transforming primary features. Feature selection is the process of choosing a subset of features from the original features so that the feature space is optimally reduced according to a certain criterion. For instance, Hasan et al. (2017) used kinematic and kinetic gait data captured by a force plate and Vicon to identify children with autism spectrum disorder. 3D GRFs from the force plate, 3D joint moments, and joint powers for the hip, knee, and ankle joints were acquired as the sampling data. In the work, 12-kinematic waveforms were calculated in the sagittal, frontal, and transverse plane for pelvis, hip, knee, and ankle, and 12-kinetic waveforms were examined in 3D joint moments for hip, knee, and ankle joint powers for hip, knee, and ankle. In the process of feature extraction, the maximum and minimum values from all waveforms, and sagittal joint angle at hip, knee, and ankle during foot contact and toe-off were extracted. Moreover, for GRF in each waveform, the instantaneous values of amplitude and its corresponding time of occurrence were extracted. In the process of feature selection, nine kinematic and sixteen kinetic gait features were statistically selected using the independent t-tests and Mann–Whitney U tests. These processes helped removing irrelevant or unrelated features for the classification so that it can mitigate the risk of deteriorating the generalized performances of the classifiers. Finally, the selected features were fed into LDA and QDA to classify the patients from the healthy controls. In conventional machine learning methods, feature selection/extraction is separated from classification.

In Medeiros et al. (2016), principal component analysis (PCA) was applied to vertical GRF data to detect abnormalities that may indicate the progression of PD. PCA is an unsupervised learning technique that uses sophisticated mathematical principles to reduce the dimensionality of large datasets (Wold et al., 1987). In the above study, a low-pass filter was used to remove noise from the raw data. Moreover, peaks and valleys were used to identify gait cycles. Each gait cycle was scaled to 100 frames to generate the principal components as feature vectors. Finally, the first three PCA values were selected as the input to the classifier, which was based on Euclidean distance.

Apart from PCA (Eskofier et al., 2013), kernel PCA (Wu et al., 2007), hill-climbing methods (Lai et al., 2008), and the genetic algorithm (GA; Su & Wu, 2000) have been used as feature selection methods for gait analysis. Moreover, artificial neural networks (ANNs; Kaczmarczyk et al., 2009), support vector machine (SVM; Daliri, 2012), naıve Bayes (NB; Manap et al., 2012), discriminant analysis (DA; Hasan et al., 2017), and k-nearest neighbors (kNNs; Chen et al., 2020) have been used as classifiers in conventional machine learning.

6.2 Deep learning techniques used for clinical gait analysis

As described in Dargan et al. (2019), the major difference between deep learning and conventional machine learning is that the feature extraction can be considered part of the model in the former. Because the multiple layers enable the progressive extraction of higher level features from the raw input, there is no need for the manual selection of relevant features that may require expert knowledge, especially for gait analysis. Due to such structure of deep learning models, there are several advantages of applying deep learning to clinical gait analysis. These benefits are briefly described as follows:

1. Automatic feature engineering reduces data exploration time and the need for domain expertise.
2. DL can handle data that are multidimensional and multi-variety in dynamic or uncertain environments such as real-world clinical environments.
3. DL can solve complex problems such as multiclass disease classification.

The deep learning algorithms mainly used in clinical gait analysis are the convolutional neural network (CNN), recurrent neural network (RNN), and auto-encoder (AE).

6.2.1 CNN

The CNN is a neural network that can extract local spatial features from 2D signals by using convolution kernels (Albawi et al., 2017). CNN is typically composed of three types of layers such as convolutional, pooling, and fully connected layers. The operation of multiplying pixel values by weights and summing them is called “convolution.” This operation in convolutional layers preserves the relationship between pixels by learning image features with a small filter called kernel. The pooling layer is commonly applied after a convolutional layer. It enables to reduce dimensions of the feature maps. Finally, a fully connected layer is the actual component that does the discriminative learning in a deep neural network. It is a simple multilayer perceptron that can learn weights to identify an object class. Multiple convolutional layers enable CNN to spatially extract high-level abstract features from images hierarchically.

Due to the ability of learning spatial features, CNN models in clinical gait analysis are often trained with image data such as frames from video capturing people’s walk. In such analysis, the CNN architecture enables the models to preserve the spatial or positional relationships between input data points. For example, Guayacan et al. (2020) applied 3D-CNN to vision-based PD detection. A 3D-CNN can effectively extract features from both the spatial and temporal dimensions by 3D convolution. In the convolution process of the proposed model, the kernel slides in three dimensions to capture Parkinsonian behaviors appeared over multiple adjacent frames. Moreover, time-series sensor data are converted into images to take advantage of the CNN ability. Those images are mainly as follows: spectrogram images generated from acceleration signals (El-Ziaat et al., 2020), gait energy images (Gong et al., 2020), recurrence plot images of vGRF signals (Lin et al., 2020), images converted from vGRF (Hoang et al., 2019), and images that represent foot plantar pressure distribution (Shalin et al., 2020).

Apart from the above, CNN can be used to extract temporal features when the kernel moves in one direction. Generally, the model is referred to as one-dimensional (1D) CNN. 1D-CNN works with patterns in one dimension so that it is useful in signal analysis over fixed length signals. The most significant advantage of 1D-CNN architecture is that the models tend to learn temporal features with fewer parameters than RNN models (Ragab et al., 2020). In other words, 1D-CNN requires less computational resources when training the models. El Maachi et al. (2020) applied 1D-CNN to PD detection and severity prediction based on vGRF from foot sensors. The proposed model is composed of two parts such as 18 parallel 1D-Convnet and a fully connected network. A total number of features used to train the model were 18. These features correspond to the signals from eight sensors placed underneath each foot and two more signals that represent the sum of the eight VGRFs for each foot. Each feature is fed into a 1D-Convnet in order to extract temporal features of the gait pattern. All the features are concatenated...
into one feature vector that is fed into the fully connected network. In the second part, the network is trained to detect PD or predict the severity level. The proposed model reached an accuracy of 98.7% and 85.3% in PD detection and the severity assessment, respectively. Therefore, it is suggested that the proposed system may be a novel approach for monitoring and analysing gait during ADLs among the elderly.

6.2.2 RNN
The RNN is a neural network that can model sequences of data so that each sample can be assumed to be dependent on the previous one (Sherstinsky, 2020). The simplest RNN is composed of just one neuron receiving inputs, producing an output, and sending that output back to itself. A layer of RNN typically consists of several recurrent neurons. It can simultaneously take a sequence of inputs and produce a sequence of outputs. Therefore, RNN models are useful for predicting time series such as future sensor values. However, the conventional RNN faces insurmountable difficulties in solving the vanishing or exploding gradient (Bengio et al., 1994), which reduces its classification accuracy. To solve this problem, Hochreiter and Schmidhuber (1997) and Cho et al. (2014) developed extended versions of the RNN, the long short-term memory (LSTM) and the gradient recurrent unit (GRU), respectively. The RNN with LSTM or GRU uses a series of gates. In one LSTM cell, there are three types of gates such as input, output, and forget gates. On the other hand, one GRU cell consists of two types of gates such as reset and update gates. These gates can learn which data in a sequence should be preserved or abandoned. This mechanism enables RNN to pass relevant information down the long chain of sequences to make predictions. The RNN with GRU uses less training parameters and therefore consumes less memory, and executes and trains faster than LSTM’s. Conversely, the RNN with LSTM is more accurate when training with longer sequences.

The RNN with LSTM or GRU is often employed in vision-based gait analysis (Ferrari et al., 2019; Kidziński et al., 2019; Lee et al., 2019; Jun et al., 2020b; Pachón-Suescún et al., 2020), because the dependence of its learning ability on a long-term time series allows to impose sequential geometric consistency by capturing the temporal correlations among frames in a skeleton sequence. Furthermore, there are several further extended versions of RNN such as bidirectional RNN, attention-based RNN, and ConvLSTM. Bidirectional RNN is a combination of two RNNs training the network in opposite directions, one from the beginning to the end of a sequence and the other from the end to the beginning of a sequence. Some work has applied bidirectional RNN to clinical gait analysis (Turner & Hayes, 2019; Butt et al., 2020; Guo et al., 2020; Lempereur et al., 2020). Due to the ability to learn bidirectional long-term dependences between sequence data, the proposed Bi-LSTM in Turner and Hayes (2019) succeeded in capturing past and future temporal relationships in time-series data from wearable sensors. The proposed model outperformed CNNs in the classification of minor gait alternations. The minor alternations in gait are simulated by adding some pads under shoe. Although the alternations did not affect much on the foot plantar pressure, the proposed model was able to detect the gait patterns with an 82% accuracy.

DL models with attention mechanism such as attention-based RNNs are applied to clinical gait analysis in Zeng et al. (2018), Ahmedt-Aristizabal et al. (2020), Xia et al. (2019), and Flagg et al. (2020). Attention mechanism is a technique that enables neural networks to dynamically highlight relevant elements of the input. Zeng et al. (2018) proposed two kinds of attention mechanisms, such as temporal attention and sensor attention, to improve RNN-based gait classification. The temporal attention mechanism highlights the important part of the time-series signals while the sensor attention mechanism reweights the sensor modality importance during training. In the proposed model, both of the attention mechanisms are applied to LSTM in order to enhance the feature extraction. As a result, the proposed model outperformed a standard LSTM, LSTM with temporal attention, and LSTM with sensor attention in human activity recognition and FoG detection.

ConvLSTM is a variant of LSTM containing a convolution operation inside the LSTM cell. In the model, internal matrix multiplications are exchanged with convolution operations so that the data that flow through the ConvLSTM cells keep the original input dimension. Yu et al. (2020) applied ConvLSTM to fall prediction for the elderly people. The advantage of ConvLSTM over CNN and LSTM is that ConvLSTM can learn both long-term temporal relationships and short-term dependences, which are spatial relationships, in the time sequence with less time consuming than LSTM. The experimental results have shown that the proposed ConvLSTM model outperformed both LSTM and CNN models in the prediction accuracy and the latency on a microcontroller unit.

6.2.3 AE
The AE is an unsupervised neural network that can learn efficient data representations with its compression and decompression functions (Baldi, 2012; Hinton & Salakhutdinov, 2006). An AE consists of three components, namely Encoder, Loss function, and Decoder. The encoder compresses the input into a latent-space representation, whereas the decoder aims to predict the output from the latent-space representation. Throughout the training process, the AE learns the most effective way of reconstructing the original data by minimizing the error between the input and the output. The error is calculated by the loss function. A deep AE consists of multiple hidden layers equally in both its encoder and decoder, whereas a simple AE consists of one hidden layer. Generally, one hidden layer is not sufficient to encode all the input data when high-dimensional data have been fed into the input layer. Therefore, deep AEs have been used preferably for data compression, dimensionality reduction, denoising, and feature extraction.

In clinical gait analysis, AE has been commonly used as a denoising method (Mohammadian Rad et al., 2018; Elkholy et al., 2019). Mohammadian Rad et al. (2018) proposed a convolutional denoising AE model to detect abnormal movements in patients with PD and ASD. Denoising AE is a stochastic version of AE, which reduces the risk of learning the identity function. In other words, the hidden layer in encoder is used to extract the nature of the input from the noisy data, while the one in decoder reverses the effect of a corruption process and reconstructs the input without any noise. Convolutional AE is an AE neural network that uses convolution layers and pooling layers to extract the hidden patterns of input features, and deconvolution layers and unpooling layers to reconstruct the features from the hidden patterns. By integrating convolutional and deconvolutional layers in an AE structure, convolitional AE is capable of learning the spatial structure of input features, and reconstructing these features while taking into account their spatial structural patterns. Mohammadian Rad et al. (2018) integrated denoising function into convolutional AE. The most remarkable advantage of the proposed model is the ability to detect atypical movements when the model is trained only with normal movements. In detail, the model learns the distribution of normal movements using a probabilistic denoising AE so that it can...
accurately reconstruct only the normal data from noisy samples. Consequently, the model can be used to compute the degree of abnormality for the input by comparing the reconstruction of the AE with the distribution of normal movements.

Furthermore, some works in various fields have demonstrated that feeding the reconstructed features by AEs to the DM as the input achieves a higher accuracy than feeding the original data as the input (Marchi et al., 2015; Zhao et al., 2017; Tu et al., 2018). Thus, in clinical gait analysis, AE is used for automatic feature extraction with other machine learning models such as RNNs (Nguyen et al., 2018c; Yang & Yin, 2020; Zaroug et al., 2020). Jun et al. (2020a) proposed an RNN AE-DM hybrid model to recognize abnormal gait from skeleton data. RNN AE is a type of AE for sequence data using an encoder–decoder RNN architecture. The advantage of RNN AEs over regular AEs is the ability of dealing with sequence as input. In detail, the RNN preserves the temporal information of skeleton sequences, and the AE architecture can automatically eliminate irrelevant and redundant information. To take advantage of the ability, the original skeleton data measured by Kinect were fed into the RNN AE part of the proposed model, and therefore the RNN DM is trained with the reconstructed data to recognize abnormal gait patterns.

6.2.4 Hybrid deep learning model
A hybrid model based on a combination of the CNN and RNN has been applied to clinical gait analysis. There are several ways to combine the two DL models. For example, in Chen et al. (2020) and Reyes et al. (2019), CNN is stacked on the top of LSTM. First, the CNN part of the model processes input data, and then the extracted features are converted into 1D data that are eventually fed into the LSTM. This structure enables the DL model to simultaneously learn spatial and temporal features in gait patterns. However, with the increase in the depth of the network, the model tends to be susceptible to the vanishing gradient problem. To alleviate the issue, Chen et al. (2020) applied skip-connection structure and batch normalization to the proposed combined CNN-LSTM network called “FMS-Net.” Skip connection in DL is a technique that allows gradients to flow easily from layer to layer (Drozdzal et al., 2016). In the structure, the output of one layer is fed to another layer while skipping a few layers in between. Batch normalization is a technique that accelerates the training of DL models by normalizing the hidden layer activation (Ioffe & Szegedy, 2015). As a result, FMS-Net outperformed a simple combined CNN-LSTM network, FMS-Net without skip connection and an LSTM in four-gait phase classification.

Zhao et al. (2018b) applied a two-channel network that takes advantage of both CNN and LSTM to PD detection and the severity assessment. The proposed model consists of two channels, such as a five-layer CNN and a two-layer LSTM, to extract features from VGRFs. The same feature vectors, which are VGRF values measured by foot sensors, are fed into each channel network as the input data. The two networks are connected in parallel and jointly trained. The weighted average of the softmax provides the final classification result such as the presence of PD or the severity level. The most remarkable advantage of the proposed model is the ability of learning features in both spatial and temporal dimensions by CNN and LSTM, respectively. As a result, the results of the proposed model outperformed both results of a CNN model and an LSTM model in the classification tasks.

6.3 Techniques used to apply deep learning to clinical gait analysis
Table 4 introduces studies that have analysed the gait data of patients for a specific disease or health issue using conventional machine learning. Such studies are still small in number, but they show differences in gait patterns between patients and healthy controls, where these differences are identifiable by machine learning models. Therefore, if a large gait database can be formed using data from such patients, it may be possible to apply deep learning models to gait analysis of this kind as well. In general, deep learning techniques are more suitable when data that the model requires to build itself are sufficient. On the other hand, conventional machine learning techniques can be taken full advantage of its ability only when the complexity of the classification problem is relatively low and input features can be directly extracted from structured data. In such machine learning, the required computational resources and size of data are significantly low compared to deep learning. Therefore, despite such constraints, they have been utilized for clinical gait analysis if the performance of the model is acceptable in practical use. However, it is hard to meet such high expectations for all kinds of applications developed only with conventional machine learning. Thus, more and more researchers have been attempting to apply deep learning techniques to clinical gait analysis in the last few years.

Tables 5 and 6 list deep learning-based studies on clinical gait analysis published from 2018 to 2020. The survey for deep learning techniques applied in clinical gait analysis has been conducted based on the listed studies.

In terms of the framework of machine learning-based gait analysis systems, there is not much difference between its application fields such as security, sport, and medicine. On the other hand, the amount of data that can be collected may cause a huge difference between these fields. For clinical gait analysis, the available gait data may be limited for reasons such as rare conditions, patient compliance, and ethical constraints. However, deep learning requires a large number of samples to train the models. Thus, the lack of training data may cause overfitting problems (Ying, 2019). Overfitting is a term used in statistics that refers to a modeling error. Specifically, the model memorizes the noise and the outliers, and therefore it fits too closely to the training set. Eventually, it fails to generalize its predictive power to unseen data. To avoid the issue, several recent studies on gait analysis have employed novel techniques that can be divided into three categories: data augmentation, weakly supervised learning, and transfer learning.

6.3.1 Data augmentation
Data augmentation is a technique that enhances the size and diversity of the training data. Training models with limited data often cause overfitting that prevents them from generalizing well to unseen data. Applying data augmentation to machine learning helps improve the generalization ability of its models, especially in deep learning (Wang et al., 2021). The available methods differ depending on whether the training data are image data (Shorten & Khoshgoftaar, 2019) or time-series data (Wen et al., 2020).

In data augmentation based on image manipulations in clinical gait analysis, geometric transformation methods are often used due to their simplicity and ability to avoid positional bias in the data. The training images are transformed by noise injection, flipping, shearing, and zooming (Huang et al., 2019a; Zhang et al., 2018, 2020).
### Table 4: Studies on clinical gait analysis using classic machine learning.

| Data acquisition    | Causes of gait disorders                              | Machine learning methods                        | Ref./year                  |
|---------------------|-------------------------------------------------------|-------------------------------------------------|-----------------------------|
| Inertial sensors    | Fabry’s disease                                      | SVM, RF, MLPs, and DBNs                          | Fernandes et al. (2019)     |
|                     | Foot drop due to L5 radiculopathy                    | 11 methods (e.g. SVM and DT)                     | Bidadabi et al. (2019), Sharif |
|                     | Hereditary spastic paraplegia                         | Hierarchical HMM                                 | Martindale et al. (2018)    |
|                     | Early-onset Ataxia and developmental coordination disorder | HMMs                                              | Mannini et al. (2017)       |
| Force plates        | Friedreich’s ataxia                                  | MLP                                             | LeMoyne et al. (2016)       |
|                     | Glaucoma                                              | DT, NB, LR, and kNN                              | Ma et al. (2015)            |
| Force plates and Vision-based MB | Autism spectrum disorder   | SVM and ANN                                       | Ilias et al. (2016)         |
| Vision-based MB     | Autism spectrum disorder                             | SVM                                              | Janssen et al. (2011)       |
| Vision-based MB     | Patellofemoral pain syndrome                          | Linear DA and Quadratic DA                       | Hasan et al. (2017)         |
| Vision-based MB     | Sleep quality                                         | SVM                                              | Lai et al. (2009)           |
|VISION-BASED ML      | Acute unilateral anterior cruciate ligament rupture   | LR, simple LR, Gaussian processes, epsilon-SVR, and nu-SVR | Liu et al. (2019)           |
|                     | Lumbar spinal canal stenosis                          | SVM                                              | Christian et al. (2016)     |
|                     | Traumatic brain injury                                | SVM                                              | Hayashi et al. (2015)       |
|                     | Hip OA                                                | SVM                                              | Williams et al. (2015)      |
|                     | Ankylosing spondylitis                                | SVM                                              | Laroche et al. (2014)       |
|                     | Multiple sclerosis                                    | LR, simple LR, Gaussian processes, epsilon-SVR, and nu-SVR | Zhao et al. (2019)          |
|                     | Polyneuropathy                                        | LDA                                              | Gholami et al. (2016)       |
|                     | Fatigue                                               | SVM                                              | Wang et al. (2015)          |

Moreover, feature space augmentation is an effective data augmentation method for gait analysis. For example, Zhang and Gu (2019) applied the synthetic minority oversampling technique (SMOTE) to an FoG dataset to generate data in the FoG category. The SMOTE is an augmentation method that mitigates the challenges of imbalances in the datasets by creating synthetic instances of underrepresented data (Zhu et al., 2017). Similarly, for such time-series data as inertial data, several data augmentation methods are available as mentioned in Wen et al. (2020). Of them, basic transformations in the time domain, frequency domain, and time–frequency domain are especially popular. In the context of clinical gait analysis, magnitude perturbation, temporal perturbation, random rotation, and noise injection were used in Tunca et al. (2019), Kirpianovska et al. (2020), Zhang et al. (2020a), González et al. (2020), and Paragliola and Coronato (2020).

Generative adversarial network (GAN) has been applied to abnormal gait recognition to extend their training datasets. GANs are a type of generative model that use two networks, called the “generator” and the “discriminator” (Creswell et al., 2018). The generator produces images while the discriminator distinguishes between real and fake images to train a model that approximates the distribution of the data. This model is mostly used for image or video synthesis tasks. Liu et al. (2020) used conditional GAN (Mirza & Osindero, 2014) to synthesize the kinematic characteristics of the feet and ankles of patients suffering from lateral collateral ligament injuries. Luo and Tjahjadi (2020) also used conditional GANs to generate a parametric 3D model of the body with an embedded skeleton and synthesized asymmetric gait samples. Song et al. (2020) applied Deep convolutional GAN to generate binary images capturing three kinds of abnormal gait patterns such as fall, reel, and drag. Deep convolutional GAN is an extended version of GAN that uses CNN instead of the multilayer perceptron in classic GAN to improve the generative ability of the generator.

#### 6.3.2 Weakly supervised learning

Weakly supervised learning is a machine learning framework where the model is trained using examples that are only partially annotated or labeled (Torresani, 2014). Weak supervision offers a promising alternative for producing labeled datasets without ground truth annotations by heuristically generating training data with external knowledge bases, patterns/rules, or other classifiers. Therefore, it avoids the challenges of acquiring a large amount of labeled data. The relevant methods are categorized into three groups: incomplete supervision, inexact supervision, and inaccurate supervision (Zhou, 2018). In the relevant papers reviewed for this survey, machine learning techniques were used for incomplete supervision, such as through active learning (Settles, 2009) and semisupervised learning (Van Engelen & Hoos, 2020), for clinical gait analysis. Incomplete supervision is a situation when only a (usually small) subset of training data are given with labels, whereas the other data are unlabeled (Zhou, 2018). Vaith et al. (2020) applied active learning with deep neural networks to gait phase classification to reduce the required number of labeled strides in the classification task. Active learning is the subset of machine learning that prioritizes the data for annotation to use only samples that improve the generalization performance of a supervised model. The experimental results of the above work showed that the model proposed by the authors achieved a high accuracy (of up to 96%) using 43% fewer samples than random sampling in an online setting involving four-phase classification. In an offline setting, the model succeeded in extracting heel strike and toe-off events with an accuracy of 99.9% with up to 58% fewer samples than random sampling.

Sheng and Huber (2019) proposed a human activity detection system based on multiple Siamese networks. A Siamese neural network contains multiple branches that have the same architecture and share weights (Bromley et al., 1993). The proposed model contained two Siamese networks: one for a time-series
Table 5: Reviewed papers related to clinical applications of gait data.

| Utilization          | Modality       | Sensor type          | Application/reference                     | Input                                      | DL                           |
|----------------------|----------------|----------------------|-------------------------------------------|--------------------------------------------|------------------------------|
| Remote               | Nonwearable    | Floor sensors        | Fall risk assessment: Liang et al. (2019) | Force sensor values                        | ConvLSTM                     |
| Monitoring           | Vision-based ML| Force sensor values  | FoG detection: Hu et al. (2019)           | Videos                                     | Graph Sequence RNN           |
| Wearable             | Insole sensors | Foot plantar pressure images | Fall detection: Song et al. (2020) | Force sensor values                        | CNN                          |
| Inertial sensors     |                |                      | FoG prediction: Shalin et al. (2020)      | Foot plantar pressure images               | CNN                          |
|                      |                |                      | Fall detection: Gonzalez et al. (2020)    | A, M, and G sensor values                   | CNN                          |
|                      |                |                      | Fall detection: Mauldin et al. (2018)     | A sensor values                            | GRU                          |
|                      |                |                      | Fall detection: Ng et al. (2020)          | A sensor values                            | LSTM + TL                    |
|                      |                |                      | Fall prediction: Yu et al. (2020)         | A sensor values                            | ConvLSTM                     |
|                      |                |                      | Fall risk assessment: Kiprijanovska et al. (2020) | A sensor values | CNN + Bi-LSTM               |
|                      |                |                      | Fall risk assessment: Martinez and De Leon (2019) | A and G sensor values | CNN + TL                    |
|                      |                |                      | Fall risk assessment and PD severity assessment: Yu et al. (2020) | A sensor values | CNN with deep multisource and multitask learning |
|                      |                |                      | FoG detection: El-Ziaat et al. (2020)     | Hand-crafted data + spectrogram of acceleration signals | CNN + RF                     |
|                      |                |                      | FoG detection: San-Segundo et al. (2019)  | Hand-crafted features                      | CNN + MLP                    |
|                      |                |                      | FoG detection: Sheng and Huber (2019)     | A sensor values                            | LSTM + CNN with siamese architecture |
|                      |                |                      | FoG detection: Zeng et al. (2018)         | A sensor values                            | Attention-based LSTM         |
|                      |                |                      | FoG detection: Zhang and Gu (2019)        | A sensor values/spectrogram of acceleration signals | CNN + LSTM                   |
|                      |                |                      | FoG prediction: El-ziaat et al. (2019)    | Hand-crafted features + spectrogram of acceleration signals | CNN + RF                     |
|                      |                |                      | FoG prediction: Torvi et al. (2018)       | A sensor values                            | LSTM + TL                    |
|                      |                |                      | Fall detection: Qian et al. (2020)        | A sensor values and pressure sensor values | Distributed hierarchical CNN |
|                      |                |                      | Fall detection: Li et al. (2019a)         | Hand-crafted features + spectrogram        | Bi-LSTM                      |
|                      |                |                      | Fall detection: Galvão et al. (2020)      | A sensor values + video                     | Parallel 2D–1D CNN + 1D-CNN/ |
| Hybrid               | Smartphone, smartwatch, and insoles | Force sensor values | PD diagnosis: Ajay et al. (2018) | Video                                      | CNN + DT                     |
|                      | IMU and radar   |                      | PD diagnosis: Reyes et al. (2019)         | Skeleton data                              | 1D-CNN + LSTM                |
|                      | IMU and vision-based ML |                      | PD diagnosis: Guayasán et al. (2020)      | Video                                      | 3D-CNN                       |
|                      |                |                      | PD diagnosis: Gong et al. (2020)          | Video                                      | Mark R-CNN                   |
|                      |                |                      | PD severity assessment: Lu et al. (2020)  | Skeleton data                              | CNN                          |
| Treatment for PD     | Nonwearable ML | Vision-based ML      | PD diagnosis: Flagg et al. (2020)         | Force sensor values/ spatio-temporal features | Attention-based Bi-RNN       |
|                      |                |                      | PD diagnosis: Hoang et al. (2019)         | 2D images converted from vGrF              | Stacked 2D–1D CNN            |
|                      |                |                      | PD severity assessment: Albarthi et al. (2019) | Force sensor values | CNN                          |
|                      |                |                      | PD severity assessment: Xia et al. (2019) | Force sensor values                        | Dual-model where each branch has a CNN followed by attention-enhanced Bi-LSTM |
|                      |                |                      | PD severity assessment: Zhao et al. (2018) | Force sensor values                        | Parallel CNN-LSTM network    |
|                      |                |                      | PD severity assessment: El Maachi et al. (2020) | Force sensor values | 1D-CNN                       |
| Utilization            | Modality          | Sensor type       | Application/reference                                      | Input                                 | DL                                    |
|-----------------------|-------------------|-------------------|-------------------------------------------------------------|---------------------------------------|---------------------------------------|
| PD severity assessment: Alharthi and Ozanyan (2019) | Force sensor values               | 1D-CNN/2D-CNN/LSTM                                   |
| PD severity assessment: Aversano et al. (2020a)  | Force sensor values               | Fuzzy neural network                                   |
| PD severity assessment: Aversano et al. (2020a)  | Force sensor values               | DNN                                                      |
| PD diagnosis: Burt et al. (2020)          | Hand-crafted features               | Bi-LSTM                                                  |
| PD diagnosis: Mohammadian Rad et al. (2019)  | A sensor values                   | Convolutional denoising AE                              |
| PD diagnosis: Zhang et al. (2020a)         | A sensor values                   | CNN                                                      |
| Medication state assessment: Hssayeni et al. (2018) | G sensor values                  | LSTM                                                     |
| Medication state assessment: Zhang et al. (2020b) | Spectrogram converted from test results (voice, balance, and gait) | CNN + LSTM with multi view learning                     |
| Treatments for other diseases | Nonwearable ML | Vision-based ML | Multiclass classification, Chakraborty et al. (2020) | Skeleton data | LSTM + AE/GRU + AE                     |
| OA diagnosis: Abid et al. (2019)           | Gait energy images                | CNN with TL + LDA                                      |
| OA diagnosis: Abid et al. (2019)           | Knee kinematic data               | Time-CNN, multiscale CNN, multichannel DCNN, time-leNet, CCN, AE, and ResNet |
| OA diagnosis: Chen et al. (2020)           | Skeleton data                    | LSTM + SVM                                              |
| OA diagnosis: Chen et al. (2020)           | Gait silhouette images            | CNN + TL                                                |
| Hemiplegia diagnosis: Patel et al. (2019)  | Videos                           | CNN                                                     |
| Vision-based MB                                | Footprint pressure images          | CNN                                                     |
| Wearable                              | Insole sensors                  | Force sensor values                                    | Bi-LSTM                               |
| HD severity assessment: Zhang et al. (2019) | Force sensor values               | Attention-based Bi-RNN                                  |
| Multiple classifications of gait abnormalities: Zhang et al. (2020) | Gait silhouette images            | CNN + TL                                                |
| Hemiplegia diagnosis: Patel et al. (2019)  | Videos                           | CNN                                                     |
| Floor sensors                                | Footprint pressure images          | CNN                                                     |
| OA diagnosis: Abid et al. (2019)           | Gait energy images                | CNN with TL + LDA                                      |
| OA diagnosis: Abid et al. (2019)           | Knee kinematic data               | Time-CNN, multiscale CNN, multichannel DCNN, time-leNet, CCN, AE, and ResNet |
| Vision-based MB                                | Footprint pressure images          | CNN                                                     |
6.3.3 Transfer learning

Transfer learning is a machine learning technique where a model exploits the knowledge gained from a previous task to improve generalization on another task. In other words, transfer learning can compensate for the lack of labeled data via the transfer of knowledge from other labeled data sources. According to Pan and Yang (2009), several taxonomies can be used to categorize transfer learning methods. Here, we review domain adaption, domain generalization, and transferring knowledge related to the parameters.

Domain adaptation aims to generalize a learning model across the source and target domains, which follow different distributions. Torvi et al. (2018), Ngue et al. (2020), and Kang et al. (2019) exploited gait data from different subjects to develop a prediction model for a particular subject. Domain generalization aims to aggregate knowledge from multiple source domains into a single model that can be generalized well to unseen target domains (Hu et al., 2020). Gu et al. (2020) proposed multimodal representation learning to enable cross-subject and cross-modal transfer. These transfer methods have contributed to solving the problem of the limited availability of accurate pathological human pose data. Multitask learning aims to learn different tasks simultaneously while maximizing performance on one or all of the tasks. Nait Aicha et al. (2018) and Yu et al. (2018) enhanced performance on the following pairs of tasks by using a limited amount of data: fall risk assessment and human identification, and the assessment of the severities of fall risk and PD, respectively. Transferring the knowledge of parameters is a technique that helps reuse the weights from one or more layers of a pretrained network to a new model, and fine-tunes the model. To address the lack of abnormal gait data, Verlekar et al. (2018), Pandit et al. (2019), Martinez and De Leon (2019), and Zhang et al. (2020c) utilized different neural networks pretrained on a large-scale dataset, such as ImageNet (Deng et al., 2009).

7 Public Datasets

A sufficiently large database is essential for the development of research on gait analysis. However, data related to pathological gaits are challenging to acquire due to the difficulty of accessing the patients and complicated arrangements needed to meet safety standards in the given environment. Various databases of data on abnormal gait have been released to the public. We highlight the promising ones that contain data on different sensing modalities. They are summarized and shown by type of abnormal gait in Table 7. This section provides a brief overview of gait databases designed for abnormal gait analysis.

7.1 Fall gait dataset

Reviewed fall gait databases (Auvinet et al., 2018; Kwolek & Kepski, 2014; Medrano et al., 2014; Chatzaki et al., 2016; Sucerquia et al., 2017; Mauldin et al., 2018) were recorded using inertial sensors and/or vision-based sensors. They included data on several types of falls and ADLs. For safety-related reasons, the falls were simulated by healthy subjects, and mattresses were used to break the fall.

To develop a robust gait analysis system, the video sequences used contained eight typical difficulties that can lead to segmentation errors, such as cluttered and textured backgrounds, occlusions, and high video compression. In the UR Fall Detection Dataset, fall events were recorded using two Kinect cameras and an x-IMU device worn near the pelvis (Kwolek & Kepski, 2014). ADL events were recorded using only one Kinect camera and the IMU. This database contained video streams, raw accelerometric data, and synchronization data consisting of frame number, time in milliseconds since the start of the sequence, and interpolated accelerometric data corresponding to the image frame.

Sucerquia et al. (2017), Mauldin et al. (2018), Chatzaki et al. (2016), and Medrano et al. (2014) captured acceleration,
Table 6: Continued from the previous page.

| Utilization                      | Modality     | Sensor type            | Application/reference                                                                 | Input                                                                 | DL              |
|----------------------------------|--------------|------------------------|---------------------------------------------------------------------------------------|----------------------------------------------------------------------|-----------------|
| Treatments for other diseases    | Wearable     | Inertial sensors       | Geriatric assessment: Jung et al. (2020b)                                             | Spectrograms of acceleration and angular velocity signals           | CNN             |
|                                  |              |                        | ITW diagnosis: Kim et al. (2019)                                                       | A and G sensor values                                               | LSTM            |
|                                  |              |                        | Abnormal gait recognition: Binary classification; Huang et al. (2019a)                  | 3D spectrogram of sEMG signals                                     | 3D-CNN + LSTM   |
|                                  |              |                        | Multiclass classification: Guo et al. (2020)                                           | DWT coefficients                                                   | Bi-LSTM         |
| Hybrid                           | Vision-based ML and EMG | Multiple classification of gait abnormalities: Gu et al. (2020) | Skeleton data                                                             | Multimodal AE + TL                                                  |                |
|                                  | Insoles and IMU | Multiple classification of pathological gait disorders: Potluri et al. (2019) | Planter pressure values, and A, M, and G sensor values | Stacked LSTM                                                       |                |
| Clinical gait assessment         | Nonwearable MB | Vision-based MB        | Estimation of kinetic parameters: Liu et al. (2020)                                     | Skeleton data                                                       | Deep convolutional GAN + LSTM |
|                                  |              |                        | Estimation of spatio-temporal parameters: Ismael et al. (2019)                         | Skeleton data                                                       | Bi-LSTM         |
|                                  |              |                        | Estimation of gait abnormality index: Nguyen et al. (2018c)                            | Skeleton data                                                       | LSTM + AE       |
|                                  |              |                        | Estimation of gait abnormality index: Nguyen et al. (2018b), Nguyen and Meunier (2019a) | Skeleton data                                                       | AE              |
|                                  |              |                        | Estimation of gait abnormality index: Nguyen and Meunier (2019a)                      | 3D point clouds representing the walking postures of a subject      | GAN + AE        |
|                                  |              |                        | Estimation of spatio-temporal parameters: Kondragunta et al. (2019)                    | RGBD data from Kinect                                               | CNN             |
|                                  |              |                        | Estimation of spatio-temporal parameters: Li et al. (2019a)                           | Skeleton and disparity images                                       | Mask R-CNN      |
|                                  |              |                        | Estimation of spatio-temporal parameters: Yu et al. (2019)                            | Video                                                              | CNN + MLP       |
|                                  |              |                        | Estimation of spatio-temporal and kinematic parameters: Kidziński et al. (2020)     | Skeleton data                                                       | CNN             |
|                                  |              |                        | Estimation of spatio-temporal and kinematic parameters: More et al. (2020)           | Video                                                              | ResNet          |
| Wearable                         | Insole sensors | Estimation of kinetic parameters: Choi et al. (2019)                               | Foot plantar pressure values                                         | LSTM                                                          |                |
|                                  | Inertial sensors | Estimation of spatio-temporal parameters: Sharifi Renani et al. (2020)               | A and G sensor values                                               | CNN                                                           |                |
|                                  |              |                        | Estimation of kinematic parameters: Gholami et al. (2020)                            | A sensor values                                                     | CNN             |
| Hybrid                           | Insoles and IMU | Estimation of gait symmetry: Steinmetzer et al. (2020)                        | The symmetry distance between the time series (strides) of the right and left feet | CNN                                                         |                |
| Classification of discrete gait phase | Nonwearable MB | Vision-based MB        | Estimation of kinetic parameters: Rane et al. (2019)                                   | Kinematic and kinetic data                                         | DNN             |
|                                  |              |                        | Two-phase gait classification: Filtjens et al. (2020)                                | Skeleton data + temporal features                                  | Temporal CNN    |
|                                  |              |                        | Two-phase gait classification: Kidziński et al. (2019)                               | Skeleton data + temporal features                                  | LSTM            |
|                                  |              |                        | Two-phase gait classification: Lempereur et al. (2020)                               | Skeleton data + temporal features                                  | Bi-LSTM         |
|                                  | Wearable     | Inertial sensors       | Two-phase gait classification: Vuih et al. (2020)                                     | A and G sensor values                                              | LSTM/DNN        |
|                                  |              |                        | Four-phase gait classification: Ding et al. (2018)                                   | A and G sensor values                                              |                |
|                                  |              |                        |                                                                                     |                                                                 | Two parallel LSTMs |

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angular velocity, and orientation data for both falls and ADLs. However, different types of devices were employed to obtain the data. The SifFall database was obtained using a self-developed embedded device containing two accelerometers and a gyroscope (Sucerquia et al., 2017). The device was fixed to the participants’ waists. For this database, 23 healthy young adults (HY), aged 19–29 years, and 15 elderly people, aged 60–75 years, were recruited as subjects.

The young adults performed the ADLs and simulated the falls, whereas some of the elderly subjects could not perform certain activities owing to personal impairment or medical recommendation. The SmartFall database was acquired using a smartwatch worn by the participants on the wrist (Mauldin et al., 2017). The MobiAct and tFall databases were collected using a smartphone put in a trouser pocket (Medrano et al., 2014; Chatzaki et al., 2016). Moreover, in tFall, real ADLs were recorded: The participants carried a smartphone in their pockets or in a handbag for at least 1 week to record their everyday behavior.

7.2 PD gait dataset

In gait databases of patients of PD, the subjects were asked to walk and perform physical activities that can manifest symptoms of PD. The Daphnet FoG dataset (Bachlin et al., 2010) collected FoG data using three accelerometers attached at the shank, thigh, and lower back of the patient. In the experiments, PD patients with a history of FoG were recruited, and were asked to walk back and forth, turn, stop, and go through narrow spaces. These walking activities were chosen as they are highly likely to cause FoG episodes.

The gait database of patients of Parkinson’s disease obtained from PhysioNet (Goldberger et al., 2000) is a preferred database for analysing Parkinsonian gait because it contains a large amount of vertical GRF data collected from a large number of subjects, including PD patients and healthy controls. The Gait in Aging and Disease database collected from PhysioNet (Goldberger et al., 2000) also contains vertical GRF data. For this dataset, five healthy young adults aged 23–29 years and five healthy old adults aged 71–77 years were recruited in addition to

| Utilization | Modality | Sensor type | Application/reference | Input | DL |
|-------------|----------|-------------|-----------------------|-------|----|
| Nonwearable ML | Vision-based ML | Estimation of lower limb joint angles: Zarouq et al. (2020) | Linear acceleration and angular velocity for thigh and shank | LSTM + AE |    |
| Hybrid | Insoles and IMU | Two-phase gait classification: Yuan et al. (2020) | A, G, and foot plantar pressure sensor values | LSTM |    |
| Hybrid | Insoles and IMU | Two-phase gait classification: Prado et al. (2019) | A, G, and foot plantar pressure sensor values | GRU |    |
| Hybrid | Insoles and IMU | Two-phase gait classification: Wang et al. (2019) | A and foot plantar pressure sensor values | Deep memory CNN (DM-CNN) |    |
| Hybrid | Insoles and IMU | Two-phase gait classification: Tortora et al. (2020a) | Sensor values from EMG and IMU | LSTM |    |
| Hybrid | Barometers and IMU | Estimation of lower limb joint angles: Yang and Yin (2020) | Sensor images converted from GRFs and air pressures of soles | LSTM + convolutional AE |    |
| Hybrid | Barometers and IMU | Estimation of lower limb joint angles: Nagashima et al. (2019) | G and foot plantar pressure sensor values | DNN |    |
| Hybrid | EMG and IMU | Estimation of knee joint angles: Huang et al. (2019a) | sEMG, G, and M sensor values | RNN |    |
| Hybrid | Encoders and IMU | Estimation of gait events: Kang et al. (2019) | 3D Euler angles from IMUs and the hip joint angle from the encoder | DNN |    |
| Hybrid | EMG and IMU | Estimation of foot plantar forces: Nakagome et al. (2020) | Sensor images converted from sEMG, G, and M sensor values | LS-M + AE |    |
| Hybrid | EMG | Estimation of lower limb joint angles: Chen et al. (2018) | sEMG intensity | DBN + RBM |    |
| Hybrid | EMG | Estimation of lower limb joint angles: Su et al. (2020) | A and G sensor values | Exponentially delayed fully CNN (ED-FNN) |    |
| Hybrid | EEG | Estimation of lower limb joint angles: Wang et al. (2019) | Frequency band features | GRU/Quasi Recurrent Neural Network (QRNN) |    |
| Hybrid | EEG | Estimation of lower limb joint angles: Nakagome et al. (2020) | Frequency band features | GRU/Quasi Recurrent Neural Network (QRNN) |    |
| Hybrid | EEG | Estimation of lower limb joint angles: Prado et al. (2019) | Spatial features across frequency and spectral features across spatial locations | Spatio-spectral representation learning (DNN) |    |
| Hybrid | EEG and IMU | Two-phase gait classification: Goh et al. (2019) | Spatial features across frequency and spectral features across spatial locations | CNN |    |
| Hybrid | EMG and IMU | Two-phase gait classification: Tortora et al. (2020a) | Spatial features across frequency and spectral features across spatial locations | CNN |    |
| Hybrid | EMG and IMU | Two-phase gait classification: Zarouq et al. (2020) | Linear acceleration and angular velocity for thigh and shank | LSTM + AE |    |
| Hybrid | EMG and IMU | Two-phase gait classification: Zarouq et al. (2020) | Linear acceleration and angular velocity for thigh and shank | LSTM + AE |    |
| Hybrid | EMG and IMU | Two-phase gait classification: Zarouq et al. (2020) | Linear acceleration and angular velocity for thigh and shank | LSTM + AE |    |
| Hybrid | EMG and IMU | Two-phase gait classification: Zarouq et al. (2020) | Linear acceleration and angular velocity for thigh and shank | LSTM + AE |    |
| Hybrid | EMG and IMU | Two-phase gait classification: Zarouq et al. (2020) | Linear acceleration and angular velocity for thigh and shank | LSTM + AE |    |

Table 6: Continued
### Table 7: Publicly available databases for clinical gait analysis.

| Name                        | Ref./year         | No./subjects | Modality                      | Size of database                          | Task                                                                 | Online access link                                                                 |
|-----------------------------|-------------------|--------------|--------------------------------|--------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------------------|
| SmartFall                   | Mauldin et al. (2018) | 7/HC        | 1 smartwatch                  | 131 falls and 29 958 ADLs                 | Simulation: 4 types of falls and 7 ADLs                              | https://userweb.cs.txstate.edu/~hn12/data/SmartFallDataset/                        |
| Stiffall                    | Sucerquia et al. (2017) | 23/HY, 15/HO | 2 accelerometers and 1 gyroscope | 4510 trials (1.5 h for each HO and 3.5 h for each HY) | Simulation: 15 types of falls and 19 ADLs                          | http://nister.uco.edu.cc/en/investigacion/proyectos/English-falls/                 |
| MobiAct                     | Chatzaki et al. (2016) | 66/HC       | 1 smartphone                  | More than 3200 trials                      | Simulation: 4 types of falls and 12 ADLs                            | https://bmi.huji.ac.il/mobi-fall-an-mobiact-datasets-2/                            |
| UR fall detection dataset   | Kwolek and Kępki (2014) | 5/HC        | 2 or 1 Kinect and 1 IMU       | 30 falls and 40 ADLs                       | Simulation: 3 types of falls and 6 ADLs                             | http://enx.univ.rzeszow.pl/~mkeps/kin/                                           |
| tFall                      | Medrano et al. (2014) | 10/HC       | 1 smartphone                  | 502 falls and 1 week of continuous ADL recording | 7 types of simulated falls and real ADLs                            | http://eduqtech.unizar.es/en/foil-adl-data/                                       |
| Multiple cameras' fall dataset | Auvinet et al. (2010) | 1/HC        | 8 IP video cameras            | 24 scenarios including 22 falls            | Simulation: several types of falls and some ADLs                   | http://www.iro.umontreal.ca/~labimage/Dataset/                                     |
| The Daphnet FoG dataset     | Bachlin et al. (2010) | 10/PD       | 3 accelerometers              | 237 FoG episodes (8 h 20 min of total data) | Straight walk, turn, 5 ADLs.                                        | https://archive.ics.uci.edu/ml/datasets/Daphnet+Freezing+of+Gait                    |
| Walking of mPower Data Streams | Bot et al. (2016) | 65/HC, 2, 148/HC | 1 smartphone                  | 34 632 records                            | Straight walk, turn                                                | https://www.synapse.org/#!Synapse:syn4993293/wiki/247859                        |
| 4GAIT-Parkinson             | Kulbacki et al. (2014) | 18/PD       | RGB cameras, Mocap, EMGs, and force plates | 1781 trials (including 803 trials of gait) | 12 tasks under 4 experimental conditions                           | The data are not publicly available, but access can be requested.                |
| Gait in Aging and Disease database | Goldberger et al. (2009) | 5/PD, 5/HY, 5/HO | Insole force sensors         | -                                          | Walk on level ground                                               | https://physionet.org/physiobank/database/gaitdb/                                |
| Gait in Parkinson's disease | Goldberger et al. (2009) | 93/PD, 73/HC | Insole force sensors         | -                                          | 2 min walk at preferred speed on level ground                      | https://physionet.org/physiobank/dataset/gaitpd/1.0.0/                          |
| Bergamini et al. (2017), Ferrari et al. (2019) | 178/Diplegia | Mocap      | 1121 trials                   | Walk at normal speed                       |                                                                     | https://github.com/cubabergamini/gait-analysis-dataset                           |
| 4GAIT-HM                    | Kulbacki et al. (2014) | 10/hip OA, 19/knee OA, 4/stroke and 1/arthritis | RGB cameras, Mocap, EMGs, and force plates | More than 1144 trials                      | -                                                                 | The data are not publicly available but access can be requested.                |
| GaitRec dataset             | Horsak et al. (2020) | 211/HC, 2085/Musculoskeletal impairments | Force plates                   | 75 732 trials                               | Walk at preferred walking speed on a 10 m walkway                  | https://figshare.com/collections/GaitRec_A_large-scale_ground_reaction force_dataset_of_healthy_and_impairments/gait4788012 |
| Gait in Neurodegenerative Disease database | Goldberger et al. (2009), Hausdorff et al. (2009) | 15/PD, 20/HD, 13/ALS and 16/HC | Insole force sensors       | 64 records                                                  | 77 m walk for 5 min at normal speed                                        | https://physionet.org/physiobank/database/gaitndd/                                |
| MMGS dataset                | Khokhlova et al. (2019) | 27/HC     | 1 Kinect camera               | 489 videos (a total of 686 strides)          | 1 normal and 3 simulated abnormal gaits                           | https://github.com/margokhokhlova/LSTM_gait_model                                 |
| INT Gait dataset            | Ortells et al. (2018) | 10/HC      | RGB cameras, Mocap, EMGs, and force plates | 160 trials (20 normal gaits and 140 simulated abnormal gaits) | 1 normal and 7 simulated abnormal gaits                             | https://www.visuon.uisi.ee/gaitDB/                                               |
| Walking gait dataset        | Nguyen et al. (2018a), Nguyen and Meunier (2018) | 9/HC    | 1 Kinect with ToF depth estimation and 2 mirrors | 9 subjects × 9 gaits × (1200 clouds + 1200 skeletons + 1200 silhouettes) | 1 normal and 8 simulated abnormal gaits                              | http://www-labs.iro.umontreal.ca/~laborimage/GaitDataset/                          |

The Daphnet FoG database contained a total of 18 PD patients. The mPower database (Bot et al., 2016) contained four databases collected from activities referred to as “memory,” “tapping,” “voice,” and “walking.” The walking dataset was acquired with a smartphone placed in the pocket of the subject. The 4GAIT-Parkinson database (Kulbacki et al., 2014) employed a multimodal sensor system to collect a variety of sensor data. A total of 18 PD patients completed 12 tasks under 4 experimental conditions, such as “Medication ON/OFF” and “Stimulation ON/OFF.”

#### 7.3 Other abnormal gait datasets

Apart from databases mentioned above, several databases related to other abnormal gait patterns have been formed. A diplegia gait dataset was established by Ferrari et al. (2019) and Bergamini et al. (2017). In this dataset, walking data from 178 patients affected by diplegia were captured by a six-camera Vicon system. Moreover, the Gait in Neurodegenerative Disease database from PhysioNet (Goldberger et al., 2000; Hausdorff et al.,...
2000) contained several pathological gait patterns associated with neurological conditions. The data were obtained from patients with three neurodegenerative diseases (15PD, 20HD, and 13ALS) and 16 healthy controls using insole force sensors. The 4GAIT-HM (Kubacci et al., 2014) and GaitRec datasets (Horsak et al., 2020) contained gait data obtained from patients with different musculoskeletal impairments. In the GaitRec dataset, force-sensitive floor plates were used to acquire vertical GRF data, anterior-posterior GRF data, and anterior-posterior and medio-lateral COP coordinate data.

The MMGS dataset (Khokhlova et al., 2019), INIT Gait dataset (Ortells et al., 2018), and Walking Gait dataset (Nguyen et al., 2018a) were recorded using vision-based sensors: a Kinect camera, RGB cameras, and a Kinect camera with a time-of-flight (ToF) depth sensor, respectively. In the Walking Gait dataset (Nguyen et al., 2018a), two mirrors were used with a single ToF camera to obtain depth information from different viewpoints. This helped reduce the cost of the devices, and did not require a synchronization solution as in the case of multiple depth sensors. For these databases, several healthy volunteers were recruited to simulate different pathological gait patterns using padding under a sole, attaching a weight to their ankles, and other physical constraints.

8 Challenges in Clinical Gait Analysis and Future Direction

There are a great deal of open issues and challenges in clinical gait analysis that have not been fully explored or addressed:

1. A lack of interpretability of DL models when the applications are used in clinical practice.
2. The limitation of computational resources and the data privacy when the IoT is applied to clinical gait analysis.

These problems are discussed, and their possible solutions are proposed in the following sections.

8.1 Explainability of machine learning-based gait analysis in clinical use

Deep learning models often achieve more accurate performance than conventional machine learning models. However, the complexity of those models tends to result in the black box characteristic (Gunning, 2017). Generally, the black box problem in machine learning is referred to as the situation where the input and the output of the model are allowed to see, whereas there is no way to understand how variables are being combined to make predictions. In medical field, it is therefore difficult for physicians and patients to trust in the model and its decision even when objective diagnosis or assessments are provided by ML-based applications. Furthermore, a lack of transparency and interpretability will raise a number of legal and ethical issues. Due to such problems, the use of ML-based applications including DL-based gait analysis may be limited in clinical practice.

In order to overcome the difficulty, there are basically two ways such as improving interpretability of the model and explainability of the model. Interpretability and explainability tend to be considered as interchangeable terms. However, there is a distinct difference between them in terms of how the term represents the characteristic of a model. According to Arrieta et al. (2020), interpretability refers to a passive characteristic of a model that highlights the degree to which a human can consistently predict the model’s result. On the other hand, explainability can be viewed as an active characteristic of a model, indicating any action or procedure taken by a model in order to provide an interface between humans and a decision maker in the model. Due to the complex structure of DL models, their level of interpretability is significantly low. Therefore, designing such models with Explainable Artificial Intelligence (XAI) techniques is the major approach to improve the transparency level of the models. These techniques are used to convert a non-interpretable model into an explainable one. The definition of the term XAI is given by Arrieta et al. (2020): “Gained an audience, an explainable Artificial Intelligence is one that produces details or reasons to make its functioning clear or easy to understand.”

To date, in research on clinical gait analysis, little work has explored the possibility of using XAI methods to improve the explainability of their proposed models. Guayacán et al. (2020) used a salient map to recover regions in gait video whose contribution is the most with classification label such as PD or HC. The proposed model is a 3D-CNN that takes video frames capturing Parkinsonian gait and normal gait as the input. A salient map is an image in which the brightness of a pixel represents how salient the pixel is (Zhai & Shah, 2006). In this work, a retro-propagation scheme was implemented to back-track activation in vectors from softmax layer to a video frame. This implementation estimates the degree of the relevance regarding the classification label and forms the salience maps that represent the relevance information by colors. As a result, the maps obtained from PD patient videos discovered that some specific regions in the frames are found to be more relevant to PD class label. Moreover, these regions indicated several Parkinsonian biomarkers such as head motion, abnormal trunk posture, and localized hand motions during swinging.

Zeng et al. (2018) visualized attention weights to understand how the proposed LSTM models give emphasis to the input elements relevant to the HAR task and achieve better performance than LSTM without attention mechanism. In the visualization, the brightness of red color indicates the magnitude of attention weights. Consequently, it is suggested that the proposed LSTM with sensor attention pays greater attention to acceleration values captured in ankles and arms.

Zeng et al. (2018) used Layer-Wise Relevance Propagation (LRP) technique to reflect which variables at what time windows of the gait cycle are the most relevant to the classification of multiple pathological gait patterns. LRP is a method that allows to decompose the prediction of a deep neural network computed over a sample, and leads to relevance scores for the single input dimensions of the sample (Bach et al., 2015). In this work, GRF valuables are fed into three classification methods such as CNN, SVM, and MLP. These values were measured from both foot of patients with gait disorders and HC. LPR decomposes the prediction of all the three trained models. It provides the relevance score per the GRF at a fixed time window that indicates whether the input is used to predict in favor or against an output class by the model. As a result, highly relevant regions in one gait cycle were identified in the signals captured from the foot affected by the gait disorder and the unaffected foot.

Dindorf et al. (2020) applied Local Interpretable Model-Agnostic Explanations (LIME) to understanding how a linear SVM model makes its decision in the detection of patients after total hip arthroplasty. LIME is a method that locally approximates a black-box model by a simpler interpretable model such as linear model (Ribeiro et al., 2016). Specifically, LIME artificially generates a dataset around a single instance by randomly sampling and using perturbations and then trains a local linear interpretable model with the dataset. The linear coefficients in the
surrogate model can indicate the contribution of each feature to the final prediction. Since it is important to understand the model’s prediction process for gait data of a single subject in the context of personalized medical treatment, LIME was used as an XAI tool in the work. Consequently, it was discovered that sagittal movement of the hip, knee, and pelvis, as well as transversal movement of the ankle, is significantly important to identifying patients after total hip arthroplasty.

As mentioned above, there are some works that used XAI tools to improve the explainability of their model. However, since such research is still very young in this domain, the number of work is yet to be small. Furthermore, a fundamental issue that can be a major obstacle to the growth of the research is the difficulty in evaluating the explainability results when using XAI tools to explain a model. Evaluation provided by clinical experts is essential to analyse those results and assess the model with them. However, finding the appropriate literature or such experts can be challenging. Without the clinical evaluation, it is difficult to understand why the model makes its decision in a certain way. Moreover, the interpretation from a clinical viewpoint may contribute to designing more effective input representation or the architecture of a model that can achieve higher performance.

For the reasons mentioned above, the corporation between people from both sides, such as health care and machine learning, is indispensable. Such corporation will contribute to increasing the feasibility of XAI methods in clinical gait analysis and spread the use of ML-based applications in clinical practice.

8.2 The IoT for clinical gait analysis

The IoT has been paid greater attention in various fields due to the rapid growth of technology. The same also applies to gait analysis. In particular, gait analysis for clinical applications takes advantages of IoT devices and platforms. Since these technologies can contribute to improving sensor mobility and automating the process of gait analysis, they have been used in the development of the applications for personal healthcare. However, the number of works that applied IoT to such development is relatively small. Therefore, the following part of this section introduces the examples of utilizing IoT for clinical applications using gait analysis.

Mauldin et al. (2018) developed an Android app called Smart-Fall, which uses accelerometer data collected from a smartwatch to detect fall events in daily life. The proposed system for fall detection is built based on a three-layer architecture: the presentation layer where the end user interacts with the application, the application layer that controls an application’s functionality by performing detailed processing, and the data layer where the information processed by the application is stored and managed. In the presentation layer, SmartFall app is a user interface that enables users to manage data collection and notify the career of the user’s status when a fall is detected. In the application layer, the app is run on a smartphone paired with the smartwatch to receive sensor data via a low-power Bluetooth communication protocol and detect falls in real time. In the data layer, the received data from the smartwatch are stored locally in the phone’s internal SQLite database. Since the storage on the smartphone is limited, archiving the measured data to a cloud server is needed. In this case, protecting data privacy is one of the top priorities due to the sensitivity of the data. The proposed system has the capability to preserve data privacy by differentiating the data archived to the server with randomly generated keys. Moreover, the three-layer open IoT system architecture can be adapted for the collection of other sensor data modalities such as heart rate, skin temperature, and breathing rate. Analysing data from multisensor modality may improve the performance of remote monitoring applications (Wang et al., 2020).

Qian et al. (2020) proposed a fall detection system that applies a distributed hierarchical neural network over a cloud server and smartphones. A smartwatch, a smartphone, and smart insoles are mounted on a patient’s body to collect acceleration and gyroscope data. The acquired data are transmitted to the smartphone via Bluetooth to detect falls with the deep learning model. The hierarchical neural network consists of two parts such as shallow-layer model and deep-layer model. The smartphone performs the shallow part of a deep neural network and then, the output is sent to the server to perform the rest of the network, which is the deep part of the model. The data privacy is protected in the proposed system since the raw data including personal information is trained on smartphones locally and the data on the server are significantly abstract. Moreover, the architecture enables to reduce the computational overhead by minimizing the amount of computation on the smartphone. That leads fall detection systems to be able to run on smart devices that have relatively small computational resources. Furthermore, implementing such system on commodity devices can reduce cumbersome process compared with other types of sensors when installing them due to the weight and the size. Kidziński et al. (2020) developed a clinical gait assessment system that uses only a single camera to collect gait data. In the work, the video recording people walking in the sagittal plane was downsampled to 640 × 480 resolution, which is available in cameras equipped with most modern mobile phones. The experimental results have demonstrated that the proposed system is a promising approach to predict gait characteristics such as walking speed, cadence, knee flexion, and gait deviation index. It is suggested that commodity cameras can be applied to clinical gait assessment. Furthermore, the reasonable cost and the availability of such devices increase access to quantitative gait analysis in clinical practice. As mentioned above, IoT devices and platforms can improve the feasibility of gait analysis in clinical use due to its advantages of the hardware and the software such as the mobility, the cost, the accessibility, and the flexibility of the system architecture. On the other hand, when it comes to IoT used for gait analysis, there are several challenges to tackle with such as the limitation of computational resources and data privacy. In particular, deep learning requires a large scale of datasets to train the models. Therefore, it is significantly important to design the system architecture with the computational overheads as small as possible. The possible solution may be the use of cloud computing so that ensuring the data privacy has a high priority due to the sensitivity of patients’ personal information. Hence, the use of IoT is a subject that requires to be further explored, and therefore resolving those challenges must be the main focus in the future.

9 Conclusion

Clinical gait analysis has played a significant role in improving the quality of healthcare. A variety of applications based on gait have been developed to support physicians and improve the QOL of the elderly people. The use of artificial intelligence and deep learning techniques has yielded promising results.
In this work, we presented a survey of research on gait analysis for health and medical care that has used deep learning techniques. The main contribution of this work is a systematic overview of clinical applications based on gait. Various sensing modalities have been used for clinical gait analysis, such as vision-based measurement, impact force measurement, inertial measurement, and biosignal measurement. This has yielded better knowledge of the compatibility between clinical applications and sensing modalities. We observed that a lack of training samples is the major concern when employing deep learning for clinical gait analysis. Thus, we also reviewed studies that focus on overcoming this issue. Data augmentation, weakly supervised learning, and transfer learning are considered to be effective solutions. Furthermore, we discovered that XAI methods and the IoT can be a promising technology in order to further promote the use of machine learning-based gait analysis in clinical practice. Thus, some challenges along with these technologies such as the limitation of computational resources and data privacy will be the main focus in the future for clinical research on gait.

A large number of diseases and conditions have been found to be associated with gait abnormalities. However, deep learning is yet to be used for gait analysis for most such diseases. We think that cooperation between researchers from medicine and information science, especially for collecting gait data, is essential for future developments in clinical gait analysis. Furthermore, exploring techniques that can be used to apply deep learning to gait analysis is the most promising direction for improving the performance of clinical systems based on gait analysis.

Conflict of interest statement
None declared.

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