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A comprehensive survey on gait analysis: History, parameters, approaches, pose estimation, and future work

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ABSTRACT

Human gait is a periodic motion of body segments—the analysis of motion and related studies is termed gait analysis. Gait Analysis has gained much popularity because of its applications in clinical diagnosis, rehabilitation methods, gait biometrics, robotics, sports, and biomechanics. Traditionally, subjective assessment of the gait was conducted by health experts; however, with the advancement in technology, gait analysis can now be performed objectively and empirically for better and more reliable assessment. State-of-the-art semi-subjective and objective techniques for gait analysis have limitations that can be mitigated using advanced machine learning-based approaches. This paper aims to provide a narrative and a comprehensive analysis of cutting-edge gait analysis techniques and insight into clinical gait analysis. The literature of the previous surveys during the last decade is discussed. This paper presents an elaborated schema, including gait analysis history, parameters, machine learning approaches for marker-based and marker-less analysis, applications, and performance measures. This paper also explores the pose estimation techniques for clinical gait analysis that open future research directions in this area.

1. Introduction

Human Gait serves as a locomotive mechanism. It is defined as a series of movements of the lower extremities in such a rhythmic motion that result in the forward progression of the body with minimal energy expenditure, as explained in Fig. 1. Extending beyond its understanding of being the pure movement of limbs, gait encompasses synthesized coordination of the brain, nerves, and muscles [1]. Gait is understood to be one of the most common traits possessed by anthropoids, but from an analytic perspective, it has bountiful potential to serve as one of the most complex phenomena worthy of being subjected to comprehensive investigation and scrutinizing [2]. Gait analysis plays a vital role in being definitive of a healthy human since any observed deviation from the normal gait can indicate an underlying abnormality or affliction. Human motion analysis is an indispensable tool for patient diagnosis, adopted by several neurologists, physiotherapists, and orthopedists. The omnipresence of gait analysis is evident from its wide-ranging applications in multitudinous disciplines of medicine, sports, genetic care, rehabilitation, and diagnostic studies [3–6].

Before proceeding with the detailed investigation and analysis of the techniques employed in gait analysis, first understand the basic, defining terms associated with this study. Coordinated movement of human limbs with flexion-extension spanned in a recurring fashion is termed walking, whereas gait can be defined as a pattern of locomotion, which can be walking, running, or crawling combined with their posture [7]. The crucial distinction between gait & walking must be noted since gait is referred to as the process of walking but is defined as the individualistic way of walking [8]. Gait analysis is a systematic way of identifying any variations in the gait pattern and trying to find out the reasons associated with it and how they can affect the human [9].

Based on neurophysiologic principles, many attempts have been made to define human gait, which have shown significant results in identifying aspects related to normal and abnormal gait patterns based on musculoskeletal pathology [10]. In the case of patients suffering from arthritic disease, the primary concern is the correction of deformity of joints and thus trying to restore the functionality of normal gait [11]. In the biomedical field, gait analysis generates valuable information regarding healthy and unhealthy gait patterns. The patterns generated are used for early disease diagnosis, surveillance, therapies, and rehabilitation [12]. Chronic or acute injuries results in dysfunction or affliction of gait. Both sensor-based and sensor-less approaches are used in clinics and rehabilitation centers to estimate the lower extremity

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parameters and thus analyze the effect of medication.

Traditionally, scaling techniques were used in clinical applications to measure gait parameters. Specialists make the person walk in a specific area for a particular time interval and observe the gait pattern. Along with this, a subjective evaluation of gait is conducted. The subjective method of gait analysis was not so accurate and had adverse effects on the diagnosis of a disease, and then treatment of the disease [13]. A method was required which provides an accurate and precise value of gait parameters to have a precise analysis. In Fig. 2 the pros and cons of subjective and objective analysis are shown. The objective method was more efficient and reliable [13]. The camera-based method with electronic goniometers [14] are available for the analysis of human motion, such as the optical 3D motion analysis system. With such standard gait analysis methods, rehabilitation training improves, as they provide highly accurate and reliable results. However, these methods require a tremendous investment like sophisticated tools or instruments, experts, and a proper lab or clinical setup. The assistance of recent advancements in technology has played a vital role in improving the applicability of gait analysis and its associated techniques in various disciplines, extending to sports, science, geriatric care, and medical diagnostics. Walking indicates individuality and liberty. Quality of life reduces with deviation in normal gait in humans [15]. Physiotherapists, neurologists, and orthopedists have been examining human motion since time immemorial to analyze, evaluate and determine a patient's status, nature of the treatment, and rehabilitation. Conventionally, the human gait is analyzed using subjective techniques, just the visual observation of gait by physicians or experts. However, human gait analysis can be done objectively and empirically with the aided reinforcement granted by technological advancement.

1.1. Motivation

The major aim of this review is to provide the researchers with a single platform to learn about gait analysis from the basics to the former and new-fangled techniques in the last decade and to review the clinical gait analysis using computer vision techniques. Some of the existing survey papers have done an extensive review but are focused on gait biometrics, or recognition like [16] have reviewed the trait of gait and specifically gait biometric, gait data-sets discussed in the paper, along with an overview of model-based and model-free techniques. An extensive survey on gait biometrics is presented in [17], the aim of the paper is application-specific which is biometric gait recognition and covers a detailed discussion on various techniques and data sets available. [18] presents the deep learning techniques for gait recognition, data-sets, and adversarial attacks. [19] discuss the techniques for gait recognition for gait biometrics and modeling environment. However, the authors of this paper tried to cover the parameters, application areas, semi-subjective, objective, machine learning, and skeleton-based approaches and provided a good discussion on clinical gait analysis, which is missing in most survey papers. Most of the existing review papers considered gait biometrics the target research area. The paper aims to provide insight into clinical gait analysis using computer vision and other techniques. In Table 1 existing review work is discussed and areas covered by previous reviews and this review are covered.

The major issues that can be faced by the researchers while learning about gait analysis are:

- **Limited resources**: Gait Analysis is a field having numerous applications, but still, there are limited resources available to learn and understand the techniques available for gait analysis. This research paper aims to provide an extensive review of this field.
- **Application specific**: Most of the review papers on gait analysis are very specific to a particular application. Specifically, most of the research on gait recognition and identification is discussed in existing surveys. The review on fields like clinical, rehabilitation has not been reviewed properly. The authors of this paper try to cover these lacking areas; an extensive study is done on the clinical gait analysis, discussed in section VI.
- **Technique specific**: Most of the review papers published are specific to either marker-based approaches or marker-less gait analysis approaches. Few articles have discussed both techniques in detail. The authors have discussed all the techniques in this review paper.

1.2. Paper outline

The paper is divided into eight sections: Section 1 discuss the introduction of gait analysis. Section 2 contains the background information, including the history of gait, parameters, and abnormalities related to the gait analysis. Section 3 presents the Research Methodology. Section 4 explains approaches used in the early times to the current methods for gait analysis like pose estimation. Section 5 and 6 contain a detailed narrative review of Pose Estimation for Gait analysis and clinical gait analysis. Section 7 includes the performance measures for efficient computation of the gait. Future Directions in terms of application areas and conclusion are discussed in Section 8. The structure of the Gait tour is discussed in Fig. 3.

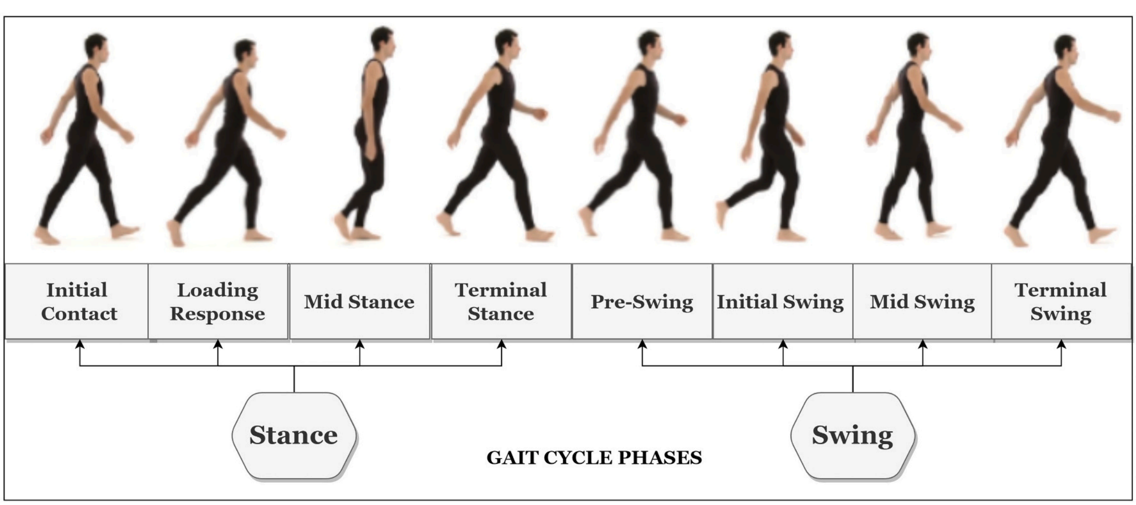

Fig. 1. Gait's mechanical nature. The gait cycle consists of the swing and stance phases, segregated into eight sub-phases. The stance phase shown on the left side makes up 60%, and the swing phase on the right side makes up 40% of the gait cycle.

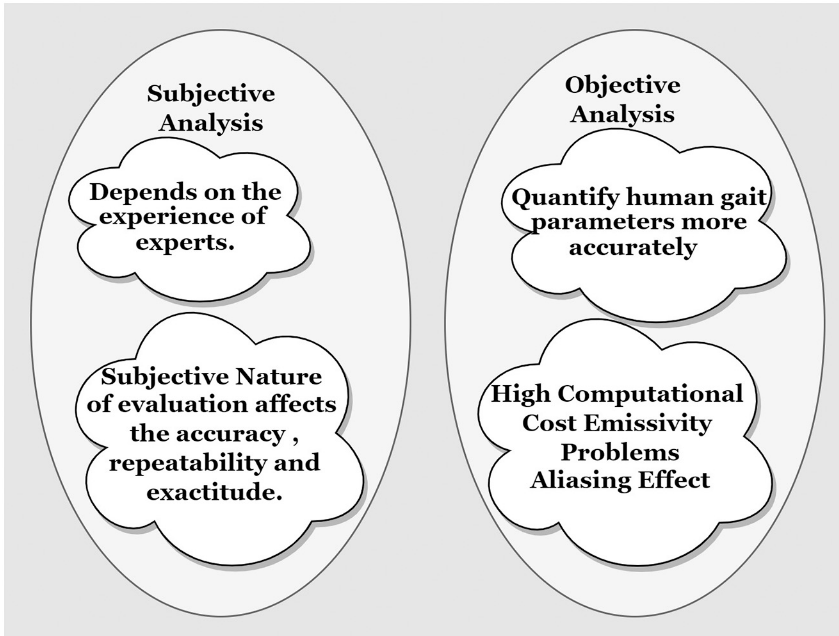

Fig. 2. Pros and cons of subjective and objective techniques.

Table 1
Comparison of existing review papers.

Year	Subject of survey	Nature	1	2	3	4	5	6	7
2007 [35]	Overview of each gait recognition category was presented and factors that may influence gait recognition are outlined.	Marker-Based	−	−	+	*	−	−	−
2010 [36]	Historical Development in accelerometer-based gait analysis.	Marker-Based	+	−	+	−	−	−	−
2012 [37]	To survey PCA and ICA techniques for gait recognition on different datasets.	Computer Vision Based	+	−	−	+	−	+	−
2013 [37]	Multiple markers tracking in a single-camera system for gait analysis.	Marker-less	−	−	+	−	−	+	−
2014 [19]	Current techniques of gait recognition and their modeling with the environment.	Marker-less	*	−	*	+	−	*	−
2016 [38]	Pervasive Analysis of gait using wearable sensors.	Marker-Based	+	−	+	*	−	*	*
2016 [39]	Accelometry based clinical gait analysis review.	Marker-Based	+	−	−	+	−	+	−
2018 [40]	To perform survey on research work in gait analysis.	Marker-less and Marker-Based	+	−	+	+	−	+	−
2018 [17]	Extensive overview for sensing modalities, features and their relationships about the appearance and bio-mechanics of gait.	Marker-less and Marker-Based	+	−	+	+	*	−	−
2018 [41]	Extensive survey on the current progress made towards vision based human gait recognition.	Marker-Based and Marker-less	+	+	−	+	+	+	−
2019 [42]	Deep learning for sensor-based activity recognition.	Marker-Based	−	−	+	+	−	−	−
2019 [16]	Review on the traits of gait recognition on the basis of their survey.	Marker-Based and Marker-less	*	−	+	*	*	*	−
2020 [43]	The trends in analyzing gait using wearable sensors and ML are comprehensively reviewed.	Marker-Based and Marker-less	−	−	+	+	−	−	−
2021 [44]	A review on gait with stroke patients in India.	Marker-Based	+	*	*	+	−	−	*
2021 [18]	Comprehensive overview of breakthroughs and recent developments in gait recognition with deep learning.	Marker-less	−	−	*	*	+	−	−
2021 [45]	A comprehensive review of existing and latest techniques of person identification on the basis of gait assessment.	Marker-Based and Marker-less	+	*	+	+	+	*	−
2022 This Survey	Extensive survey on state of art work marker-based and current work marker-less approaches	Marker-Based and Marker-less	+	+	+	+	+	+	+

1: Parameters of gait; 2: Semi-subjective analysis; 3: Objective analysis; 4: Machine learning algorithms; 5: Pose estimation techniques; 6: Performance measures; 7: Gait abnormalities; +: Area covered in detail; *: Overview of area covered; Area not covered;

2. Background of gait analysis

Walking is one of the most common traits possessed by anthropoids. Still, from an analytic perspective, it has bountiful potential to serve as one of the most complex phenomena worthy of being subjected to comprehensive investigation and scrutinizing [2].

2.1. History of human gait analysis

The earliest comments on the mannerisms of the human walk were first recorded in (384–322 BCE) and have been attributed to Aristotle [20]. Giovanni Borelli (1608–1679) subsequently conducted experiments and presented theories, contributing further to the progress of the domain of gait analysis. Many scientists wrote about the human walk during the enlightenment period. Still, the brothers of Leipzig, Willhelm (1804–1891) and Eduard (1806–1871) Weber, made the most noteworthy contributions in this field, with straightforward measurements [21].

Eadweard Muybridge (1830–1904), while working in America, and Jules Etienne Marey (1830–1904), while working in France, both made

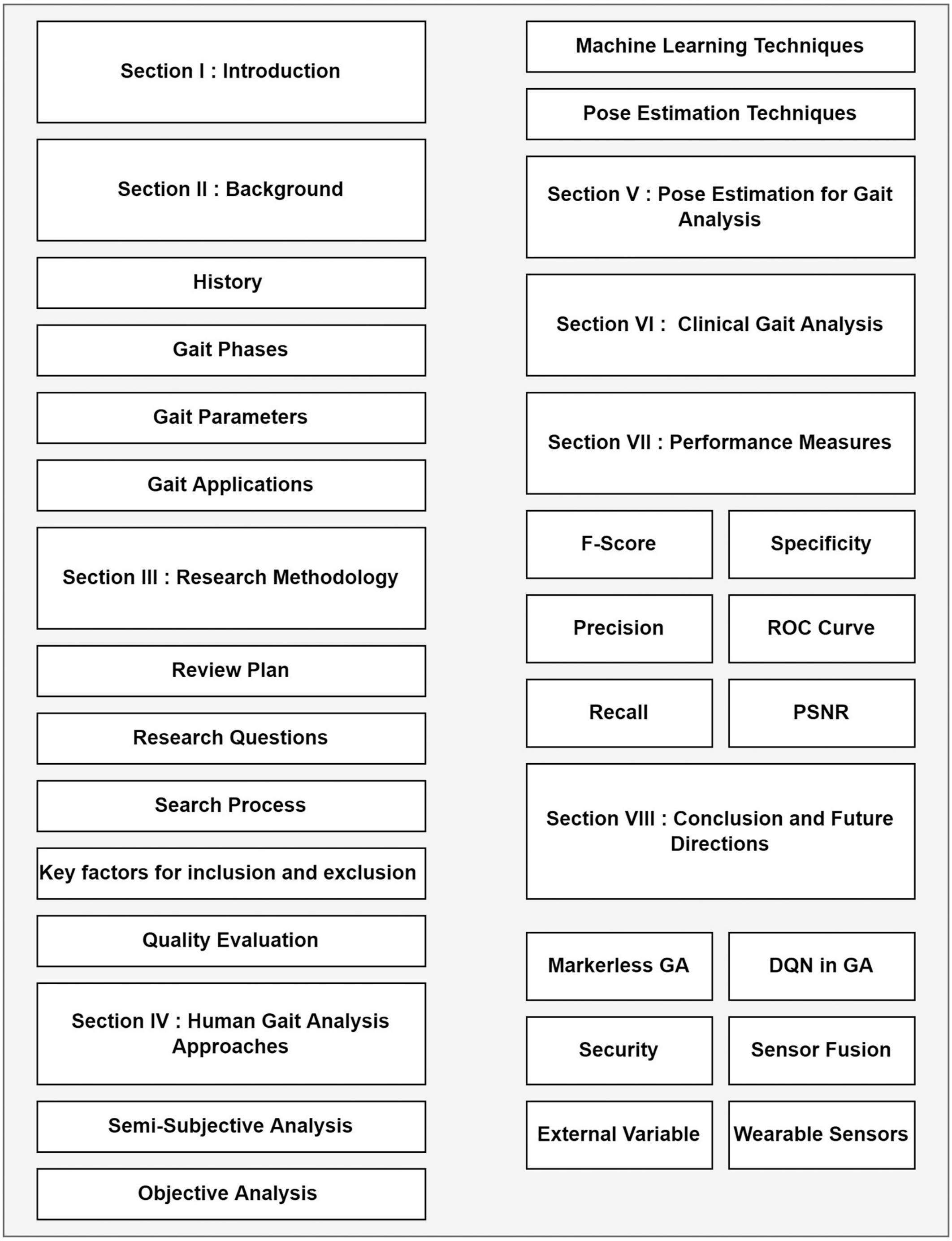

Fig. 3. Road map for the presented paper. The paper is divided into eight sections and respective sub-sections.

significant advances in gait measurement technology [22]. Otto Fischer (1861–1917) further facilitated the work with the aid of Willhelm Braune (1831–1892). An enhanced understanding of Kinetics and the development of force plates in the early twentieth century have been considered the most significant advancements were contributing to remarkable progress. After the second world war, Verne Inman and Howard headed the team and led the significant advances witnessed in America [23]. With the continuing evolution of modern computers, clinical gait analysis became widely available.

2.2. Gait phases

Human gait is defined as a repetitive movement of body segments and is considered as a periodic motion of body segments [24]. The entire process of walking can be pertinently described using the gait phases and facilitate a better understanding of the mechanisms of periodic walking. Earlier, regular events were considered for the separation of gait phases. Still, such distinction witnessed restricted application to amputees and failed to analyze patients inflicted with paralysis, arthritis, or any other form of gait impairment.

Different motion patterns generated by individual joints and segments can be easily identified using gait phases and help in the analysis of walking [8]. Following defined are the phases of gait:

2.2.1. Initial contact

When the foot comes in touch with the floor, it mainly comprises the initial contact phase, while the limb's loading response is determined by the joint posture presented at this phase.

2.2.2. Loading response

This phase is considered the initialization of the double-stance period. The beginning of the phase is marked with the initial contact of the foot with the floor and continues until the other foot is ready for swing or is lifted for a wing. For shock absorption, the knee is flexed, and the heel is used as a rocker, while with the contact of the forefoot, the heel rocker is limited with the help of ankle flexion [25].

2.2.3. Midstance

This phase comprises the first half of the interval, which is a single-limb support interval. Here, advancement of the limb takes place over the stationary foot with the rocker of the ankle, which is dorsiflexion of the ankle. The mid-stance phase begins when the foot is lifted and ends until the body's weight aligns on the forefoot.

2.2.4. Terminal-stance

With single-limb support, this phase gets completed. With the heel-rise of the foot, the terminal stance phase begins and remains until the other foot hits. During this phase, the heel rises, and the forefoot rocker leads to the advancement in the limb. In this phase, the body's weight shifted ahead of the forefoot.

2.2.5. Pre-swing

In the gait cycle, the Pre-swing phase is the second double stance interval of the gait. It begins with the initial contact of the other limb and ends with the toe-off. The primary function of this phase is to position the limbs for swing.

2.2.6. Initial swing

One-third of the swing phase comprises this phase. It begins with lifting the foot from the floor and ends when the stance foot is opposite the swinging foot. Increased knee flexion and hip flexion are the parts of this phase where the flexion limb advances occur.

2.2.7. Mid-swing

The beginning of this phase contrives when the stance limb is opposite to the swinging limb, while the ending occurs when the tibia is vertical, and the swinging limb is forward.

2.2.8. Terminal swing

This phase begins with the swing of the vertically positioned tibia and ends with the strike of the foot on the floor. Limb advancement completes when the shank moves ahead of the thigh, accompanied by the knee extension. Each phase of gait has a particular objective and a critical pattern for a selective motion to achieve the goals [26]. Majorly, three tasks are accomplished through the sequential combination of these defined phases:

- ***Weight acceptance***: It begins with the initial contact in stance period and loading response.
- ***Single-limb support***: It continues throughout the midstance phase and terminal stance phase.
- ***Limb advancement***: It occurs mainly in the swing phase, as it starts from the pre-swing phase and continues through all the swing phases like the initial swing phase, mid-swing phase, and the terminal swing phase [27].

2.3. Gait parameters

Dysfunctional gait arises because of improper biomechanics, which may lead to serious health issues if timely diagnosis and subsequent treatments are not observed [28]. Gait parameters are considered very important for the proper analysis of the gait. So to analyze gait thoroughly, a detailed understanding of these parameters is imperative to the process. Tables 2 and 3 present the benchmark datasets for gait, and Table 4 resents a healthy gait parameter range for different age groups.

2.3.1. Spatio-temporal parameters

Inertial sensors extract temporal information to preserve the nature of time-series data at a high sampling rate. More depth information is required to relate the data to clinical outcomes. Gait signal possesses the property of repetitive events, so gait signals have pseudo periodic nature. This property helps us detect the gait cycle events and thus the temporal features of the gait. Spatio-Temporal falls under the general category of gait parameters. These parameters are considered as the basis of objective gait evaluation [29]. Time-distance parameters are employed in the analysis of the gait. These include: step length, stride length, cadence, step width, velocity, heel strike, toe off, foot pattern [30]. Stride length is considered one of the most critical parameters for the clinical analysis of the gait. These parameters find their extended applications in the field of computing as well.

- Walking velocity: Walking velocity can be defined as the distance humans cover per unit of time. It is measured in meters/s. Slower velocity is observed in the patients inflicted with abnormality [31]. It happens due to their need to decrease the movements and apply forces to deal with the gait. Once the recovery from the said affliction and the consequential dysfunctional gait occurs, the velocity may improve comparatively.
- Step length: Distance between successive heel contact points of the opposite feet. In the case of a normal gait, the step length of the left side is equal to that of the right side [32]. Unequal step lengths serve as an indication of the prevalence of an abnormality in the gait. This parameter is essential to gather insight into the patient's affliction. Consider the case of a patient suffering from knee osteoarthritis: the affected side's step length will be reduced compared to the other side. Hamstring Muscle Bracing can be detected with this inequality.
- Stride length: It is defined as the distance between two successive heel contact points of the same foot. In the case of normal gait, the stride length is equal to that of double-step length.
- Single limb support: It is the measure of time spent on expressed limb w.r.t percentage of the gait cycle. This parameter is related to the knee joint, and its value decreases if the patient is experiencing an issue in their knee.
- Swing time: Amount of time taken to complete one extremity of the gait cycle during the swing phase is termed as Swing Time [33].
- Cadence: It is defined as the number of steps taken per unit of time.
- Stride time: It can be defined as the time between the first contact of two successive footsteps of the same foot and is measured in milliseconds.
- Step width: It is defined as the distance calculated between the left and right foot line of progression [34].

Methods for Detecting Critical Gait Events: Fig. 1 represents the decomposition of normal gait into multiple phases. Let the left leg as a representative limb; for forwarding propulsion, the first step is heel off: the subject will lift their left heel, then the body will lean forward as the subject pushes the ground backward until the left toe-off. Toe-off is when terminal contact is made with the toe and is a special case of terminal contact in clinical terms, which denotes the interval at which the foot leaves the ground. As a pendulum maximizes its potential energy, the shank energy is maximized while the left leg continues to swing backward. After a particular interval, the energy is transferred from potential energy to kinetic energy, and the left leg swing in the forward direction. At the lowest point, a left Heel-Strike occurs, which is termed as Initial contact in gait and land to support the body weight, and the other leg enters the swing phase. The same cyclic motion is found in the right leg, continuing the cycle. [69,70] proposed the peak detection

Table 2
Summary of well-known gait data-sets used in the literature.

Database	Year	Subjects/ sequences	Approach	Walking environment	Organisation	Application	Parameters/device detail
Gait Dynamics in Neuro-Degenerative Disease Database [46]	1997	64	Marker-based	Indoor	Physio-Bank	Health Care	Ground Reaction Time and Stride Interval/Force-Sensitive Resistors
UCSD ID [47]	1998	6/042	Vision-based	Outdoor	University of California	Gait Recognition	View/Sony Hi8 camera: 640 × 480
Gait in Aging and Disease Database [48]	1999	15	Marker-based	Indoor	PhysioBank	Analysis of Parkinson's Disease	Force Sensitive Resistors
MIT Database [49]	2001	24/194	Vision-based	Indoor	MIT	Gait Recognition	Sony Handy-cam, 720 × 480
CMUMobo Database [50]	2001	25/600	Vision-based	Indoor-treadmill	Robotics Institute Carnegie Mellon University	Gait Recognition	Six Color Camera, 60 degree each
Georgia-Tech Database [51]	2001	20/188	Vision-based	Outdoor, Indoor, Magnetic Tracker	Georgia Tech, Atlanta, GA	Gait Recognition	–
HID-UMD dataset 1 [32]	2001	25/100	Vision-based	Outdoor	University of Marlyland	Gait Recognition	4 View Points
HID-UMD dataset 2 [52]	2001	55/220	Vision-based	Outdoor	University of Marlyland	Gait Recognition	2 View Points
USF Gait Database [32]	2001	122/1870	Vision-based	Outdoor	University of South Florida		2 View Points left and right
Gait in Parkinson's Disease [53]	–	166	Marker-based	Indoor	PhysionBank	Parkinson's Disease Analysis	Demographic Interval/16 Force Sensitive Sensors
SOTON Small Database [54]	2001	12	Vision-based	Indoor	University of Southampton	Gait Recognition	5 Shoe, 3 Clothes, View, Speed, 5 Bag/Green Background
SOTON Large Database [55]	2001	115/2128	Vision-based	Indoor, Outdoor, Treadmill	University of Southampton	Gait Recognition	6 View points
SOTON Temporal Database [47]	2011	25/2280	Vision-based	Indoor	University of Southampton	Effect of time on Gait Recognition	Time (0,1,3,4,5,8,9 and 12 months) and 12 viewpoints
CASIA Database A [56]	2001	20/240	Vision-based	Outdoor	Institute of Automation Chinese Academy of Science	Gait Recognition	3 View points
CASIA Database B [57]	2005	124/13640	Vision-based	Indoor	Institute of Automation Chines Academy of Science	Gait and Gender Identification	Carrying 4 walking conditions and clothing/11 view points
CASIA Database C [58]	2005	153/1530	Vision-based	Outdoor, at night	Institute of Automation Chinese Academy of Science	Gait Recognition	Speed, Carrying condition
CASIA Database D [59]	2009	88	Vision-based	Indoor	Institute of Automation Chinese Academy of Science	Real surveillance scenes	Camera and Rscan Footscan
BUAA-IRIP [12]	2008	86/3010	–	–	Beihang University	Gender Classification	Multiview/7 viewpoints, Thermal Cameras
HumanEva I [12]	2006	4/057	Vision-based	Indoor	Brown University	Human motion tracking and pose estimation	Walking, Jogging, Gesturing Combo, Throwing and catching a ball, boxing and combo/7 viewpoints
HumanEva II [12]	2010	2	Vision-based	Indoor	Brown University	Human motion tracking and pose estimation	Walking, Jogging, Gesturing Combo, Throwing and catching a ball, boxing, and combo/4 viewpoints
TUM-IITKGP [60]	2010	35/840	Vision-based	Indoor	Technical University of Munich, IIT Kharagpur	Gait Recognition	Dynamic Occlusion, walking style and carrying conditions
Indonesian Gait Database [12]	2012	212	Vision-based	Indoor	Institut Teknologi Bandung	Kinematic and Spatio-temporal parameters	Viewpoint, carrying conditions, surface,/ 1 camera 90 fps.
KIST Human Gait Pattern Dataset [12]	2013	113	Vision-based	Indoor(Treadmill)	Korean Institute of Science and Technology	Gait Recognition	Multiview/8 Cameras
AVA Multi-View Dataset (AVAMVG) [12]	–	20/1200	Vision-based	Indoor		Gait Recognition	Multiview/6 Cameras
WOSG [61]	2013	155/684	Marker-based	Active-Outdoor	–	Gait Recognition	8 viewpoints/High Sensitivity InGaAs SWIR Camera (640 × 512 pixels)
TUM GAID [62]	2012	305/3370	Marker-based	Indoor		Multimodal Gait Recognition	Microsoft Kinect Sensors 640 × 480 pixels, 30FPS
OU-ISR Interial Sensor Dataset [63]	2011	744	Vision-based	Indoor, slope based	Osaka University	Gait based human identification	Age Variation/Center IMUZ
OU-ISIR Database Treadmill [54]	2012	122	Vision-based	Indoor	Osaka University	Recognition of Gait	Variable walking speed, clothing/25 views
OU-ISIR Large Population Dataset [64]	2012	4007	Vision-based		Osaka University	–	Age variable(1–94)/2 cameras, 30fps
OU-ISIR Speed Transition Dataset [65]	2014	179	Vision-based	Indoor, treadmill	Osaka University		Variable Speed/1 Camera

(continued on next page)

Table 2 (*continued*)

Database	Year	Subjects/ sequences	Approach	Walking environment	Organisation	Application	Parameters/device detail
						Recognition of Gait under Speed Transition	
OU-ISIR LP Bag [66]	2017	62,528/ 187,584	Vision-Based	Indoor	Osaka University	Recognition of Gait	7 Different objects carrying/1 View
MNIT Gait Dataset	2018	120	Vision-based	Indoor, Outdoor	RAMAN LAB MNIT, Jaipur	Extraction of Gait Parameters	Kinematics parameters (angles) and Spatio-temporal parameters
OU-MVLP [61]	2018	10,307/ 259,013	Vision-based	Indoor	Osaka University	Recognition of Gait	Normal Walking/14 views
CASIA-E [67]	2020	1014/–	Vision-based	Indoor, Outdoor	Institute of Automation Chinese Academy of Science	Real surveillance scenes	3 Scenes; Normal Walk; Carrying a Bag; Wearing a Coat/15 views
OU-MVLP Pose [68]	2020	10,307/ 259,013	Vision-based	Indoor	Osaka University	Recognition of Gait	Normal Walking/14 views

Table 3
Gait parameters and applications.

Gait parameters	Clinical	Surveillance	Sports
Body posture	✓	✓	✓
Gait phases	✓	✓	✓
Step length	✓	✓	✓
Swing time	✓		
Step width	✓	✓	✓
Stride length	✓	✓	✓
Stance time	✓		
Muscle force	✓	✓	
Rhythm	✓	✓	✓
Momentum	✓	✓	
Joint angle	✓	✓	
Stride velocity	✓	✓	✓

Table 4
Healthy gait parameters for different groups.

Parameters	Children	Adult	Elderly
Stride length (m)	0.23–0.57	1.68–1.72	1.66–1.70
Walking velocity (m/s)	0.64–1.14	1.30–1.46	Declines with decade
Stance phase (s)	0.32–0.54	0.62–0.70	0.68–0.72
Swing Phase (s)	0.19–0.27	0.36–0.40	0.42–0.44
Double support	22.5–23.9	21.2–23.8	23.4–25.8
Cadence (steps/min)	176–144	113–118	58–70
Single SUPPORT	64.4–65.6	60.6–62.0	61.7–62.9

method to identify the gait events. [71] proposed a method to model gait using dense trajectories. [72] proposed a method by computing many local gait descriptors like Histogram of Oriented Gradient and Motion Boundary Histogram. [73] shows good accuracy results with less prominent peaks in signal wave-forms with a Hidden Markov model to identify events. Other temporal features like swing time, double stance time, and stance phase time. Swing time is the interval between the Toe-off and Heel strike gait event of single-limb in a single gait cycle. The maximum values of angular velocity signals and acceleration are noticed when the leg pushes backward and swings forwards, converting the potential energy into kinetic energy. A sorting algorithm is used to estimate the duration between two sequential labels, several samples between the Toe-off and Heel-Strike events(adjacent events) as shown in eq. 1.

$$SwingTime(SWT) = T_{Toe\_off} - T_{Heel\_Strike} \tag{1}$$

The single support time of one leg is the same as that of the swing time of another leg, as stated in eq. 2 and eq. 3. It is the duration between toe-off and heel strike gait event of one leg. These features are dependent on one leg's inertial data.

$$SST_{LeftLeg} = SWT_{RightLeg} \tag{2}$$

$$SST_{RightLeg} = SWT_{LeftLeg} \tag{3}$$

Stance phase time (SPT) is when the foot lands on the ground and gradually leg rotates and is centered around the foot until the whole body's center of mass moves forward. SPT is the duration between the heel strike and the toe-off event of one leg during one gait cycle as stated in eq. 4.

$$SPT = T_{Heel\_Strike} - T_{Toe\_Off} \tag{4}$$

Double stance time is when both the feet are in touch with the ground during walking. It is the duration between the Heel strike event of one leg and the Toe-off event of another leg. It is not easy to obtain this phase information, as it involves coordination from both legs. The accuracy of this depends upon the time stamp of both legs. The DST can be calculated as:

$$DST = SPT_{LeftLeg} - SWT_{RightLeg} \tag{5}$$

$$DST = SPT_{RightLeg} - SWT_{LeftLeg} \tag{6}$$

2.3.2. *Ground reaction forces*

According to Newton's third law of motion, ground reaction force (GRF) is the force strived by the ground on the body in contact with it. With the movement of the human body, the ground reaction forces increase because of acceleration forces. Contrarily, when a person is not in motion, for example, if a person is standing, the Ground Reaction Force corresponds to the individual's weight. Whereas, when a person is running, the GRF increases up to two to three times the body weight [74].

Various types of ground reaction forces are as follows:

- Vertical ground reaction forces
- Head and trunk ground reaction forces
- Upper limb ground reaction forces
- Lower limb ground reaction forces
- Anterior-posterior ground reaction forces
- Medial-lateral ground reaction forces

Joint moments and their power were obtained using the information obtained from force plates. Foot plantar pressure distribution can be obtained using wearable sensors (insole pressure sensors) and thus can derive ground reaction forces. [75,76] used insole pressure sensors and mapping techniques to obtain GRFs and achieved minimal error rates. [77] shows spinal cord injury patients, the pattern during the stance phase is estimated using the vertical ground reaction forces. [78] demonstrates that classification of normal gait and Parkinson's gait is done using GRF data. Such research works have shown the importance of ground reaction forces.

2.3.3. Gait speed

Mobility of an individual can be assessed using the speed of gait. It is the time taken by the person to cover a particular area over the shortest distance.

2.3.3.1. Gait speed extraction methods.

The gait speed estimation model can be classified into three categories: The abstraction model, which uses a machine learning approach, numerical integration, and the human gait model. Inertial sensors are used to estimate the gait speed by modeling human gait as an inverse pendulum [79]. Single-axis gyroscope method using a single pendulum model was firstly devised in [80] to estimate the gait speed and stride length. With the speed range of 0.5–1.7 m/s, the model achieved accuracy with an error of 15–25%. With a constant treadmill speed of 1.11 m/s, [70] proposed a better geometric model which uses shank and thigh mounted inertial sensors and achieved an error rate of 0.06 m/s. Thigh nodes were used in more refined models [80] are invasive to wear. [69] achieved a better accuracy rate by using the single mounted inertial sensor on the shank. [81] used the concepts of biomechanics to predict thigh measures and reduced the thigh nodes required for the double pendulum model. [82] used Kalman filter with a dual pendulum model to cancel the effect of drift in gyroscope signals, and the RMSE achieved is 0.05 m per stride. Machine learning approaches are used to estimate the gait speed in [83–85]. A nonlinear regression approach was used in [84] specifically, the Gaussian process regression model is used to estimate the speed of gait from frequency domain features, and the average error rate achieved is 0.0027 m/s for a single subject. Accelerometer signals are used as features in [86] by decomposing the wavelets, an average error more petite than 5% is achieved, and a linear regression model is used to estimate gait speed. Cadence is tracked using the hip-mounted accelerometer, estimated gait speed as an energy expenditure feature, and achieved an error rate of 0.18 m/s. [87] used foot-mounted inertial sensors to calculate the linear velocity by using information obtained from gyroscope and accelerometers and achieved RMSE from 0.03 to 0.06 m/s for five subjects. [88] used shank-mounted sensors and achieved an RMSE of 0.05 m/s. Proper noise and drift cancellation methods are required to achieve better results.

2.3.4. Histogram features

- Variance: Variability plays a significant role in gait analysis. It is the fluctuation in various kinds of measurements encompassing the joint angles (kinematic), various forces (ground reaction forces, which fall under kinetic features), stride interval (Spatio-temporal parameters), or measurement of electromyographic.
- Skewness: Lack of symmetry is considered an important parameter for the gait analysis. Skewness deals with the symmetrical distribution of the data. It can be categorized as positively skewed or negatively skewed.
- Kurtosis: Kurtosis is a statistical measure to describe the distribution. Kurtosis is used to measure extreme values in either of the tail.

2.3.5. Angles

Joint angles can be directly measured through the kinematic data acquired from portable systems. Angular velocity and acceleration of the body part at which the sensor is attached can be recorded. [89,90] Electro goniometers can be used to measure joint angles. Relative angles between two blocks can be calculated using flexible goniometers like Giles Sensors. Advancements in Micro-electromechanical systems lead to the use of gyroscopes and accelerometers because of their small size and robustness. However, these devices come up with computational problems [91]. Double integration of angular acceleration can be used to calculate the angles, but it suffers from the problem of drift [92]. However, multiple methods have been discussed in the literature to reduce the drift. Filtering techniques are used on the thigh and shank angle inclination signals. However, in real-time processing, vital information is lost. Measured accelerations calculate the inclination angle between the vertical and the segment and then subtract the angles from the adjacent body segments. [93] has discussed such results that are applicable in cases where accelerations are small as compared to gravity. Kalman filters can reduce the drift and use data for real-time applications. For error minimization, proper calibration is required between the data collected from the sensors [94]. Lower limb angles can also be estimated by using the inertial sensors along with the Kalman filter [95]. The weighted acceleration method estimates the joint angles in which the pair of accelerometers is mounted on the adjacent legs. However, the method was not applicable in real-time processing. Nowadays, computer vision techniques are deployed and can use that to estimate joint angles. Microsoft Kinect, introduced in 2010, plays an important role in skeleton tracking and thus helps researchers to extract the joint positions and lower extremity angles. [96] used Kinect skeletons to estimate the joint angles for the detection of the right posture for exercise. TCN-Networks [97], ODENets [98] are suitable for extracting the temporal information through human pose recognition. Deep learning techniques are evolving at a higher rate and would benefit the gait analysis domain. Some of the main lower extremity angles are defined below:

- Ankle Angle: It is the relative angle between the plantar of the foot and perpendicular to the shank's long axis.
- Pelvis Angle: The inclination angle between the right anterior superior lilac spine w.r.t the horizontal axis.
- Hip Angle: Relative angle between the plane perpendicular to the pelvic and long axis of the thigh.
- Knee Angle: Relative angle between thigh's long axis and shank's long axis.
- Trunk Angle: The angle of inclination of the lateral long axis of the torso concerning the coordinate system provided.

2.3.6. Variability

When the subject does not walk in the same way while analyzing them, such variation is termed Biological variation. Normal biological variation means that subjects never walk quite the same each time experts analyze them [99]. Coupled with this inherent variation, variability is also introduced by the measurement procedure:

- Identification of body joint centers and landmarks.
- Environmental constraints.
- Artifacts of skin movements.
- Skin marker wobbles.
- Motion analysis system calibrations.

Above mention variation sources cannot be separated from each other. True variations observed in the subject's gait and the artifact obtained from the measurement procedures go hand in hand. Variability standards are required to compare a patient's gait with the normative standards.

- Standard Deviation: Standard Deviation is frequently used in variation estimation. These are obtained by plotting the dotted line for gait curves around the mean. At each point of the cycle, the standard deviation changes slightly.
- Coefficient of Variation: It is defined as the standard deviation average in the gait parameter divided by the average mean.

2.3.7. Gait instability

Gait instability is a significant risk factor that leads to falls and is an essential measure for identifying the probability of falls in old patients [100]. Subjective observation methods are still used in large numbers in most clinical practices. The pull test is most commonly used for gait stability, but studies show no such correlation between a pull test and fall prediction risk. Nonlinear analysis techniques and inertial sensors are used to assess gait stability quantitatively. With quantitative data captured by nonlinear analysis approaches and inertial sensors, stability of gait can be characterized by the Lyapunov exponent, which describes how a pseudo periodic dynamic system responds to “minimal perturbations continuously in real-time” [101].

2.4. Gait applications

Gait Analysis has numerous applications. In every field, gait analysis has gained popularity. Fig. 4 shows the application areas of gait analysis; also, major application areas are discussed in detail.

2.4.1. Analysis

Identification of normal and abnormal gait patterns for medical diagnostic, geriatric or elderly care, tactics, and sports monitoring is a part of the analysis-based, practical applications of gait. Analyzing measurable normal gait parameters is essential for diagnosing gait abnormalities, assessing medical gait interventions, recognizing balance features, and rehabilitation developments. To identify an abnormal gait, healthcare practitioners apply the gait phase identification concept in their routine practice for detecting any underlying irregularities, if present. Contributing extrinsic factors which can consider are footwear, terrain, cargo, and clothing. Intrinsic factors can be sex, weight, age of a person, physical, psychological parameters such as type of personality and emotion, and pathological factors like neurological disease, musculoskeletal, trauma, considered can influence the standard way of walking. Since a single individual is likely to have a wide-ranging gait behavior, thus identification of the normal gait parameters becomes a very complex task.

Clinical Gait Analysis can be defined as a technique that deals with diagnosing hidden impairments and can affect gait patterns. Fig. 5 shows the gait abnormalities. Table 5 shows a different type of gait abnormalities. Healthcare practitioners can apply the gait segmentation technique in their routine practice to evaluate the status of a patient, determine the appropriate type of treatment, and rehabilitate from musculoskeletal and neurological disorders using the kinematics and Spatio-temporal parameters. Healthcare professionals can monitor patients' progress by drawing comparisons with the defined, standard gait patterns and their records.

2.4.2. Bio-metric trait

Identification and recognition of individuals using biological traits come under Biometric Systems. Nowadays, Biometric systems have gained much popularity; it includes fingerprints, iris, face, palm, and voice recognition. Nevertheless, these systems have specific limitations such as scrawled fingerprints, iris scans hidden by eyelashes, eyelids, face impediment due to glasses, facial expressions, and different hairstyles [102]. Due to the current situation, people are now more concerned about touching scanning devices or waiting in line for using biometric systems. Recognition of a person can be made by the way a person walks. This way of recognizing a person by way of their walk comes under biometric identification using gait. Gait analysis can be further used to improve authentication and security by combining gait with other biometric traits like face, voice, and palm. Researchers have discussed the improvement of authentication rate while combining gait and face biometrics. Table 6 summarizes the approaches for gait recognition. However, this is just the first attempt in this field [103]. Further analysis of other multiple biometrics with gait is an exhilarating future challenge. Except for authentication, the design of a gait analysis secure mechanism is required to prevent various external attacks.

2.4.3. Artificial gait

New investigative, research, and developmental activities are being undertaken in several countries across the globe to improve the quality of life. Identification of various forms of deformities and diagnosing impairments in gait has become a widely-favored topic of research [104]. Analysis of gait can provide information about kinematics and kinetics of human walk to deployment (including designing and manufacturing) of humanoid robots. Research on the deployment of robots in rehabilitation systems is an example of artificial gait application. Designing artificial limbs for patients who have suffered from amputation and locomotive control systems used in robotics and exoskeletons are aided with the help of gait.

2.4.4. Control applications

In the field of crash biomechanics, for the areas of vehicle production and pedestrian detection, the principles and techniques of gait analysis can be applied [105]. In the automotive industry, exhaustive research is being conducted to utilize the principles of gait analysis for the precise, realistic, and error-free placement of handles on car doors. In the automotive ergonomics industry, work related to virtual reality and simulation of models is being carried out to ensure proper customer satisfaction.

3. Research methodology

A systematic and qualitative review is employed to study good quality papers on gait analysis using marker-based and marker-less

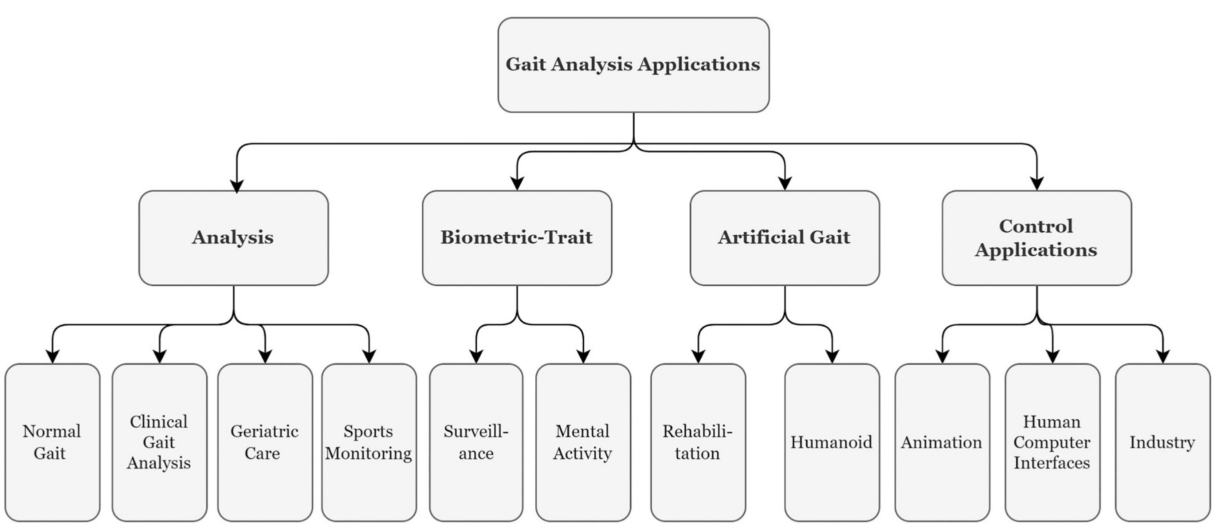

Fig. 4. Human gait analysis applications: 4 main sections for the application domain and subdivision into specific application area is shown.

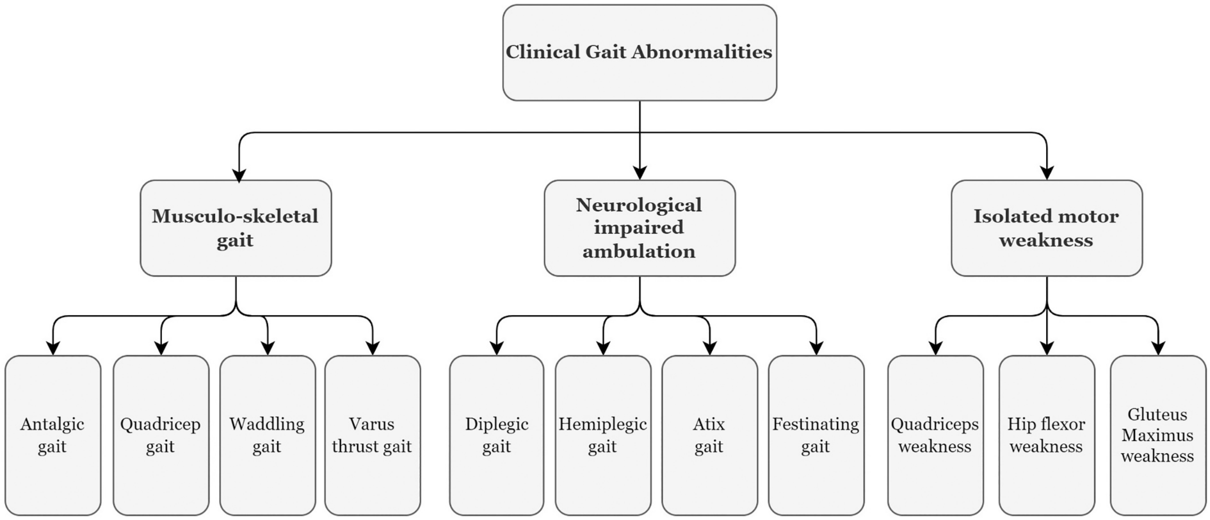

Fig. 5. Overview of abnormalities in Gait and their specific classes.

approaches. The findings from this review paper are well-discussed to guide researchers in performing good quality results.

3.1. Review plan

This review starts with a well-defined review plan, identification of questions related to research, and efficient searching process, factors for inclusion and exclusion of research papers. Relevant research articles surveys were searched analyzed based on quality, and then the selected content is used in this review paper, which will help eliminate research biases.

3.2. Research questions

To generate a better quality of the survey, many research questions were defined about gait and its related aspects for marker-based and marker-less gait analysis. The Main Research questions and targets relevant to this review paper are:

- How can marker-less approaches be used in gait analysis?
  The survey aims to provide proper steps and design for using the latest techniques like deep learning methods and pose estimation techniques.
- How Pose Estimation contributes to Gait Analysis?
  It targets a detailed review of pose estimation techniques deployed in gait analysis.
- What are the upcoming techniques for gait analysis?
  It targets explaining the techniques of deep learning approaches, pose estimation approaches, and computer vision approaches with their detailed design and work.
- What are various gait abnormalities, and how are they related to neurological disorders?
  Its target is to account for all the symptoms observed in the patient having abnormalities related to the gait.
- Discussions and comparative analysis of gait analysis related to classification and survey?
  This survey aims to identify various approaches, parameters, scope, limitations related to gait analysis.

3.3. Search process

A proper systematic process for literature selection is adopted to select appropriate content for this review paper. The content relevant to this review is scattered across various Journals, Book Chapters, and Conferences. Popular digital libraries and repositories were explored to extract the relevant content, such as IEEE digital library, Springer, Science Direct, IGI Global, Taylor and Francis, etc. The Lemma used while searching these digital libraries were 'GAIT', 'GAIT ANALYSIS', 'Sensors in Gait', 'Gait Challenges', 'Machine Learning in Gait', 'Gait Recognition', 'Acoustic Gait', 'Gait Abnormalities', 'Gait Assessment', 'Gait Modeling' etc.

3.4. Key features for inclusion and exclusion

The research papers are selected based on two categories: The first category includes articles related to Marker-based gait analysis approaches, and the Second category contains papers related to Markerless Gait analysis. Also, a further division is considered based on techniques deployed and the application domain of gait. Quality papers are included, and the rest are excluded.

3.5. Quality evaluation

Estimation of the quality of the papers is done in this section, and the process follows the rules of the Database of Abstracts of Reviews of Effects (DARE) and Center for Reviews and Dissemination (CDR) [106].

4. Human gait analysis approaches

Gait analysis has gained a great deal of interest in most research areas. Applications domain areas of gait analysis are discussed in section II. Gait analysis is not a new area of research. Many approaches were used traditionally to analyze gait. After intensive research, it is concluded that gait analysis approaches have been categorized into four major parts: Semi-Subjective Analysis, Objective Analysis, Machine learning techniques, and gait analysis using pose estimation. Traditional methods used to analyze gait come under the Semi-subjective approaches, which require proper human intervention. With the advancement in technology, new devices were introduced to estimate the gait parameters and perform the objective evaluation, which requires less human intervention and thus reduces the marginal errors and provides more efficient and accurate results. Advancements in Machine learning techniques and Pose estimation techniques have boosted the area of gait analysis. Table 7 shows various marker-based approaches and their limitations.

Table 5
Type of abnormal gait.

Type	Symptoms	Related disease
Hemiplegic gait	Unilateral weakness on the side which is affected, an arm is flexed, internally rotated, and adducted. The affected leg of the patient starts making semicircular motions while walking. One side bending is usually seen in such patients.	Seen in stroke Patients or with mild hemiparesis.
Diplegic gait	Patients have debilitated involvement on both sides in which lower extremities are worse affected than upper extremities. The patient walks with affected toes, pulling both legs and a narrow base.	Seen in patients with bilateral periventricular lesions or cerebral palsy.
Neuropathic gait	Patients may experience a drop in foot which is considered foot dorsiflexion weakness; the main reason behind such gait is an attempt to lift the leg high enough while walking such that the foot does not drag on the floor.	Seen in a patient with diabetes.
Choreiform gait	patient will show jerky, involuntary, irregular movements in all extremities. Baseline movement disorder may get accentuated with walking.	Seen in patients with disorders like basal ganglia disorders, including Huntington's Disease, Sydenham's chorea, and other forms of chorea.
Myopathic gait	Weakness in Hip girdle muscles. Drop in the contralateral side of the pelvis can be seen because of weakness in one side of the leg while walking. In the case of bilateral weakness, the patient may experience dropping of the pelvis on both sides while walking.	Seen in patients with myopathies, such as muscular dystrophy.
Ataxic gait	Body of the patient may drop back and forth and from one side to another, termed titubation. Walking moving inline or heel to toe is difficult for patients. The patient's gait will resemble the gait of an acute alcoholic person.	Seen in patients with cerebellar disease.
Parkinsonian gait	the patient will suffer from bradykinesia and rigidity. The patient's head and neck can be bent down, and the knees flexed. The upper extremity is inflection and has extended fingers.	Seen in a patient with Parkinson's disease.

4.1. Semi-subjective analysis

These methods include analysis carried out in the clinical environment under the proper supervision. Various gait parameters of the subject are being recorded, and evaluation is done [107]. The subject walks on a pre-determined circuit to evaluate a person's gait. Practical and popular techniques are illustrated in Fig. 7 and defined below used by various medical experts.

4.1.1. 25-foot timed walk

This technique is known as (T25-FW) 25-ft evaluation of walk. In Multiple Sclerosis Functional Composite (MSFC), this is considered the first part [108]. A standardized measurable assessment instrument comprises different parts for usage in clinical studies, which are mainly used in clinical tests for the diseases like multiple sclerosis [20]. Seven and a half meters is the defined distance by the experts, which is subject needs to cover in a straight line.

4.1.2. Multiple sclerosis walking scale

This technique is also known as (MSWS-12). Twelve parameters are measured by this method which is observed from the interviews conducted with 30 subjects [109]. Also, professional/expert opinions and literature review explain the impact and extent of multiple sclerosis on patients' gait. A general profile was generated later on for the identification of disturbed motor skills, and the generalized term given to this was Walk-12 [110].

4.1.3. Tinetti performance-oriented mobility assessment

This method is commonly known as the POMA test. In this examination, the subject is asked to walk in a forward direction for a minimum of 3 m, make a turn at an angle of 180° degree after that walks swiftly back to the chair. In this, subjects are allowed to make use of their usual help like a walker or stick [34] also presented a reduced scale that consists of 7 parameters which more accurately work with two levels and hence predicts the risk of fall in a more precise way. In the detailed form of this test, 13 parameters were considered, and identified the balance disorders. Further, these are arranged in three levels, and additional nine parameters were used for the human gait study based on four levels. In inference, with the help of this test, one can efficiently analyze the balance of aged persons and disorders in gait in ordinary day-to-day situations. The major drawback of the test is that it requires a reasonable amount of time and active involvement from the subjects.

4.1.4. Timed get up and go

In the TUG test patient stands up from a position like sitting, then asked to walk on a short defined distance, make a turn and go back to the chair and then move back to the sitting position. It is a timed test that requires patients to stand up from a sitting position, walk a short distance, turn, move back to the chair, and sit again in the same position.

4.1.5. Gait abnormality rating scale

Sixteen gait features of humans are studied from the video [111]. The GARS includes four types for the lower limbs, five general types, and seven for the upper limbs, trunk, and head.

4.1.6. Extra-laboratory gait assessment method

It is a technique that assesses gait either at home or communal [111]. The attributes considered include speed, step length, ability to turn the head while still walking, static balance, initial gait style, slow speed (below 0.5 m/s), lack of balance, problem in head movements, and short steps that are suggestively related to unbalanced gait.

4.2. Objective analysis

The objective analysis methods use various devices to capture and measure the evidence interrelated to the several gait attributes. Can separate these approaches into three types: those depending on sensors located on the body, Image Processing (abbreviated as 'IP'), and Floor Sensors (abbreviated as 'FS'), performed by the users (Wearable Sensors— denoted as WS). Figs. 7 and 8 discuss the approaches and subdivision of human gait objective analysis approaches.

4.2.1. Floor sensor

In these systems, the placement of sensors is on the floor, called "force platforms" or "instrumented walkways," where gait is computed either by pressure/force sensors or moment transducers only if the subject walks on them. Broadly two types of floor sensors: Pressure Measurement Systems and Force Platforms, are present. Force platforms could be differentiable from pressure measurement systems which, in addition to measuring the center of pressure, indirectly measure the force vector applied. These pressure measuring systems help compute

Table 6
Gait recognition approaches.

Reference	Year	Objective	Concept	Data-set	Model-based	Model-free	Results
[113]	2006	Improving gait recognition using normalized gait dynamics	Shape information and normalized dynamics are used for gait recognition pHMM(population Hidden Markov Model) is used	Speed Database used is CMU MoBo and for Time UMD Database.	✓		
[114]	2010	Model-based human gait recognition using leg and arm movements	Model: Active Contour Model Features: Gait Kinematic Features.	20 Subjects are taken, Database of Georgia Tech	✓		94.5% accuracy achieved with the use of arms features and without the use of arm features the accuracy: 93.1%
[115]	2011	Automated markerless analysis of human gait motion for recognition and classification	2D stick figure and parameters covered are gait speed and cycle time KNN classifier	30,60 and 100 Subjects were taken in different categories and evaluated	✓		With 30 subjects accuracy of 96.7% obtained with k value 1 and 5 With 60 subjects and k = 1 accuracy of 91.7% With 100 subjects and k = 1 accuracy of 84.0%
[116]	2014	Markerless extraction of gait features using a haar-like template for view-invariant biometrics	Haar Template Matching with kinematic features of gait KNN Classifier	CASIA dataset -B	✓		Accuracy achieved:73.06%
[15]	2014	3D gait recognition using Spatio-temporal motion descriptors	Least Square -Support Vector Machine, Multilayer Perceptron, and Naïve Based algorithm	22 subject	✓		93.5% accuracy achieved with SVM at Rank 1 99.6% accuracy achieved with SVM at rank 3
[6]	2015	Parametric elliptic fourier descriptors for automated extraction of gait features for people identification	Legs angular measurement, Body trunk spatial displacement, Dynamic and static features	Sequences: 120 and Subjects: 20 Indoor Southampton gait database	✓		86.67% accuracy
[117]	2015	Human body part selection by group lasso of motion for model-free gait recognition	PCA(Principal Component Analysis), MDA (Multiple Discriminant Analysis), and CDA (Canonical Discriminant Analysis)	Discriminative features extracted using segment GEI approach CASIA Dataset-B		✓	88.75% overall accuracy
[118]	2016	gait recognition based on 3D skeleton joints captured by Kinect	Features like length between skeleton (static features) and skeleton angles under dynamic features Neural Network algorithms.	Kinect V2 tool is used to collect gait data of 52 subjects	✓		Accuracy of 94.23% is achieved using static and dynamic features
[119]	2016	Cloth invariant gait recognition using pooled segmented statistical features	Classification Algorithms: Random Forest, Naïve Bayes, kNN t-statistics used: Intersubject distance f-statistics used: Intra cloth variant Statistical features from edge contour of GEI used	Treadmill Dataset of OU-ISIR		✓	83.30% of accuracy obtained with segmented features of GRID 79% accuracy achieved with combinational features
[120]	2016	Gait recognition based on modified phase-only correlation. Phase-only correlation is used	Gait Energy Image approach	CASIA Dataset B		✓	81.40% accuracy
[121]	2017	Multi-gait recognition using hypergraph partition	Neural Networks are used, Features: Tensor 3D gait features, Hypergraph approach used for separation	With 120 subjects multi gait dataset is created Frontal and lateral viewpoints	✓		89.2% recognition rate from frontal view and 80.3% from lateral view with 2 participants. 88.3% recognition rate from a frontal view.

the pressure patterns below a foot over time but lack the calculated horizontal or shear components of the applied forces [112].

4.2.2. *Wearable sensors*

Wearable sensors are located on several parts of the patient's body, including the knees, feet, or hips; the primary purpose is to calculate the different features of human gait. Defined in several new reviews like [122]. A brief outline of the various types of sensors most frequently used in research is shown in Fig. 10. These include active markers, gyroscopes, force sensors, accelerometers, inclinometers, goniometers, extensometers, electromyography, etc. Fig. 6 shows wearable markers used in gait analysis.

4.2.3. *Image processing*

Numerous analog or digital cameras design the characteristic image processing scheme with lenses that can be used to collect gait-based data. Threshold filtering methods then convert those images into white and black, the count of pixels to compute the count of dark/ light pixels or segmentation of background which eliminates the image background, are better ways to collect data is to measure the variables of gait. This technique has been extensively studied to recognize people by the manner of the way they walk [123]. In the medical field, [124] represented a fuzzy system able to deliver a linguistic understanding of the kinematic study for the knee and thigh. [125] solves the issue of reduced accuracy of recognition based on varied views related to the probe and gallery, implementing an authentication technique that is gait-based, using a random view conversion scheme. Among image processing approaches, range imaging, also known as depth measurement, has become very significant at the current time. It can be defined as a group of practices used to compute and find a map of distances from a lookout. Such methods make them conceivable in obtaining significant essentials of the image additionally an improved and quicker real-time process. Numerous skills are helpful for this determination, like Time-of-Flight methods, laser range scanners, and camera triangulation (stereoscopic vision). Organized light and infrared thermography are used in various other studies.

- Stereoscopic Vision: This method is extensively used for gait analysis. This technique regulates the points of depth in the division, starting from the center of the line between their focal points [13]. Can

Table 7
Marker-based techniques.

Technique	Approach	Limitations
Inertial systems		
	• Used Accelerometers and Gyroscopes.	• Subject become uncomfortable as the sensors are attached to the body.
	• Inexpensive, light weight sensors.	• Segment exact length and rotational axis difficult to calculate.
	• Easy signal recording.	• Limited battery duration.
Electro-goniometers (EGM)		
	• Use of electro-mechanical instrument to measure joint movement angles.	• Subject becomes uncomfortable as the sensors are attached to the body.
	• Potentiometric EGM and Flexible EGM are used.	• It does not show accurate and quality results for the lower limb part.
	• Output generated can be immediately used for computation and recording purpose.	• Limited number of gait parameters can be calculated.
Motion capture cameras		
	• Features extracted from image sequence.	• Special setup is required with an active line of sight.
	• Features used: joint Positions, joint angles, joint motion trajectories and variations.	• Fast sampling rates are required for faster movements.
	• *Re*-usability of captured sequence.	• Do not work well in low-intensity light because of high shutter speed.
Opto-electronic systems		
	• Active or passive markers are attached to the subject's body.	• Accuracy decreases as the movement become quicker.
	• Active markers use small LEDs, and Passive markers use infrared rays.	• Issues arises when surface become transparent and reflective.
	• Acquisition of physical movements is robust.	• Expensive lab setup is required.
Gait and pressure mats		
	• It is a special arrangement of sensors embedded within a mat.	• Proper laboratory setups are required.
	• Low cost and portable.	• System scan rate decreases with increase in resolution.
	• High-Resolution mats are available for both adults and children.	• Will work only in combination with limb kinematics.
Force shoes		
	• To measure the distributed foot pressure, force sensors like Force Sensitive Resistors are fitted to the sole of shoes.	• System needs to combine with the limb's kinematic data.
	• Can use portable shoes anywhere.	• Proper positioning becomes difficult for non-distributed arrangement.
	• Large range of foot sizes is allowed because of distributed sensors.	• Surface is bumpy and uneven; it becomes less effective.
Magnetic systems		
	• Ferromagnetic markers are applied on the subject's body.	• Magnetic materials may distort the signals.
	• Sensors detect distorted points to analyze the pattern movement of markers.	• Requires complex data processing.
	• This system does not depend on line-of-sight.	• The subject becomes uncomfortable because of the attached marker.
Medical imaging techniques		
	• Limbs static movements and positioning can be measured.	• Need to combine with other systems for gait analysis.
	• Kinematic information can be easily captured.	• Expensive to generate good data set.
	• Reusable data.	• Errors may occur.
Force plates mechanism		
	• Force, plate mechanism approach, contains metal plates that have load cells attached at each corner of the plates.	• Contact of foot sometimes misplaced.
	• Directly, no attachments are there with the subject body.	• Proper laboratory item settings are required.
	• Calculating Ground Reaction Force is easy.	• Expensive procedure as it involves the proper setup of a laboratory.
Electromyography		
	• While walking muscles contract and produce small electric signals, electromyography is used to sense those signals.	• Very uncomfortable for the subject.
	• In S-EMG, electrodes are placed on the skin of a subject, and in I-EMG, fine wires are inserted into muscles.	• For gait analysis combination of systems is required.
	• External devices for amplification and filtering of signals is required.	• Medication related to the nervous system may affect the results.

resolve depth measurement problems via a stereo camera system; it becomes imperative to identify consistent points in multiple images. Built the method with the formation of a model with similar triangles between the light-emitter, optical sensor, and the specific object in the scene are calculated. Producing a camera model includes gaining multiple images from various panes and calibrating them into a grid.

- Time-of-Flight Systems: This scheme is built on cameras that use modulation signals that measure the distances based on phase-shift belief [126]. The detected scenes are highlighted with near-infrared light, whereby the modulation signal must be sinusoidal with frequency. The imitated light can be seen on the charge-coupled device (CCD) or CMOS.
- Structured Light: Structured light is the forecast pattern of light. It can be coded light, grid, beam, etc., with symmetrical calibration of the objects whose shape needs to be recovered. Based on the beam used, the light pattern obtained may vary like strip patterns, single slits, or dots. In these methods, 3D data is obtained by analyzing the projection distortion of the unique pattern projected in ordinance with the scene. 2D structured illumination is created by a different projector or a light source modulated by a spatial light modulator as in [127]. Kinect Sensor is a prevalent device that uses such skills to generate a real-time marker-based gait retraining system. Various gait parameters can be calculated without the use of markers, as Kinect sensors can be used in these cases [6].
- Infrared Thermography: Infrared Thermography is the procedure of generating pictorial representation that relies on the surface's temperature. It can measure the human body's infrared thermal intensity very precisely. This way was helpful in [128] to identify gait patterns in humans and has achieved 78% - 91% for the likelihood of precise recognition.

4.3. Machine learning-based gait analysis techniques

Machine Learning is widely used in all areas. In gait analysis, the growth of Machine Learning is modeling a biomechanical system T(x) by identifying the relationship between provided input data X(x) and desired output Y(x). Sometimes the input data can be corrupted by external or internal noise n(t). In such cases, data is pre-processed before feeding input data to the model or network. The input data is a collection of raw multidimensional data consisting of several subjects considered for the process, or it can be the number of trials performed, and the other dimension can be the features selected. These features are used to train the network or the model; these parameters are spatiotemporal, kinematic data, age, height, gender, kinetics, etc. The output of the model is

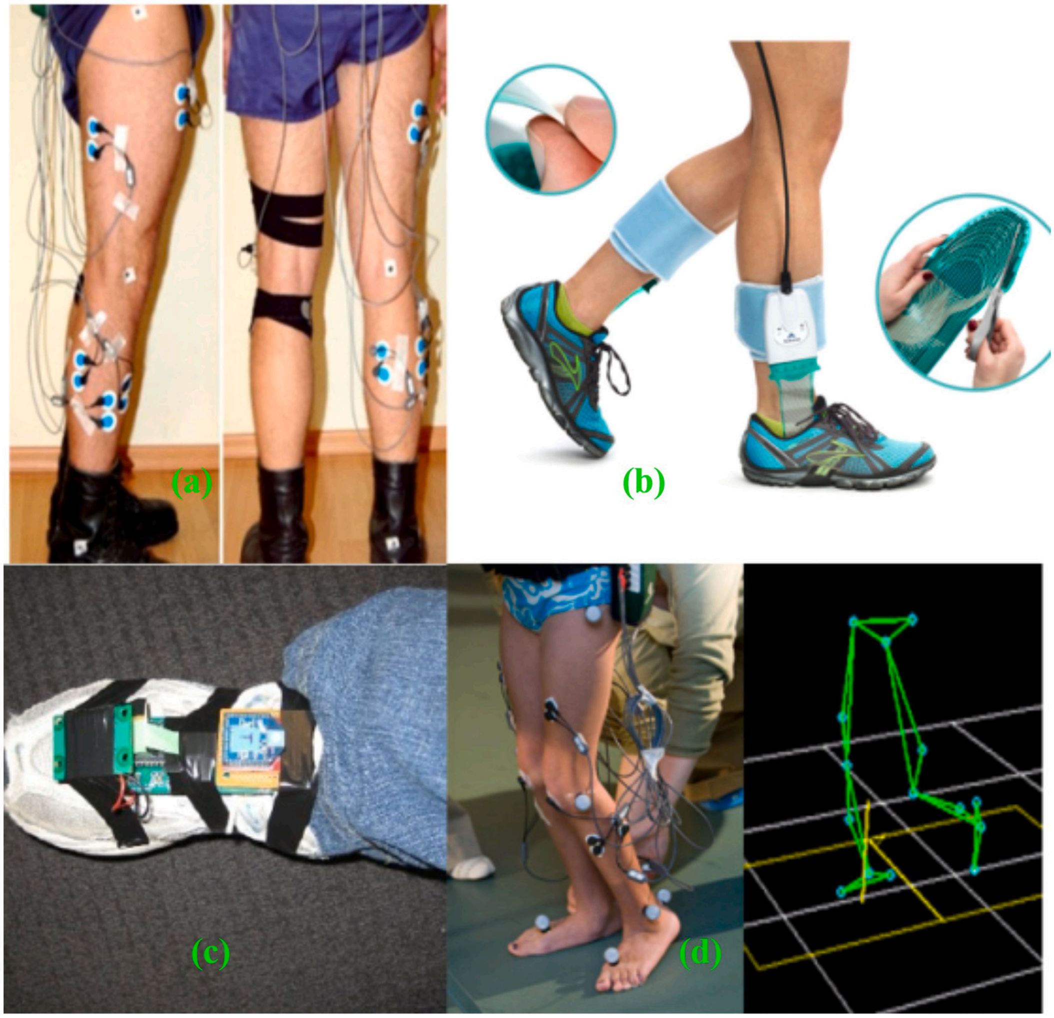

Fig. 6. Example of Markers on Human body: (a) Surface Electromyography (b) F-Scan in-shoe systems for timing, pressure, and force information (c) Use of accelerometers (d) Active markers for 3D skeleton construction for analysis of the gait [6].

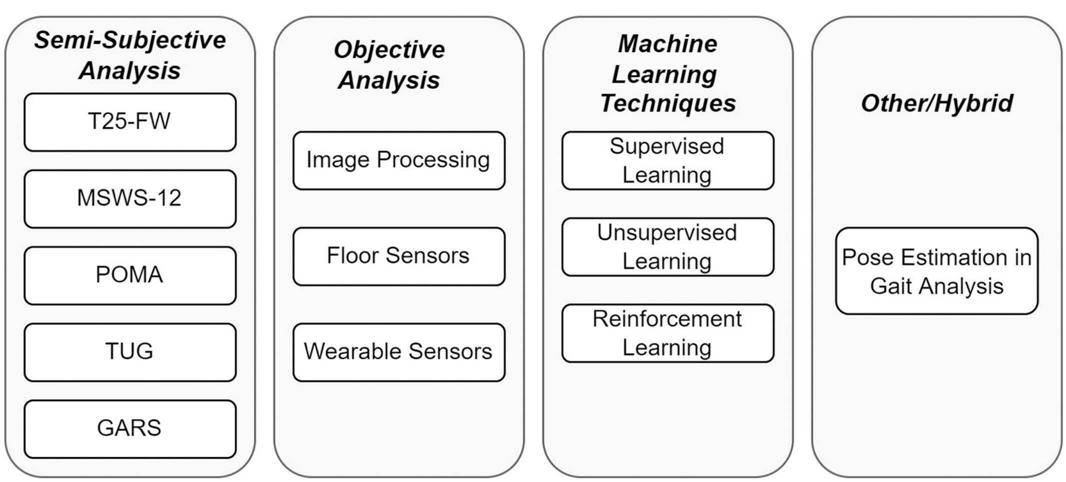

Fig. 7. Four different approaches in the context of analysis of gait (a) Semi-Subjective Analysis learn from the experts and human intervention(b) Objective Analysis requires less human intervention (c) Machine Learning Techniques: trained the model for analysis using supervised, Unsupervised and Reinforcement Learning Techniques (d) Hybrid Analysis of gait using Pose Estimation Techniques.

based on the objective of the task. The output can be distinguished in gait phases, classification of healthy and unhealthy gait, identification of abnormal gait patterns, analysis of gait patterns of patient-related with a specific disorder. Evaluation can be done using the testing and the validation set. First, the model is trained using a percentage of the available data set (training set); after the complete training of the model,

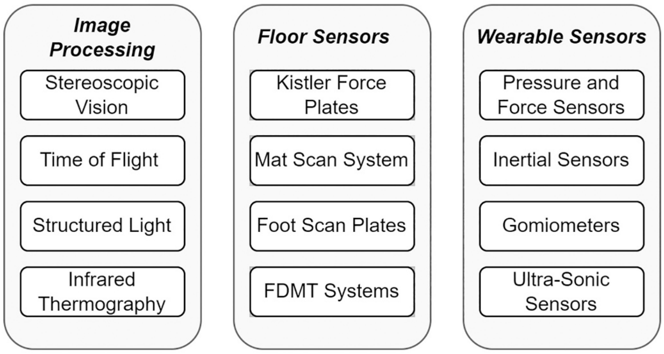

Fig. 8. Sub-Division of human gait objective analysis approaches in context for analysis of gait (a) Image Processing Techniques using standard methods (b) Using standard floor and mat scan sensors (c) Using wearable sensors(including light-weight sensors).

a test phase is performed, in which separate data set is provided for testing and validation of data. Finally, the model's performance is evaluated on an unseen dataset used for testing purposes. The term used is epochs. The process terminates when a reasonable accuracy is achieved. Over-fitting and under-fitting problems can occur, so selecting training and testing data sets needs to be done correctly. Feature Selection also plays an important role, so the feature needs to be selected carefully concerning the desired objective. Various categories of machine learning are Supervised Machine Learning, Unsupervised Machine Learning, and Reinforcement Learning. Table 8 summarizes the machine learning techniques used for gait analysis.

4.3.1. Supervised learning

In supervised learning, a feature vector comprises data having a label to identify a function that will provide the best map between input feature vectors and the corresponding label vectors. Machine Learning algorithms that were used in gait studies are neural networks (NNs), support vector machine (SVM), random forest (RF), k-nearest neighbor (kNN), ensemble learning, hidden Markov model (HMM), and decision

Table 8
Gait analysis using machine learning techniques.

Reference	Objective	Parameters/activity	Data-set	Method	Results	Future scope
[138]	Recognition of gait with pose estimation and processing of signals.	Coordinates of body parts are retrieved using pose estimation, They are used to get movement histograms and signals and generate descriptors.	CASIA Dataset A	The descriptors are used in Subsequence Dynamic Time Warping (DTW), which compares signals from gallery and probe. Euclidean distance is used to find the person gallery closest to the probe.	Accuracy Lateral View: 92.5%, Oblique View: 97.5%,Frontal View: 98.75%.	Can consider external factors like clothing, carrying conditions, and movement in future works.
[139]	To identify 3D pose from a 2D image using one camera, camera calibrations and sensor	Input: RGB Image to the model Libraries: 3D mocap and 2D off-the-shell pose were implemented.	CASIA-B gait database	Model-Based method is deployed. An extended short-term memory algorithm is used for extracting temporal features. Convolutional Neural Networks for Spatial Features. Softmax function to improve accuracy rate.	Input: 14 joint positions, 3 gallery angles: 54,96,126. for estimation Result: cross-view average recognition is 55.96% better.	Further research with more databases can be conducted to improve the recognition rate.
[140]	Gait Analysis based on human pose estimation based on CNN methods.	Body Coordinates points extracted using Visual Geometry Group-19 (VGG-19) architecture. Classification is done using CNN.	Offline Collection and labeling of the dataset were done.	Body Points extraction using skeletal images. Classifier: CNN Based. Metrics: Sensitivity, Precision, and Frames per Second.	Sensitivity: 0.9795 Precision:0.9728 FPS: 20.	Further research aims at working on more precise whole-body points posture analysis.
[141]	Gait Parameters are extracted for robotic rehabilitation in gait.	Parameters: Age, Height, Weight, Walking Speed, stride length, cadence.	Number of Subjects: 50 Male:26 Female:24 Location: Singapore	The two-Stage Gait regression neural network method is deployed.	Confidence level: 95% with a 5% error rate.	Can reduce error rated by taking considering more data.
[68]	Multi-view database performance evaluation with the use of model-based gait using pose sequences.	Coordinate Points are extracted using Deep Learning Methods. Input: RGB videos. The pose data were extracted using deep learning-based pose estimation methods from the RGB videos in the OU-ISIR multi-view large population database (OUMVLP).	OU-ISIR multi-view large population database (OUMVLP). AlphaPose and OpenPose.	Two methods were used: model-based methods and appearance-based methods. Fourier Transform (FT) method is used to calculate the thigh and knee angles is model-based. CNN is used for feature extraction.	Average Recognition Rate using Fourier Transform: 0.73%. Random Guess Recognition Rate using Fourier Transform: 0.0194%.	2D pose data is estimated for more robust data 3D can be used for further work. Multiscale gait Database of pose sequences It can be used for further observation and research as it contains 10,307 subjects with a wide range of views (14 views, 0o–90o, 180o–270o at 15o intervals).
[142]	GEI computation for each pose and to segment the gait cycle into various bio-mechanical poses.	Given a test gait sequence, the plain GEI of the whole sequence and four pose-based GEI during the complete sequence are computed.	CASIA- Gait Database B - This dataset consists of videos for 124 subjects.	Individual frames are divided into one of 4 different poses. Silhouettes of a specific pose are average to calculate the corresponding GEI. Labeling is based identity of the subject. All decisions are fused by majority voting.	Correct Classification Rate 97% and Using Principal Component Analysis:94%.	The proposed method was found robust to noisy data. Also, it suffers from view dependence and is limited to classifying test sequences taken from almost the same view angle as training sequences.

trees (DTs). Support Vector Machines are more popular for gait analysis as they are good at generalization, even for not too large datasets. Kernels are used to deal with both linear and nonlinear problems.

The classification problems were not only limited up to binary class but were extended to multi-class as well [129] which is helpful in gait studies. The productive technique in gait analysis uses Neural Networks consisting of a single layer or multi-layer perceptron. Feed-forward networks and backward propagation algorithms are used in Neural Networks and are free from the need to extract features manually but sometimes act as a black box. Neural Networks are widely used in gait studies for the abnormality prediction and recognition of various gait patterns. Decision Trees, a sub-class of Random Forest, are widely used for nonlinear data and data with complex relationships among variables. The decision trees do not provide the optimal solution. Can improve the efficiency by using ensemble learning of randomized decision trees. The K-nearest neighbor algorithm measures the distance, finds the nearest distance, and clusters the data. Asymmetry gait studies make use of various membership functions to represent linguistic information that other techniques like fuzzy logic are not able to present [11].

4.3.2. *Unsupervised learning*

In unsupervised learning, no labeled data is available, so the learning algorithm works without any labels. The algorithm needs to identify the relationships on its own, to have the desired output [130]. Distance plays a vital role in performing clustering; usually, the data is clustered into one category if they lie near each other. Such techniques are less explored in gait analysis studies because precisely defining the objectives for learning and dealing with a vast number of feature vectors becomes a tedious task [12]. However, such techniques can be used when the relationship between various observations is unknown. For massive datasets, it is required to use a dimensionality reduction approach with the classification process. Unsupervised techniques can learn various patterns. Specifically, they can learn about various disorders. Various methods like distance metric, latent profile analysis can be used for subgroup classification.

4.3.3. *Reinforcement learning*

To deal with the dynamic environment, RL must interact with the system, various devices like walking assistive devices, exoskeletons make use of Reinforcement learning. Such devices are used in the rehabilitation process. DNN (Deep Neural Network) and RL are widely used in gait rehabilitation. The various control strategies were developed for gait rehabilitation [131]. The RL and (deep) neural networks (DNNs) were widely used with rehabilitation devices due to their ability to capture the participants' variability better and thus, resulting in automation according to subject-specific needs.

To enhance the processing capabilities, feature selection and extraction techniques are used, whereas, to reduce the complexity, dimensional reduction processes are used. Feature selection works with the selection of suitable features and pruning out the rest without changing the originality of features [132]. Extraction is a mathematical process of extracting new features from the original features. Classifiers like convolutional neural network (CNN), artificial neural network (ANN), and Deep Neural Networks (DNN)automate the process of feature selection and extraction.

5. Pose estimation in gait analysis

In the model-free approach of gait recognition image, measurement is done by analyzing the subject's motion. Shape variation within a particular region of the walking subject falls in the category of the model-free approach. In recent times, several features have been included in the model-free approach of gait identification, based upon the movement of shape [133]. The characteristics of the model-free approach are extraction of whole body moment, silhouette width vector, or Fourier description; the mentioned characteristics can further be used for pattern recognition. The methods used in the model-free approach are simple and demand fewer computational requirements. Since real-time inputs are taken, clothing style, objects carried in arms can affect the model analysis (Fig. 9).

Estimating human pose in 3d images or videos has recently gotten attention in the scientific era. The main reason for this trend is the rapidly increasing new range of applications (like gaming, human-robot interactions, sports performance analysis) [134]. In clinical practices, gait analysis can be widely used for understanding the abnormalities associated with gait and their related medical conditions for better diagnosis [135]. The 3D human pose estimation can be used to visualize or analyze the movements of sportspersons to increase their performance. In Physiotherapy 3D, gait analysis using gait analysis helps identify the causes of abnormal gait in patients and anomalies like stroke or other neuromuscular problems. The area of video surveillance is one other emerging application of pose estimation. 3D analysis of human pose helps identify various events, such as walking, running, wall-climbing, and many other activities, even if they are not common. It can also help athletes visually analyze and improve their performance in sports [136]. In medical fields like physiotherapy, the 3D human pose is used in Gait analysis to identify causes for anomalies in a patient's movement, which many different medical conditions like a stroke can cause, neuromuscular problems, or cerebral palsy. Pose estimation is also used in video surveillance, which relies on computing power and efficient algorithms resulting in less quality and quantity requirements of cameras that can accurately analyze 3D human poses from the video. That helps surveillance operators identify unwanted events like shoe-lifting, wall-climbing, and other abnormal human activities. Fig. 12 shows the percentage distribution of approaches covered. In [137] authors proposed a method for markerless gait analysis from the human pose by using an open pose library. The proposed method used two stereo cameras for recording human motion. The two cameras were calibrated for better synchronization. The marker-based method was used for reference. The open pose library was used to process the video recorded from both cameras. Two skeleton joints named S_a and S_b were obtained and triangulated to provide the 3D coordinates of the joints. Basic gait parameters such as gait cycle time, step length, and step distance were calculated, and the authors found that the accuracy of the analysis was affected by the factors such as camera relative length, gait direction concerning camera axis, and video resolution of the camera. The parameters considered for gait analysis are insufficient, affecting the accuracy. As all the joints were considered individually, the processing time will increase.

In [143] authors proposed a gait analysis method for person identification. The data acquisition process used three datasets named UPCV gait, UPCV gait K2, and SDU gait. The images acquired from the datasets were pre-processed for better noise reduction. The 3D skeleton joints were estimated by using a human pose algorithm—the spatial geometric features such as joint distance, joint angles, and temporal features such as mean and variance were calculated and fed into the Deep Convolutional Neural Network to classify a person further. The result showed that the proposed method was said to have remarkable identification accuracy. The proposed method has high time consumption because it considers each joint individually. The computation of features is not carried out for each gait cycle, thereby reducing the accuracy of gait analysis.

In [145] authors proposed a method for gait analysis of polyneuropathy patients by validating the RGB-D camera against the reference motion capture system. Kinect V2 camera for the data acquisition process is used. Used Microsoft SDK to process the depth image and provide the skeleton joints. Both methods calculated the 15 spatial-temporal gait parameters, and both methods calculated eight kinematic parameters. All the parameters were processed using a zero-lag low-pass Butterworth filter. The mean value of each parameter is computed, and finally, the Bland Altman's bias and Pearson's correlation coefficient are determined for both systems. The result showed that the

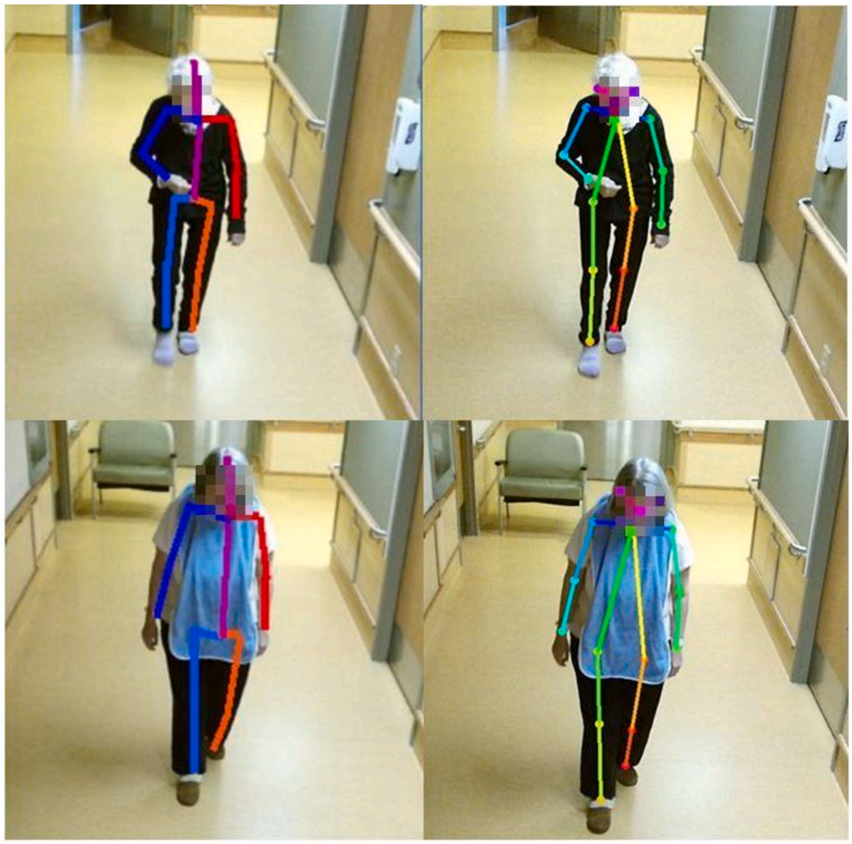

Fig. 9. Skeleton representation of human pose: extraction of key joints for analysis of gait. Left side represents the output from stacked hour glass network and right side represents the output from Open Pose model on two images [144].

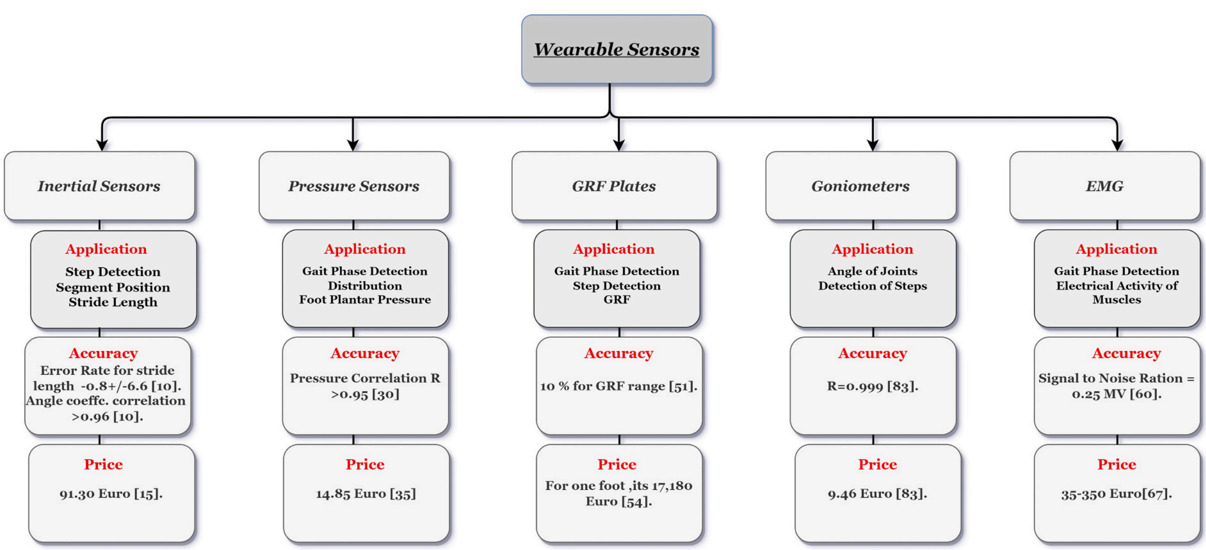

Fig. 10. Overview of Existing Wearable Techniques: Level 1 represents the sensor's name, Level 2 represents the application domain in which the sensor is used, Level 3 represents the accuracy of the sensors, and Level 4 represents the price detail of the sensor.

low-cost and non-invasive RGB-D camera accurately determined the gait parameters and detected the affected gait.

The skeletal joints obtained from the model-free approach are inaccurate, affecting the efficiency of the method. The stability of the gait is not determined by the proposed method; computing the analysis for all gait cycles will increase the latency.

In [146], the authors proposed a method to validate the performance of the markerless system to evaluate the forces of upper joints in exoskeleton users. The proposed method used four kinectV2 sensors for the data acquisition process. Also, performed a Marker-based gait analysis to compare both methods—using Microsoft SDK to process the depth information and provide the skeleton joints. The patient used the crutches having a simplified electric circuit for better performance. The gait parameters were calculated, and the gait analysis was carried out.

The proposed method was used to learn how to use the exoskeleton effectively. The result showed that the method performed efficiently when compared to a marker-based method.

Only depth images are considered input for the joint extraction process, which will not be accurate. The gait parameters described in the proposed method for the process of gait analysis are not sufficient to carry out an effective gait analysis process.

In [68] authors proposed a performance evaluation method of model-based gait on multi-view very large population database. The data acquisition process was carried out from the OUMVLP database, which consists of two data sets extracted by two deep learning algorithms named open pose and alpha pose. The deep learning algorithms used Convolutional Neural Network (CNN) based on the part-affinity approach for joint extraction. The Long Short Term Memory encoded the temporal information extracted from the pose sequence. Combined the features extracted from CNN and LSTM to capture the dynamic state information from gait poses. The proposed method was validated, and the result showed that the model-based approach had better performance.

It is not sure that all the gait cycles are stable; hence, the unstable gait cycle will reduce the accuracy and increase the time consumption. The proposed method considers each joint individually for gait analysis, increasing the latency.

In [147] authors proposed a model-based gait recognition method based on human pose named posegait. The proposed method overcomes the problems faced by the traditional appearance-based gait analysis. The data acquisition process is carried out from two different data sets named CASIA —B and CASIA-E. The model-based approach used Convolutional Neural Network (CNN) to extract the skeletal joints based on the part affinity approach. The proposed posegait method extracted up to 18 joints from the image. The extracted joints calculated the spatial-temporal parameters such as joint angle, step length, etc., were calculated from the extracted joints. The CNN classifier was used to recognize the abnormal gait. The proposed method was validated, and the result showed that it has better performance than the model-free approaches.

The number of joints extracted from the proposed method is low, affecting the model's accuracy. Lack of depth image smoothing causes noise in in-depth images, further affecting the accuracy of gait analysis.

In [148] authors proposed a cross-subject and cross-modal transfer for abnormal gait recognition. The proposed method focuses on noise obtained from the depth images taken from the RGB-D camera and signals from the wearable sensors. The cross-modal transfer maps the noise to get a better 4D representation of the joints. The subject-specific features are disentangled from the abnormal pattern-specific gait features by cross-subject transfer based on multi-encoder architecture. The proposed method was validated using electromyography data and the 4D data obtained from the RGBD camera. The result showed that the proposed method performs better than other models using unprocessed depth images.

The proposed method considers each joint individually for gait analysis, increasing the latency. The stability of the gait is not determined by the proposed method; computing the analysis for all gait cycles will reduce the accuracy.

In [149] authors proposed a real-world gait detection method using wrist sensors. The proposed method detected the gait patterns by using a wrist mount accelerometer. Various features such as intensity, periodicity, posture, and other non-gait dynamicity were calculated to determine the gait and non-gait movements. These extracted features were used to train the Bayes estimator to estimate the probability of gait occurrence. The individual's gait is analyzed only when the gait movement is recognized. The proposed method is validated by using the leave-one-subject-out method, and the result showed that this method had better performance.

It is hard to estimate the gait movement during real-time life situations, thereby increasing the latency. The noise level from the electromyography signals is not filtered, which will reduce the accuracy of the proposed method.

In [150] authors proposed an efficient method for video-based gait analysis—the proposed method used 2D video as input to extract the skeletal joints. Twelve gait parameters were calculated for each gait cycle. The distinct gait patterns were obtained by following three steps named gait pattern standardization, gait pattern clustering, and gait pattern averaging. The gait phase classification was done by feature alignment based on temporal gait parameters and feature mining. Two mining approaches were proposed to extract the feature pairs named the Filtering method and the optimized method. Finally, the gait phase reconstruction was carried out to improve the method's performance.

The input video is in two dimensions which will contain a greater noise level, lack of noise level filtering leads to reduced accuracy. The number of parameters obtained from the skeleton joints to process the gait pattern is not sufficient for better performance.

In [151] authors proposed a gait analysis model during walking and running through wearable sensors attached to the shoes. The model was named SportSole, which consisted of a multi-cell piezoresistive sensor, an inertial measurement unit, and a logic unit for the data acquisition process. A vision-based optical motion capture system was used as a reference system, synchronized the reference and raw data to extract the gait parameters for each gait cycle. Two regression models, subject-specific and generic models, were trained with the gait parameters. The LASSO and SVR models were used in both regression models to compare the model's efficiency. Evaluated the proposed method, and the result showed that the SVR model in both the regression models had better performance.

The gait patterns obtained from the wearable sensors contain noise, and the lack of noise filtration affects the accuracy of the proposed method. The efficiency of the gait analysis obtained by the proposed method is lower when compared to the gold standard system.

[152] worked on gait rehabilitation using robot assistance. A robot is developed that can imitate the working of a human body and is designed in a manner identical to a human shape. When it comes to a human expert, the abilities are limited in exertion and fatigue. For better treatment, more aids are required. Robotic assistance can be helpful to provide worthwhile rehabilitation. Robots have better mechanical potential; they can provide better results and control without fatigue. Standard of safety and usability are the main parameters to take care of when human is considered.

Daily training becomes difficult for the patients because of traveling and the hospital's limited resources. Robots are the future of rehabilitation as they can be used in a home environment.

Automated measures are used in [153] to conduct a Short Maximum Speed Test on subjects suffering from Multiple Sclerosis(PwMS). Depth images are analyzed using Kinect SDK, and the Skelton model is generated as output. With a frame rate of thirty, twenty joints are extracted. Gait parameters are computed from body elements. The system is evaluated using the Kinect sensing element.

A head-on viewpoint is considered to trace the human skeleton using the Kinect SDK. Single-camera captures an individual's walking pattern; accuracy can be improved if the data for the complete body is recorded instead of the head only.

In [154] In-shoe plantar measurement systems are used for the identification and monitoring of gait disorders. Accelerometers and gyroscopes are used together with pressure-sensitive elements. Essential parameters for better-working wearable sensors are sensor size, placement, flexible electronics, and embedded electronics. Issues like accuracy and comfort arise with such systems. Pressure Sensor technologies discussed in the paper are capacitive, resistive, optoelectronic, Piezoresistive, and Piezoelectric.

[155] shows the use of automatic support for gait analysis. Motion capture is an important technique used for gait analysis. The measurement is done by placing markers on the target areas and processing them. A cloud of points is generated from the human skeleton model obtained from the markers. Mocap systems are accurate but are

expensive and specialized laboratories are required.

[155] discuss "An Inertial Measurement Unit based network (IMU) is a chip equipped with an accelerometer, magnetometer, and gyroscope. A network of such units works similarly to a marker-based mocap system". The framework of the human skeleton uses frames. The advantage of using IMU systems are: economic and can be used in the outdoor environment. IMU has limitations, like noisy data leading to less precise results and increased sensitivity towards damage.

[156] shows the use of a depth detector for side view in measuring spatiotemporal gait parameters. Clinical walking trials are recorded using the side view Kinect. Six joints were tracked by the system and produced the score for the "Get up and go test." Frontal sensors are used instead of frontal depth sensors. A single-camera is deployed to record the walking pattern of the person. The system for each trial overestimated step width. The system can efficiently extract standard spatiotemporal gait parameters. Efforts should be made to extract the location of the rear foot to make measurements more consistent.

In [157], the authors proposed a method to find the relationship between temporospatial gait and muscle coactivation measures in patients without hypertonia after stroke. The coactivation magnitude and duration for various muscle strands were calculated using the electromyography signals, and these measures were compared with each stage of the gait cycle, such as late single support (SS2), early double support (DS1), early single support (SS1), late double support (DS2) and swing (SW). These comparative studies showed that muscle coactivation increases and decrease bilaterally in both the ankles during sub-acute strokes. The proposed method was found to help examine the muscle coactivation between sub-acute and chronic stroke.

In [158] authors proposed a novel method for gait analysis on the center of pressure excursion based on a pressure-sensitive mat. The center of pressure (COP) was calculated from the pressure mat, and parameters such as time points and sub-phase duration of stance phase, displacement ranges, mean location, and velocity of the center of pressure were obtained. The threshold number of footfalls to obtain the reliable parameters was seven. The proposed method was validated against the standard gait analysis system, and the result showed that the proposed method based on the center of pressure had better performance and accuracy in gait analysis.

In [159] authors proposed a method to validate the accuracy of the Microsoft Kinect V2 sensor for human gait analysis. Two Kinect V2 sensors were used for the data acquisition process, and a vision system comprising six M2 MCAM cameras was used as a reference system. The skeletal joints were extracted concerning the reference system. The time series of both systems were synchronized to obtain better performance. The Dynamic Time Wrap (DTW) algorithm was used to overcome the latency of the Kinect V2 sensors and thereby increase the system's accuracy. Finally, the gait analysis was carried out with the spatial-temporal features, and the system's efficiency was compared with the known older methods. The result showed that the proposed method had better accuracy.

In [14] authors proposed a gait analysis method to evaluate the symptoms in patients with anterior cruciate ligament (ACL) rupture before and after the reconstruction of ACL. Compared features such as walking cycle duration, impact load, and amplitude of the main flexion of the knee before and after the ACL reconstructions. In addition to this, the gait parameters were calculated to get a better idea of the recovery status of patients. The sensors which were fixed to the lower back of the patients were used to calculate the gait parameters such as walking cycle duration, walking speed, etc. the gait analysis was performed, and it was clear that the recovery status of the patients was exactly obtained with the help of the proposed method.

In [160] authors proposed a wearable sensor-based gait analysis for estimation of age and gender. The wearable sensor-based gait data-set, which consisted of data from 745 subjects, was used for the data acquisition process. Three inertial measuring sensors placed on the waist belt were used to collect the gait sequence. Several gait features were calculated from the patterns and are used to train the Convolutional Neural Network (CNN) to estimate the age and gender of an individual. Several solutions from several teams were obtained and compared to select the optimal method. The result showed that using a conventional temporal network reduced the estimation error and increased the accuracy.

6. Clinical gait analysis

[161] focuses on determining the validity of clinician's visual observations of gait deformities limiting the movement after Traumatic Brain Injury (TBI) and determining key factors affecting the accuracy. Thirty-six gait variables were used in the study, including spatiotemporal, kinetic, and kinematic. The mean gait velocity(self-paced) for the TBI group was 1.07 m/s; for the HC group, it was 1.43 m/s. There is no direct relation between heterogeneity of variables observed and accuracy of judgment made; thus, authors tend to infer that "the severity of gait disorder does not influence observer accuracy." Fig. 11 shows the percentage analysis of several research articles and diseases covered. In Table 9, various techniques used for gait analysis are discussed. There is no concrete relationship between the impact of walking speed on judgment created on each kinetic and kinematic variable. 3DGA approach to facilitate 'evidence-based practice' is also excusable; however, results support the requirement for "objective quantification" of gait for individuals with severe TBI.

[162] evaluates an "adaptive gyroscope-based algorithm" for automated temporal gait analysis using a body-worn wireless gyroscope and takes nine healthy subjects and one poliomyelitis patient for analysis. The parameters considered were angular velocity signals, temporal gait parameters like swing, stride, step, and stance time. A good agreement (ICC 0.80) between temporal gait parameters derived from each -adaptive gyroscope mechanism algorithmic program and the HMA at four completely different speeds(fast: 1.56 m/s, normal: 1.10 m/s, slow: 0.65 m/s, shuffle: 0.48 m/s). The "adaptive algorithmic program with success extracted IC and TC points from the rotating mechanism signal," even if the legs made differing signals. Adaptive threshold calculation for IC and TC + artifact rejection would lead to better results.

[163] focuses on the estimation of the credibility of "gait variability during continuous and intermittent walking in elder and Parkinson's Disease suffering patients" and the determination of the optimal count for an appropriate level of assurance of gait. Intra-class correlation of the gait variability ranged from (0.041) to (0.860) and depended on whether "continuous or intermittent walks" were performed and the gait variables. The best improvement was seen in 30 steps. Step breadth variability was the foremost definitive, whereas the stance time was the least. More reliability is observed when the analysis is integrated from both the left and right steps. Based on the observations, the continuous working protocol is best suited to intermittent walking. Intermittent walking means at least 30 steps should be used for analysis(though 50 or above is optimal). For better calculation of variability in gait, should integrate the data from both left and right steps. In Table 10 various machine learning techniques for clinical gait analysis are discussed.

In [164] the relation between gait variability with falls in patients suffering from cerebellar disorders is presented. "CV of stride length, stride time, support base, and speed-dependent integrals were used as covariates." In the linear regression model, the proper prediction was "higher for the AUCs than for the raw (0.83 vs. 0.54 for the CV of stride time)". The best AUC values were for the slow speed (0.25 of PWS to 0.75 of PWS). The study indicated that increased levels of gait variability within the fore-aft direction area unit connected with a better chance of dropping in patients with Cerebellar Ataxia. The documentation of "fall events, fall-related morbidity, and mobility markers" should be focused on. In physiotherapeutic practices, exercises at variable gait speeds and transitions between different gait speed sections are emphasized.

[165] ascertain the dependability of 3DGA kinetic and kinematic data and further evaluation of variations in "joint angles and net joint

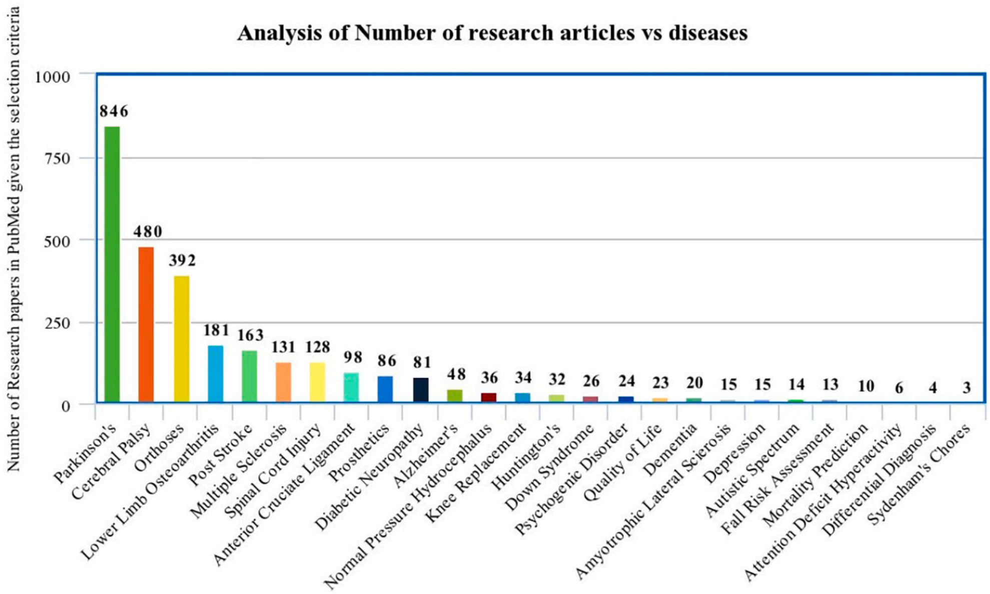

Fig. 11. Overview of research papers published for gait related disease.

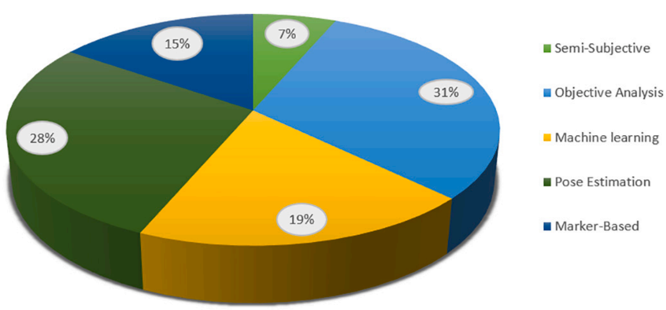

Fig. 12. Percentage distribution of approaches covered for gait analysis.

moments using IK & DK models." Cerebral Palsy (CP) and Tardive dyskinesia (TD) disorders patients were considered in this study. The four models used for analysis were "gait2392' OpenSim (3-1-1-DoF-IK), Vicon Plug-in-Gait (PiG-DK), 3-3-2-DoF-IK, 6-DoF-DK,". Markers were employed at the ankle joint, thigh, pelvis, foot, shank. For all joint angles, IK models had SDs less than 5; for the PiG-DK and 6-DoF-DK models, SDs were predominantly less than 5; RMSD in joint moments was beneath 0.6 Nm/kg, and "kinematics waveforms were similar between the PiG and different models."

[166] focuses on the "reflective cross-sectional analysis" of the variations in parameters used for CGA, emphasizing patients who have Multiple Sclerosis. Levels of disability were estimated using 6MWT speed & EDSS on 52 CGA-based parameters. A strong correlation is seen between all-Time/Distance parameters and 6MWT speed, 6MWT speed, and knee parameters. A negative correlation is seen between stance duration and cycle duration and 6MWT speed, speed, and timing of peak knee adduction. A positive correlation is seen between stride length, cadence, velocity, and 6MWT speed. Temporal parameters showed a weak correlation between gait speed and EDSS. "Gait speed during 6MWT" better differentiates patients wrt EDSS. CGA-based parameters show optimal results and are used in the in-depth analysis of gait kinematics while analyzing gait biomechanics during rehabilitation therapy.

[167] determines the relation between spatiotemporal, kinetic, and kinematic gait features in COPD suffering patients. The measurement techniques employed are 6MWT, step width and step time variability. Extracted eleven gait variables in the study, including spatiotemporal, kinetic, and kinematic parameters. COPD was associated with taking steady steps and "with reduced cadence increased double support time and altered gait variability." Homogeneous cohorts and longitudinal studies can be thought of as future directions.

[168] works on Multiple Sclerosis prediction with the help of Gait Dynamics. A treadmill is deployed for the extracting gait data. The normalization was achieved using two strategies- "size-N (standard body size-based normalization) and regress-N (regression-based normalization using scaling factors derived by regressing gait features on multiple subject demographics)." Gait parameters and other measures such as height, weight, age, gender were also taken for normalization. The optimal subject classification accuracy was 94.3%. Machine Learning techniques can give better gait analysis results, which can help in clinical applications such as disease tracking or classification.

In [169] deep learning techniques are used to track gait. Wearable sensors are used to record the gait data. Extraction of spatiotemporal features was done using convolutional neural networks. Two long-term memory models are used to extract the features from wearable sensors and to process the output. A Grey wolf optimizer is used to merge the output generated from two LSTMs. The classification results are more accurate when compared with integrated spatial results. The overall accuracy achieved by the model is 91.3%.

[170] shows infirmity-based changes in kinetic and spatiotemporal gait features are normalized to examine Persons with Multiple Sclerosis (PwMS). "Multiple Sclerosis is a neurodegenerative and chronic demyelinating disorder." It affects the "central nervous system" of the patient. The research was performed using a data set of 20 people. To collect the data, an instrumented treadmill was used. Along with gait measurements such as timestamp, heel strike, toe-off position, and mid-stance, other parameters like a person's age, body weight, and total height were also documented. The data was analyzed by using two ML models. The regress-N model gave more accurate results for identifying pathological gait than the results by size-N. Normalized gait features using regression can be used for better future implementation of disease prediction using ML-based models. It can be used for progression monitoring in Persons with Multiple Sclerosis. The classification accuracy of 94.3% is achieved when the system uses a gradient boosting machine and an accuracy of 80% with multi-layer perceptron.

[171] has classified Parkinson's Disease using 'accelerometry based digital gait characteristics'. "Parkinson's Disease is a common neurodegenerative disease after Alzheimer's disease." Research on 142 participants was performed to classify people with PD. 6 "partial least square

Table 9
Different techniques in clinical gait analysis.

Source	Objective of the study	Application area	Data set	Measurement technique	Parameters	Limitation	Future scope
[161]	Determining validity of clinician's observations after TBI	Traumatic Brain Injury (TBI)	30 Subjects	Physiotherapists observed and evaluated 36 gait variables	36 gait variables, which included spatiotemporal, kinetic and kinematic	Results cannot be generalized	3DGA approach to facilitate evidence-based practice may be justifiable
[162]	Gyroscope based algorithm evaluation for temporal features	Poliomyelitis	Nine subjects + One subject with polio	Gyroscopes, Force plate, Optical Motion Capture system,	Step time, Angular velocity signals, stance, stride, step time and swing.	IC and TC times estimation automatically was not possible	Calculation of suitable threshold calculation for IC and TC and rejection of artifact would lead to better results
[163]	For Parkinson's disease patients estimation of gait protocol reliability and determining appropriate count of steps for analysis	Parkinson's Disease	27 elder and 25 PD participants	Instrumented track (7 m * 0.6 m)	Step velocity, length, stance, width, swing duration.	Outcomes are refined to variability in gait evaluated using the instrumented track, so it cannot be generalized.	The authors suggest the use of a continuous walking protocol and at least 30 steps for analysis
[164]	Relation between variability in gait with fall risks in "Cerebellar Ataxia"	Cerebellar Ataxia	48 Subjects	6.7mlong pressure-sensitive carpet	CV stride length, stride time, speed-dependent integrals, the base of support	History of fall may impact results, analysis based on 15–20 steps so results cannot be generalized	Gait speed be included in physiotherapeutic exercises
[165]	Dependability of 3DGA kinematic as well as kinetic data-sets by IK DK models	Cerebral Palsy (CP),	11 with CP and 7 with TD	"Vicon Plug-in-Gait (PiG-DK) 6-DoF-DK, 'gait2392' OpenSim (3–1-1-DoF-IK), 3–3-2-DoF-IK"	Markers employed at ankle joint, thigh, pelvis, foot, shank	Generalization of results not possible	The "3–3-2-DoF-IK" model would be appropriate for clinical 3DGA as it allows musculoskeletal analysis.
[166]	Analysis of variations in gait parameters for Multiple Sclerosis patients	Multiple Sclerosis(MS)	51	Speed: 6MWT	52 CGA-based parameters.	Time/Distance, kinematic and temporal parameters	CGA based parameters show optimal results during rehabilitation therapy
[167]	Determining the relation between gait features in COPD suffering patients	Chronic obstructive pulmonary disease (COPD)	Seven research papers were reviewed	6MWT, step width and step time variability	Used 11 gait variables, which included spatiotemporal, kinetic, and kinematic	Heterogeneity of manifestation of COPD in samples	Stricter cohorts characterization and longitudinal studies
[170]	To evaluate disability based changes in spatiotemporal as well as kinetic gait features	Multiple Sclerosis (MS)	20	Instrumented treadmill, ML algorithms,	Age, weight, height, mid-stance, heel strike, Toe-off, position time stamps		"Regression normalized gait features" can be used to give predictions based on Machine Learning
[171]	Classification of Parkinson's Disease:	Parkinson's Disease (PD) 142	PLS-DA models	RMS, 'Spectral density power,' step velocity, length, gait regularity, patient's age.		Not generalizable for prodromal PD	A model trained on the prodromal cohort.
[172]	Comparison between gait variables measured with RehaGait in osteoarthritis patients	Severe knee osteoarthritis	22	Inertial sensor system RehaGait, placed bilaterally on the lateral foot, lateral lower leg, and lateral thigh, and on the pelvis	Spatiotemporal parameters, sagittal kinematics	Findings may not be generalized	The results obtained from RehaGait are comparable with the known literature and are thus suitable for the clinical environment

discriminant analysis" (PLS-DA) models have been designed and trained. The parameters used were root mean square(RMS) values, age, step length, step velocity, power spectral density, and gait regularity. The model accuracy ranged between 70.42 and 88.73%, however, this model may not be able to classify prodromal PD accurately. More work is required to test the working of modals on a diverse prodromal cohort.

[172] shows a comparison of the difference between "spatiotemporal and discrete kinematic gait variables measured with RehaGaitÂ® (inertial sensor system) between the affected and unaffected side in patients with unilateral knee OA and between patients with severe knee OA and asymptomatic control subjects" is presented in this study. Spatiotemporal-based parameters and sagittal kinematics (at hip, knee, and ankle joint) were analyzed using the RehaGaitÂ® system while the patient walked at a self-decided speed for approximately 20 m. "Patients with knee OA had steadier walking speed, longer stride duration, shorter stride length and lower cadence (P less than 0.001)". The results obtained from RehaGait® are comparable with the known literature and are thus suitable for the clinical environment.

In [173], the authors proposed a classification method based on Gated Recurrent Unit (GRU) classifier and 3D skeleton joint data. Six Kinect-v2 depth sensors were positioned to acquire the depth images. Microsoft SDK collected the depth information and provided the skeleton joint data. According to the pathological gait guidelines, ten subject data were acquired. Grouping of joints is done to train the classifier model on the most relevant groups. The proposed method has classified the gait into six classes: antalgic gait, normal gait, Trendelenburg gait, stiff-legged gait, steppage gait, and lurching gait. Leave-one-subject-out validation method was used to estimate the accuracy of the proposed method. The result showed that the GRU classifier achieved a classification accuracy of 90.13% for all skeleton data. When one leg joints are considered, the accuracy increases to 93.67%.

In [174] authors proposed a gender classification model based on gait analysis. Input depth images are acquired using two Kinect v2 depth sensors. Skeleton join data is obtained using the Microsoft SDK. For the data acquisition process, 81 participants are considered. The Microsoft SDK was used to process the depth information and provide the skeleton joint data. Eighty-one participants were used for the data acquisition process. The parameters such as principle frequency, gait cycle, central

Table 10
Comparison of classification and event identification results.

Source	Objective	Measurement technique	Parameters	Methods	Results
[181]	Classification of 5 walking conditions	Accelerometer and Gyroscope sensor unit attached on the shank and foot.	Stair ascending (SA) Upslope (SU) Level ground (LG) Stair descending (SD) Downslope (SD)	SVM RBF-ANN Bayesian Belief Network	High accuracy for classification was achieved using SVM.
[128]	Muscle activities are used for recognition of the walking movement in humans.	Kinematic data were obtained with the help of a motion capture system. EMG data and joint data.	EMG data two components are used along with stance and swing phase of walking.	Feature Extraction using LLE Classification using HMM.	Accuracy of Eighty percent is achieved, increased depending on the speed of the person.
[182]	To differentiate between various patient groups like healthy or unhealthy patient groups.	Tri-axial Accelerometers	Sitting, Stair up, Stair Down, Walking, Running.	Random Forest	Accuracy of 84.2% and 81% achieved for global and personal models.
[183]	Identification of impairments in human movements	Microsoft Kinect	walking, rising from chair, tandem movements	SVM + RF + Bagging +LLE + GRBM +AdaBoost+RUSBoost.	RF produced maximum accuracy 87.10% and GRBM with lowest accuracy 73.08%.
[184]	Activities recognized by using accelerometers wear across waist	Accelerometers	Lying Sit Stand Walk Wheeling Stair climb	SVM + Naive Bayes + Linear Regression + Decision Trees + Random Forest +HMM.	Hybrid RF HMM achieved an accuracy of 88.9%.
[185]	Gait events identification using accelerometers and gyroscopes	Sensor units at shank, foot and thigh.	Turning points classification in stance and swing phase.	Threshold detection method	Reliable results are obtained using a combination of sensors compared to single sensors.
[186]	Using sEMG detection of stance and swing phase events	At hallux and under the sole of foot two FSR's are attached	domain features Standard Deviation, Root Mean Square and IEMG.	Artificial Neural Networks	Accuracy of 87.5% is achieved using ANN.
[187]	Recognition of Gait phases	IMU sensors and Feature Selection and ranking.	IMU motion sensors for knee and hip and Feature Selection and ranking for toe and heel.	C4.5 decision tree Multilayer Perceptron and NARX	For a more extensive training set C4.5 decision tree accuracy 100% Multilayer Perceptron accuracy 94.79NARX accuracy 98.76
[188]	Human identification using various pattern recognition methods.	Use of Microsoft Kinetic Sensor	Angle of Pelvis, Hip Flexion Angles, Knee angles, Ankle angle, angles of abduction.	Probalistic Neural Network, Learning Vector Quantization, Deep Neural Network, K-Nearest Neighbor, Random forest Support Vector Machine and Naïve Bayes	A high response time of 99.51 s is achieved using Deep Neural Network, and the least response time of 0.63 s is achieved using KNN.
[189]	Identification of various gait phases with variation in walking surface and speed.	IMU sensor attached with thigh and knee.	Level Right cross-slope Left cross-slope Up-slope Down-slope	Transition sequence verification and correction (TSVC) and Logistic model decision tree.	LMT accuracy was 90.60% and TSVC 98.61%.
[190]	Classification of abnormal and normal gait using hill-climbing method.	Ground Reaction Forces and kinematics of rearfoot	GRF 14 and Kinematic features 16.	Support Vector Machines	Accuracy of 85.19% achieved using GRF features Accuracy of 74.07% was achieved using kinematic features.
[191]	Identification of muscles of Arthritis patients using gait.	Electromyography pattern of both legs	Gastrocnemius medialis Soleus Tibialis anterior Biceps femoris Vastus lateralis	Self Organising map, Learning Vector Quantization, Multilayer Perceptron and Linear Discriminant Analysis.	Dominating muscles for Rheumatoid arthritis (RA) are biceps femoris and soleus, and for osteoarthritis (OA) is gluteus medialis.
[192]	Classification of subjects with various foot lesions.	kinematics of the foot	Leg Midfoot Heel Hallux First metatarsal	Kernel Principal Component Analysis Fisher Linear Discriminant Analysis.	accuracy of 94.1% achieved using KPCA and FLDA.
[193]	Cerebral Palsy gait classification using membership degrees	ankle and knee 3D gait analysis	Movement patterns of the ankle and knee joints	Bayesian Networks	Accuracy of 82–91% is achieved for different movements.
[194]	Using foot pressure data-set of young children classification between normal and pathological gait.	GAITRite foot pressure data	Spatiotemporal parameters	Principal Component Analysis, Random Forest, Discriminative Analysis and Support Vector Machines.	accuracy of 94.3% using SVM and 97.50% using Random Forest.
[195]	Classification of patterns of sagittal gait in children having cerebral palsy.	Kinematic signals from knee, ankle, hip, and pelvic joints.	classification groups Jump gait True equinus Crouch gait Apparent equinus	Artificial Neural Networks Naïve Bayes Discriminant analysis K-nearest neighbor Decision tree (DT) Random Forest Support Vector Machine	Accuracy of Neural Network 93.5% Decision Tree 84.3%, SVM 85% Random Forest 83.6%.

tendency and spatial variables, dispersion, and center of mass were calculated. One hundred eight features are presented with the significant difference and are used to train the model, and classification is achieved using a Support vector machine classifier. The proposed method classifies the gender-based gait analysis and achieved an accuracy of 96.7%.

In [175], the authors analyzed pose estimation based on abnormal and normal gaits. The camera recorded video is considered the input for the system. CNN is used for human pose estimation along with a part affinity field. For training the classifier, skeleton joints were used. Data classification is classified into various classes: standard, abnormal right foot, abnormal left foot, abnormal right toe, and abnormal left toe. The data is split into 80:20 ratio, in which training is performed on 80% of the data and testing is performed on 20% of the data. The performance is evaluated on the designed method, and it is observed that the method Tested the proposed method, and the result showed that it had good accuracy in classifying the abnormal gaits.

In [176] authors proposed a gait analysis method to classify gait.

Depth images and RGB images were input. A bilateral filter pre-processing of depth images was done, and the pose estimation was achieved using a Deep Convolutional Neural Network. Surrounding were obtained using a 6D camera in three dimensions. SLAM, Simultaneous Localization, and Mapping algorithm fuse the 3D canonical coordinates with the 3D lower limb skeletons. Sixteen subjects were used in the process. Joint angle features are extracted from the lower skeleton, statistical features such as gait cycle, step length, gait symmetry, and time are trained in the SVM classifier, and temporal features like joint angles in the Bi-LSTM classifier. Leave one subject out; protocol is used to test and validate the system, and the result showed that the method proposed has achieved an accuracy of 82%.

Based on virtual sample generation, authors in [177] proposed a classification model for abnormal gaits. Depth information was used to generate the 3D skeleton model. Parameters considered for the model are joints, age, gender, height, and weight. Machine learning models are deployed to predict the stability data in abnormal gaits. Conditional adversarial methods are used to label the information. The model has achieved an average accuracy of 98.18%.

7. Performance measures

To evaluate the performance of techniques, metrics or performance measures are used. Important performance measures used in the field of gait analysis are F-Score, Precision, Recall, Specificity, ROC curve, PSNR.

7.1. Accuracy

Accuracy defines as the measure of closeness between the predicted value of the quantity and its actual value. For clinical diagnosis or treatment, accuracy and precision both play an essential role. The control and patient groups are assessed quantitatively for the same reference, and the assessed value should be close enough to the ground value. Thus, specific, well-defined procedures are required for data collection to ensure reasonable accuracy.

7.2. F1-score

A model's accuracy on a data-set can be determined by calculating a parameter F-score, also known as F1-score [178]. It helps estimate binary classification systems that categorize examples as either 'negative' or 'positive.' The recall's harmonic mean and precision of the model is called F1-score.

$$F_1 = 2^* \frac{Precision^*Recall}{Precision + Recall} \tag{7}$$

7.3. Precision

Precision is the portion of true optimistic examples among the examples that the model categorizes as positive [179]. It can also be defined as the count of true positives divided by the total cases i.e., the summation of false positives and true positives.

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \tag{8}$$

7.4. Recall

Recall, also called sensitivity, is the portion of examples categorized as positive among the total number of positive examples. It can also be defined as the count of true positives divided by the total cases, i.e., the summation of false negatives and true positives.

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives} \tag{9}$$

7.5. Specificity

Computes the value of negatives that are correctly recognized (i.e. the proportion of negatives predicted actually as true negatives). Specificity is defined as the measure of the negative proportion of a process. It is otherwise termed a true negative. The specificity is a significant process in the classification of gait patterns.

$$Specificity = \frac{TrueNegatives}{TrueNegatives + FalsePositives} \tag{10}$$

7.6. ROC curve

This is a method to perform a comparison among diagnostic tests. It is a plot between the true positive rate vs. the false-positive rate [180]. The ROC plot represents the association between specificity and sensitivity. They are inversely proportional; if one increases, the other decreases. Test accuracy: A more precise test is expected if the graph is nearer to the left-hand and the top borders. Similarly, a less precise test is expected if the graph is nearer to the diagonal. An optimal test would go straight from 0 to the top-left corner and then straight across the horizontal. The likelihood ratio: is specified by the derivative at all specific cut-points.

7.7. PSNR

The peak signal-to-noise ratio is the quantity measured as the ratio between the power of the signal noise and a signal's maximum power.

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M^*N} \tag{11}$$

$$PSNR = 10log_{10}\frac{R^2}{MSE} \tag{12}$$

The higher the PSNR, the higher is the quality of the extracted image. This is performed by reducing the noise in the input image.

7.8. Log loss

ROC curve uses the predicted probabilities for determining the model's performance. However, it considers only the order of probabilities, and hence it does not consider the model's capability to predict the greater likelihood for the data-set, which is more likely to be positive. For such conditions, the log loss function can be used. It is the opposing average of the log of corrected predicted probabilities for each instance.

$$logloss = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i)) \tag{13}$$

where $p(y_i)$ is positive class predicted probability, $1 - p(y_i)$ negative class predicted probability. For positive class $y_i = 1$ and for negative class its 0.

8. Conclusion and future directions

In this review paper, the authors provided the current state-of-the-art in a systematic review, a stepping stone for researchers working in this direction. The main points of this paper are outlined as follows:

- **Single Platform to Learn**: The survey aims to furnish systematic insights into Gait analysis. The authors try to cover the basics aspects, early to current techniques, parameters, applications, narrative reviews, performance measures, and future directions in gait analysis. These all available in the review paper will work as a single platform for learning.

- **Review on lagging Areas**: Areas that are not mainly covered in review papers like clinical gait analysis and rehabilitation are covered by the authors in this paper.
- **Latest Trends**: Design and developments of the latest technologies for gait analysis are discussed in the paper. The latest technology used in gait analysis, like computer vision, pose estimation, is adequately discussed in the paper with a systematic up-gradation of review work of pose estimation in gait analysis.
- **Open issues and Future Directions**: For future researchers, valuable suggestions are provided, which will guide them while analyzing the field of gait analysis.

In gait analysis, there are measurement techniques. Usage of Machine learning and deep learning to give more accurate results has been increased [104]. Gait features can be normalized to train Machine Learning models and make predictions. Clinical Gait analysis has future applications in the fields like tracking human gait, extracting gait patterns, rehabilitation, and detecting gait disorders, [196]. Development in wearable robots is also nurturing. Robotic rehabilitation can provide efficient and consistent therapy without exhaustion and the potential to amplify the treatment beyond the therapist's potential. If provided with proper safety and comfort measures, future rehabilitation robots can develop that are portable. In Persons with Multiple Sclerosis (PwMS), ML-based disease prediction strategies show good hope for a better diagnosis. Future Areas for gait analysis are discussed below:

8.1. Marker-less gait analysis

The gold standard system for gait analysis was carried out using the Opto-photogrammetric system, which involved using retro-reflective markers fixed onto the human body to extract the gait patterns. Even though the marker-based gait analysis provides accurate gait measures, it is carried out in extensive laboratories and is highly expensive. To overcome the limitations of the traditional marker-based gait analysis, alternative methods using wearable sensors such as wrist sensors, shoe sensors, etc., were introduced. However, these invasive methods' performance was not satisfactory compared to the gold standard system. The amelioration in technology has resulted in the development of markerless gait analysis systems, which are low-cost and non-invasive. The future challenge is markerless gait analysis that can be done to achieve high accuracy results at a low cost.

8.2. Gait analysis using deep-Q learning

Q-learning is a model-free reinforcement technique that is used for learning the optimal policy in the Markov Decision Process. The agent tries to maximize its points using exploitation and exploration both. This new technique can be used for classification purposes in gait analysis instead of traditional supervised and unsupervised machine learning techniques. Q-learning aims to find the optimal policy by learning the optimal Q value for each state-action pair, thus providing highly reliable results.

8.3. Sensor fusion

Fusion means merging the data from multiple sources into single data. It will improve the accuracy of the data in comparison to the single-source data accuracy because this will blend the data collected from multiple sources [197]. There are two main categories of Sensor Fusion, Homogeneous Fusion and Heterogeneous Fusion [198]. When fusing the same category of sensors, such as wearable sensors and wearable sensors, then it becomes homogeneous fusion whereas, in the case of heterogeneous fusion, merging the data collected from different types of sources such as vision sensors and wearable sensors [199]. Such approaches have the potential to ameliorate the effects of the data leading, which in turn would lead to better decision accuracy. While developing gait-based applications, this technique would be highly efficient.

8.4. Security

Authentication that is gait-based has attracted various researchers. Security and authentication can be improved by gait analysis, by combining gait and biometrics such as the face, retina, voice [200]. Considering this context, the researchers have improved the authentication rate by blending face biometrics and gait. However, this is considered as just starting in this area [201]. An exciting and promising future challenge could be the analysis of biometrics, either single or multiple, with the help of gait. In addition to authentication, spoofing attacks can also be detected and prevented using a proper security mechanism with gait analysis.

8.5. External variants

Gait recognition efficiency has been increased or boosted using the state of artwork which is vision-based. With external co-variants decreasing, the efficiency of recognition algorithms [202]. The co-variants can be anything like clothes, bags, and shoes challenging research area would be the development of such algorithms, which are independent of the presence of co-variants; researchers are working on these areas [119]. However, the maximum accuracy achieved in cloth invariant recognition is 80%. Thus more efficient and accurate methodologies approaches are required to resolve such issues.

8.6. Wearable sensors optimal position

Analysis of gait provides insights into human movement, specifically security, health, and fitness. The maximization of the interpretable information using wearable sensors is its primary focus. Nevertheless, factors like vibration, placement of sensors in pockets, and the movement of clothes introduce obstruction leading to degradation of the quality of data [203]. Thus, the quality of data generated for analysis depends on the location of sensors, so optimal placement of sensors is crucial to developing good quality results. The authors [204] find the right location on foot for placement of IMU sensors to generate good quality results. Also, depending on the requirement of the application, the exact location of sensors may change. So, this area of research needs quality work to be done to detect the optimal location s for the placement of sensors such that fall prevention detection and monitoring can be done in a much better way.

Various aspects of gait analysis ranging from basic terminologies to parameters, approaches, and techniques, are covered in the paper. A comprehensive and detailed review was done from reputed journals and relevant conferences. Development trend in the gait approaches has been discussed in detail. Gait Analysis approaches have been categorized into four major parts: Semi-Subjective Analysis, Objective Analysis, Machine learning techniques, and gait analysis using pose estimation. Gait has healthcare analysis, bio-metric, artificial gait, and control applications. Various techniques have been discussed in the paper, such as Semi-Subjective Analysis(25-Foot Time of Flight, Multiple Sclerosis Walking Scale, Timed Get up and Go, Tinetti Performance-Oriented Mobility Assessment, Gait Abnormality Rating Scale, and Extra-Laboratory Gait Assessment Method), Objective Analysis(Image Processing Techniques, Floor Sensors and Wearable sensors), Machine Learning Techniques (Supervised, Unsupervised and Reinforcement) and Pose Estimation techniques in gait analysis. A comprehensive and narrative review of all the techniques is discussed in detail. The paper also discusses performance metrics such as F-Score, Precision, Recall, Specificity, ROC curve, and PSNR.

It is observed that the objective techniques are most applied more widely and used for gait analysis. Data for gait is highly heterogeneous, multi-dimensional, temporal dependent, variable. It is not easy to process such data. Deep learning techniques have a vast scope in Identification, detection of abnormality, classification of gait data. The authors hope that this paper will provide valuable references for future research on gait analysis approaches, application, and deep learning techniques in gait analysis.

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