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Towards Enhanced Biometric Systems: Insights into Human Gait Recognition

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Abstract

Gait recognition is a biometric method of identifying people based on their walking pattern, which is the result of the coordinated action of the brain, nervous system, and muscles. Historically, gait analysis has been performed using a simple visual approach, but now several new tools have emerged, such as wearable sensors and vision-based motion capture, and a nonintrusive approach to facilitate gait analysis. In this paper, a detailed review of human gait recognition is presented. This is followed by a bibliometric analysis of the trends of publication, major sources, and country-wise research contributions. The current state of the art of research is then summarized, ranging from handcrafted feature-based approaches to recent deep learning architectures and the public datasets and benchmarks that have been used, from 2005 onwards, to demonstrate how performance has improved over time using the CASIA-B dataset. In addition to the technical aspects, the applications of gait recognition in surveillance, healthcare, sports, and defense are discussed. Last, we discuss some future directions, including cross-domain learning, transformer-based models, etc., and present key challenges, including domain shift, covariate sensitivity, data dependency, and privacy concerns. The collective discussions provide a framework for researchers and practitioners in gait recognition and identify the gaps that still need to be filled to enable more widespread adoption of gait recognition in practice.

Keywords: Gait Recognition, deep learning, soft biometric, gait cycle, biometric system

Introduction

From the analytical point of view, one of the most difficult things to understand is the ability to move, and this is one of the most basic functions of the human body. When the nervous system, brain, and limbs function together properly, walking arises. Gait is a symbol of freedom and individuality - hence any alteration in one's usual gait can have a marked impact on a person's quality of life. Qualitative gait assessment has traditionally been done through simple visual inspection, but now gait can be assessed scientifically and practically (Deligianni et al., 2019).

Gait is the characteristic way that people walk, run, or creep, and the general posture pattern; it is the most important way in which humans move and propel themselves. Humans are bipedal animals, and there are two legs that allow them to walk – it is important to note that gait is the manner of walking but not walking itself (Etemad & Arya, 2016). In this respect, gait and walking are not synonymous but rather reflect a more significant distinction. This is the study of this locomotion pattern we call gait analysis.

Over the last few years, the use of soft biometrics has increased significantly. They can recognize people from a distance; they are not intrusive; they are potentially predictive of human activity; they are not dependent on a single modality, and they have generally high recognition rates, all making soft biometrics more and more relevant in today's digital world (Etemad & Arya, 2016). Notwithstanding these obvious benefits, soft biometrics have several unanswered research questions that remain and need to be resolved before soft biometrics can be used as a viable alternative to traditional biometric methods (Etemad & Arya, 2014). In parallel with the development of computer vision, machine learning, wearable sensing and deep neural networks, there has been a significant increase in interest in gait recognition. The previous work focused on silhouette-based handcrafted features, gait energy templates and body-part measurements, which were found to be limited by viewpoint variations, sensor noise and cluttered real-world background. Deep learning techniques in recent years, like set-based convolutional models, part-based frameworks, graph neural networks, neural architecture search, and attention-driven architectures, have brought a significant boost in recognition accuracy and scaling to benchmark datasets. Although there have been advances, human gait recognition is not reliable enough to be used in real-world applications. Many models that work well in laboratory settings fail to work well in practical settings, in part because of the messy nature of the real-world environment: silhouettes are often incomplete, background clutter can significantly vary an individual's appearance, and clothing variations can have a significant impact on the look of a person walking from one place to another. We need to think about how people walk, how we collect data, how we design models, and how we test them. We also need to think about what we do not know, and about unresolved research gaps. This review of human gait recognition research aims to give an organized summary of what we know now. It will focus on learning how datasets have changed, what we have learned from benchmarks, and where we need to go next to make biometric systems better. It will look at the relationship between how people walk, data acquisition strategies, model design, and benchmark protocols to find out what is still missing in human gait recognition research.

Literature Review

The way a person walks is called their gait. It is a fact that every person walks differently. Doctors have found that each person has their own way of walking. You can actually tell who someone is by the way they walk (Etemad & Arya, 2015). Human Gait is generally affected by several factors, including shoes, clothing, objects, context, as well as the view angle of the human and other obstacles (Echterhoff et al., 2018). People do research to learn more about how humans walk and stand. They want to know about how people move around. This approach is known as gait analysis (Zhang et al., 2020). The uniqueness of an individual's gait arises not from a single parameter but from the complex interplay of multiple spatial, temporal, and dynamic characteristics.

Gait Cycle

The gait cycle refers to the sequence of cyclic events that occur during walking. The concept of human locomotion and the gait cycle was first introduced and described by the Weber brothers in 1836 (Bei et al., 2018; Wan et al., 2018). A gait cycle begins when one foot makes initial contact with the ground and ends when the same foot contacts the ground again. It primarily involves the coordinated movement of the lower limbs, pelvis, and spinal column. One complete gait cycle is referred to as a stride.

The gait cycle begins with the initial heel contact of one foot and ends when the same foot makes initial contact with the ground again. A complete gait cycle, or stride, consists of two phases: the stance phase and the swing phase. While walking, the gait cycle alternates between the right and left lower limbs. The stance phase corresponds to the period during which the foot remains in contact with the ground, accounting for approximately 60% of the gait cycle, whereas the swing phase represents the period during which the foot is off the ground, comprising the remaining 40% of the cycle (Jarchi et al., 2018). According to Perry and Burnfield (2010), Figure 1 shows that the gait cycle can be divided into distinct functional phases corresponding to specific movements and muscle activities during walking. The key functional divisions focus on the transition between stance and swing, along with the roles of various muscles and joints in providing stability, propulsion, and balance throughout the cycle (Stöckel et al., 2015).

The stance and swing phases are further divided into eight subphases, each representing a distinct segment of the gait cycle. These subphases provide a comprehensive description of the sequence of movements and joint positions throughout a complete stride and play a critical role in gait pattern analysis and identification.

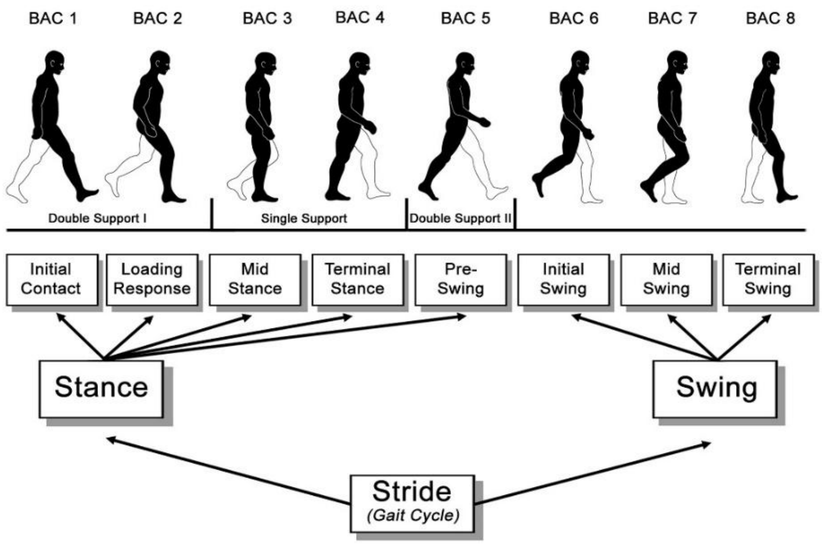


Figure 1. Phases of a gait cycle (Masood & Farooq, 2017)

All these eight phases or segments are defined below:

i. Initial Contact (IC): The gait cycle starts from this phase when the heel of the first leg strikes the ground. This phase contains nearly 0-2% of the total stride.

ii. Loading Response (LR): This phase starts when the other leg begins to be lifted for swing with reference to the first leg. The first leg is in full contact with the ground, and the weight of the person due to gravity is completely transferred to the first leg. This phase takes at most 2-10% of the total gait cycle.

iii. Mid Stance (MS): This is the third segment of the Gait Cycle. In this phase, the heel is completely swung in the air, and the gravity force is completely over on the first foot. This phase starts when the shin bone of that leg, which is in the air, is upright on the ground. This phase contains around 15% to 30% of the overall cycle of gait.

iv. Terminal Stance (TS): In this phase, the movement of the other leg is going to come into the rest position. It is the point where the movement of hip extension occurs just before the pre-swing phase. This phase contains at most 30-50% of the total gait cycle.

v. Pre-Swing (PSw): During this subphase, the contralateral heel makes initial contact with the ground, while the ipsilateral foot begins its backward swing and lifts off the ground. This phase occurs near the end of the stance phase, which accounts for approximately 55%–60% of the gait cycle.

1. Initial Swing (ISw): This subphase marks the beginning of the swing phase. During this stage, the hip of the swinging limb begins to flex while the knee remains flexed to facilitate foot clearance. It extends from approximately 60% to 73% of the gait cycle.

2. Mid Swing (MSw): This segment of the swing phase is. In this phase knees bending of the first leg is at its peak. It contributes around 75% to 87% of the total stride.
3. Terminal Swing (TSw): The last phase of the stride is the swing phase. In this phase, the shin bone is perpendicular to the floor. It contributes 87-100% of the overall gait cycle.

Attributes involved in Gait Analysis

The distinction between normal and abnormal gait has been discussed in the previous section. To characterize normal gait patterns, researchers and clinicians have investigated a wide range of gait parameters and biomechanical variables. Consequently, understanding these parameters is essential for gait analysis. Previous studies have classified gait variables into six major categories (Hausdorff, 2005; Nambiar et al., 2019; Rida et al., 2018). Historically, gait analysis dates back to 1878, when Eadweard Muybridge conducted the first systematic motion analysis of a horse, published as The Horse in Motion (Clayton & Hobbs, 2019).

Here we have defined all those categories in Table 1.

Table 1. Attributes Involved in Gait Analysis

Sociodemographic	State-space	kinematic	Motion Based	Electromyography	Hybrid
height, BMI, age, gender, weight, head circumference, head length and width, finger length, foot length, leg measurement, waist, hip, and limbs.	Step width and length,8 phases of a gait cycle, speed of a gait cycle, action taken at foot end or foot strike.	Joints, hip motion, knee motion, acceleration, Segment Trajectory.	Gravity Force, torque, momentum	Motor Unit Action Potentials (MUAPs)	Combination of more than one category.

It is important to choose the variables and parameters of humans carefully and after analyzing the problem statement. As different problem statements prefer different gait parameters. For example, if any study analysis over gait is needed in the sports field, it will be better to prefer the analysis of muscle force applied on the foot over other parameters. If gender classification needs to be performed, then anthropometric features and the measurement of body needs to be considered, etc.

Types of Gaits

- Normal Gait: It is not easy to define the normal gait pattern of a person. Various factors are involved while analyzing the normal gait of the human. Age and gender are two of the important factors of a person while analyzing the gait pattern or cycle. A review of the literature identified several parameters used to characterize healthy gait across different age groups. However, these reference values are largely heuristic and may not be universally applicable, as gait patterns can vary across populations due to regional, cultural, and sex-related differences. Table 2 summarizes the key parameters commonly used to describe healthy human gait. It is important to have the numeric estimation of normal gait variables for the detection of any gait disorder, for measuring the correct balance feature, and for the need for any medical gait intervention and reformation. Orthopedists and physio experts generally take care of or analyze the attributes involved in the process of gait movement, attributes like complete gait length, length of each step taken by the person, rhythm of walking pattern, including complete cycle of both stance and swing phase, etc., of such individuals, to detect any abnormality while comparing with the parameters of normal healthy gait.

Table 2. Performance of healthy subjects divided by age decade

Age Decade	Speed (m/s)	Stride Length (m)	Cadence (steps/min)	Double Support Time (s)	Trunk Rotation (°)	Step Width (m)
10–19	1.15 (0.12)	1.25 (0.11)	115.3 (9.5)	0.15 (0.02)	12.4 (2.5)	0.11 (0.03)
20–29	1.20 (0.14)	1.30 (0.12)	110.4 (8.9)	0.16 (0.03)	11.8 (2.7)	0.12 (0.02)
30–39	1.18 (0.13)	1.28 (0.10)	108.7 (8.7)	0.18 (0.03)	11.5 (3.0)	0.13 (0.02)
40–49	1.12 (0.15)	1.22 (0.13)	106.2 (10.1)	0.21 (0.04)	10.9 (3.2)	0.13 (0.03)
50–59	1.08 (0.16)	1.18 (0.14)	103.5 (9.8)	0.24 (0.05)	10.4 (3.5)	0.14 (0.03)
60–69	0.98 (0.17)	1.12 (0.15)	98.7 (11.2)	0.27 (0.06)	9.8 (3.8)	0.15 (0.03)
≥70	0.85 (0.19)	1.05 (0.16)	91.2 (12.5)	0.30 (0.07)	9.0 (4.2)	(0.04) 0.16

- Abnormal Gait: Abnormal gait can result from short-term or long-term trauma, or even from poor kinematics. It affects ligament surface tensions and prevents the leg from carrying pressure normally. Generally, when a person cannot walk properly or has an unusual walking style is treated as an abnormal gait. Numerous types of abnormal gait have been documented, each associated with specific underlying conditions. These abnormalities may manifest as involuntary bending and rotation of the elbow while standing, differences in muscle rigidity between the upper and lower extremities, difficulty lifting the foot during walking due to nerve weakness (resulting in foot dragging), or impaired hip stability during locomotion. Furthermore, several neurological disorders, including Sydenham's chorea, Parkinson's disease, Huntington's disease, other forms of chorea, sensory impairments, athetosis, and dystonia, are commonly associated with abnormal gait patterns.

Process of Gait Analysis

Generally, we have seen that vision-based approaches are used to capture the gait pattern of a human. Due to the advancement in the field of IoT, we have several sensors or wearable devices through which we can be able to perform the process of gait analysis. The general process of Gait Analysis needs to follow the following steps: Data Collection->pre-processing-> Feature Extraction-> Dimension Reduction-> Classification.

There are several ways to collect the data based on the problem statement. Two methods that are discussed here for data collection are the vision-based method and Sensor-based method.

Vision-based method: Vision-based gait analysis captures walking sequences using video cameras and can be categorized into marker-based (direct) and markerless (indirect) approaches (Etemad & Arya, 2014; Masood & Farooq, 2017). In the marker-based approach, also known as direct vision-based gait analysis, active or passive markers are attached to the subject's body, and an optoelectronic system tracks the emitted or reflected light from these markers to analyze body movements and dynamics. In contrast, markerless gait analysis does not require physical markers. Instead, gait characteristics are extracted from recorded video sequences using model-based, appearance-based, or hybrid techniques. Owing to its non-intrusive nature, the markerless approach is widely employed in surveillance-based human gait recognition.

Sensor-based method: Sensor-based gait analysis employs sensors placed either on the participant's body or on the ground to capture gait characteristics. Wearable sensors commonly include electromyography (EMG), accelerometers, gyroscopes, and surface EMG systems, which are attached to the participant's body to measure movement and muscle activity (Muro-de-la-Herran et al., 2014). Force platforms are also widely used to assess gait dynamics by measuring ground reaction forces. Among these sensing technologies, EMG is frequently employed to identify gait phases and analyze muscle electrical activity during walking. Various techniques have been proposed to collect and process data from wearable sensors for gait pattern analysis (Zhang et al., 2020). Inertial sensing systems operate based on the principle of resistance to changes in motion, whereas floor platform-based sensors are used to measure parameters such as plantar pressure distribution, ground reaction forces, gait phases, and footstep events. Pressure sensors, typically embedded within shoe insoles, are used to capture plantar pressure and stress distribution during walking.

Research Questions

The core components of research questions are used to review the literature. In Table 3, the investigation issues about the identification of a person's walk are listed.

Table 3. Research question and answer

S/R No.	Question	Answer
1	What is gait?	Gait is the walking pattern of a person.
2	What is gait recognition?	Every individual has a unique gait or walking pattern. To recognize or identify a person through their gait or walking style is called gait recognition.
3	Is it better than other recognition techniques?	Gait recognition can be done from a distance, unlike face or iris recognition. Therefore, it is most effective in crowded place surveillance.
4	Why will people use gait recognition?	For security purposes, especially in public places like airports, malls, or railway/bus stations.
5	Where can gait recognition be used to serve society?	Gait analysis helps in many fields like monitoring soldiers' or sports persons' health, for surveillance, during old-age health monitoring, in robotics, and for normal or abnormal gait analysis.

6	What are the challenges faced during gait recognition?	Every machine needs a good dataset to provide efficient learning results. Collecting a proper dataset with appropriate attributes and multiple viewpoints while covering all covariate issues is the main challenge in gait analysis.
7	What are the techniques used in gait recognition?	Using various sensors like accelerometers, floor sensors, cameras, and radar, data for the gait of people has been collected.
8	Which technique is best or widely used?	Camera recording in the form of images or videos is widely used and considered a more convenient technology for data collection.

- What biomechanical properties of gait support its use as a biometric and behavioral signal?(Munusamy & Senthilkumar, 2024b)
- How have gait representations evolved from handcrafted descriptors to deep spatial–temporal embeddings?(Filipi Gonçalves Dos Santos et al., 2023)
- Which benchmark datasets and evaluation settings dominate the field, and how do they shape reported progress?
- What are the major limitations of current gait recognition methods under clothing variation, view changes, occlusion, and domain shift?
- How can future gait systems integrate identity recognition with soft biometrics, affect, health status, and privacy-aware deployment?

Methodology

Gait recognition has emerged as a critical research area in biometrics, artificial intelligence, and machine learning. This section presents a bibliometric analysis of gait recognition research based on data collected from multiple scholarly databases. The bibliometric dataset was compiled from Web of Science, Scopus, Google Scholar, Dimensions AI, and Semantic Scholar. Various tools like VOSviewer and Mendeley were used for various kinds of analysis and reference coordination, respectively. The core search query was:

TS= [{Gait Recognition} AND {Deep Learning OR ML OR AI OR Gait}]

This search gave us a lot of results at first: 328,955 papers to look at from decades. We found that 1,960 papers about this were published between 2020 and 2024, which shows that this area is growing fast right now.

Methodology

To pick the papers, we used keywords like “Gait Recognition”, “Deep Learning”, “Machine Learning,” and “Artificial Intelligence”. We looked at papers from 1982 to 2025. We paid special attention to the 1,960 papers from 2020 to 2024. The following inclusion criteria were applied:

Language: English.

Document type: Research and review articles, including original research and empirical studies.

Indexing: All indexes available across the selected databases.

Publication period: Publications up to December 31, 2025.

The exclusion criteria eliminated non-article publications, studies unrelated to gait recognition, and papers that did not satisfy the predefined eligibility criteria. Following the screening process, 135 studies remained for detailed analysis of gait recognition.

Results

Publication Trends: The 2,500 selected papers included both foundational and cutting-edge research, most of which (≈1,960) was published within the last five years. The overall trend of publications on gait recognition shows continuous and significant growth from 1982 to 2025, as shown in Figure 2. The first record is from 1982 with 228 publications, and the output is generally increasing over time with some fluctuations, which is indicative of the slow growth of interest in the field. A major growth phase can be observed from the early 2000s onwards, followed by sharp increases in the 2007-2025 period, indicating strong impact of advances in deep learning, artificial intelligence and biometric technologies. The highest annual output is observed in 2025, with 20,036 publications, while other peak years include 2021 with 20,366 publications, 2023 with 17,062 publications, and 2024 with 16,714 publications. Overall, the graph demonstrates that gait recognition research has developed into a rapidly growing and highly active research domain.

Keyword Frequency: For this purpose, a keyword analysis was performed to identify the most used and relevant keywords in the research of gait recognition. To ensure that only significant and impactful keywords were part of the analysis, a minimum of 25 appearances for a term was established. From the 54,351 keywords extracted from the dataset, 699 terms met this threshold. The most common keywords are “Gait Recognition”, “Deep Learning”, “Machine Learning”, “Artificial Intelligence”, “Biometrics,” and “Neural Networks,” suggesting the technological and methodological focus of the research in this field. Furthermore, some terms such as “Feature Extraction”, “Pattern Recognition”, “Human Identification,” and “Surveillance” emphasize the main applications and goals of studies on gait recognition. A relevance score was calculated for each of the initial 699 terms that met the minimum threshold of 25 occurrences, to identify the most impactful and significant keywords for the study. The default approach used the relevance scores to keep the top 60% of the terms, resulting in a refined set of 419 keywords.

Sources: In our full analysis of 634 sources over 2,500 documents, we identified the 14 most relevant journals at the threshold of a minimum of 25 documents with a source (See

Figure 5). The mentioned journals were selected based on their document count, citations, and link strength to indicate their influence in the field. Figure 7 is the VOSviewer image of the journal linking map that visually depicts the connections between these prominent sources. The comparison highlights the dominance of citation influence in established venues such as Sensors, Scientific Reports, and Gait & Posture, while document contributions vary significantly across publication sources, as shown in Figure 3. Regarding the authors presented in Figure 9, the visualization highlights prominent contributors, including Wang Liang, Nikolaos V. Boulgouris, and their collaborators, revealing interconnected research communities and multidisciplinary collaboration patterns within the field.

Country-Wise Contributions: The most prolific countries in gait rehabilitation research are the United States, Canada, and Switzerland, according to the study "Global Research Trends on Gait Rehabilitation in Individuals with Spinal Cord Injury". The country-wise analysis reveals the international contributions in gait recognition research, where China is the most productive contributor with 613 documents and 7863 citations, with the maximum total link strength of 824, which indicates excellent international collaborations and significant research output.

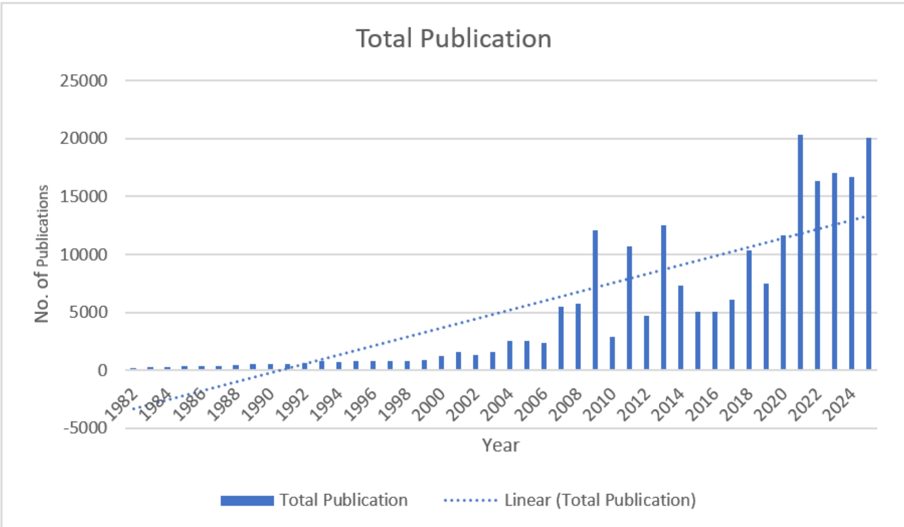


Figure 2. Total publications on gait recognition from 1982 to 2025, showing the annual publication trend and the strong growth of research output in recent years

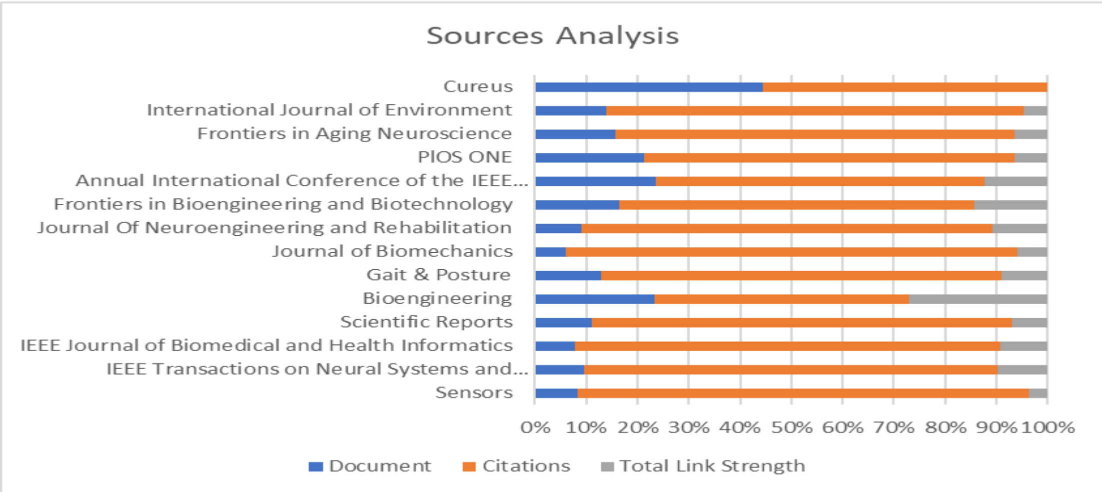
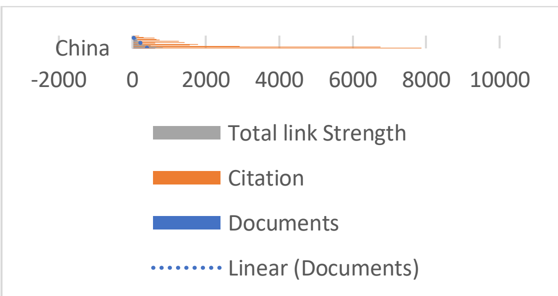


Figure 3. Sources analysis showing the relative contribution of document count, citation impact, and total link strength across major journals and conference proceedings in gait recognition and biomedical research.

The United States follows with 567 documents, 6750 citations, and a total link strength of 649, showing its considerable influence. The UK has 218 documents, 2915 citations, and a total link strength of 501, reflecting its high-impact research and active collaborations. Major contributions are from European countries such as Italy (150 documents), Spain (84 documents), and Germany (127 documents), with an emphasis on interdisciplinary research. India (85 documents) and Japan (117 documents) are emerging as key players for the advancement of gait recognition technologies. Other significant contributors are Canada (137 documents), South Korea (128 documents), and Australia (97 documents), which focus on biometrics and AI-based solutions. The results indicate that China and the United States dominate the field in terms of citation influence and research productivity, while countries such as the United Kingdom, Canada, and Italy demonstrate strong collaborative link strength and sustained research activity. Figure 8 shows the network highlights strong collaborative relationships between China, the United States, the United Kingdom, and South Korea, indicating their central role in global research partnerships and knowledge exchange within the domain.



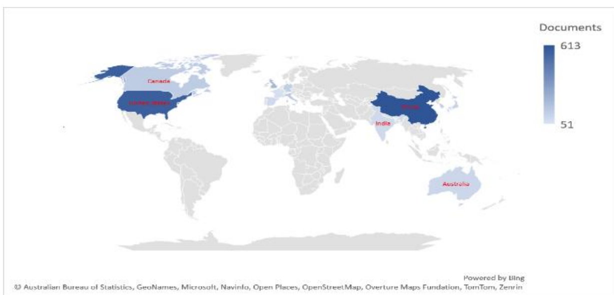


Figure 4 (left). Country-wise scientific contribution analysis in gait recognition research based on document count, citation impact, and total link strength
Figure 5 (right). Country-wise distribution of gait recognition research output, citations, and collaboration strength among the leading contributing nations

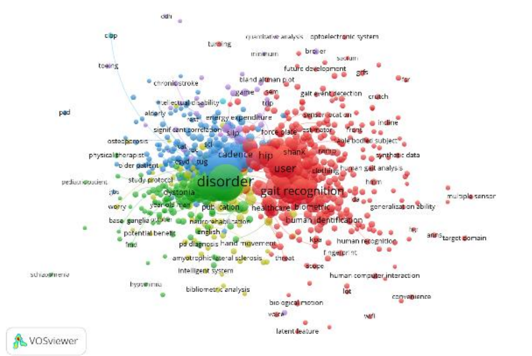


Figure 6. Keyword co-occurrence network of gait recognition research illustrating major research themes and thematic clusters.

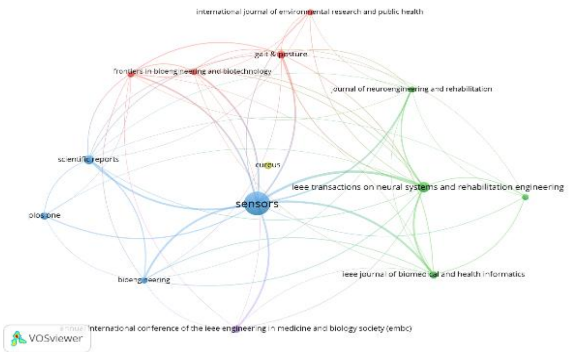


Figure 7. Journal co-citation and source-linking network of the leading publication venues in gait recognition research

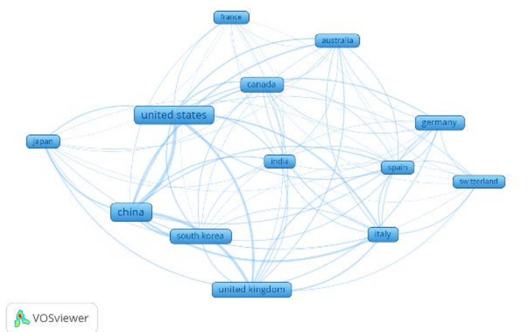


Figure 8. An international collaboration network visualization generated using VOSviewer, illustrating research connectivity among countries contributing to gait recognition studies.

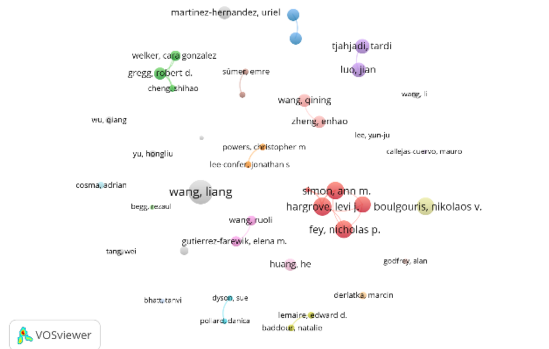


Figure 9. Author collaboration network generated using VOSviewer, illustrating co-authorship relationships and research clusters within gait recognition and biomedical analytics studies.

Related Work

Gait analysis and recognition enable the identification of individuals from a distance, making gait a distinct advantage over other biometric modalities, such as facial recognition, iris recognition, and fingerprint recognition, which typically require subjects to be in proximity to the sensing device (Ali et al., 2016; Hutchison & Mitchell, 2005; Nguyen et al., 2024; Nixon et al., 2002). Consequently, gait has attracted considerable attention in the biometrics community, leading to numerous review studies and surveys on gait recognition (Munusamy & Senthilkumar, 2024a).

As human behavior becomes increasingly diverse and complex, accurately understanding an individual's state has become increasingly important. Human gait, posture, and body movements can provide valuable information about an individual's emotional and behavioral state, enabling the inference of characteristics such as happiness or sadness, fatigue or vitality, as well as demographic attributes including sex and age (Deligianni et al., 2019). By analyzing human gait, one can help to provide a real-time application for the same to implement in any scenario. Basically, they have included the evolution of gait analysis from machine learning techniques to deep learning. Descriptions of publicly available gait datasets that are used by the researchers are mentioned. They have properly bifurcated the dataset types in terms of subjects, environments, view angle, etc. Some of the studies also introduce the roadmap taxonomy and default architecture to understand the process of gait analysis. A number of methods have been mentioned based on model-based and appearance-based theory. The study has deeply focused on state-of-the-art techniques as well to introduce the common methodology and base techniques for further work.

Gait feature extraction is the process of extracting meaningful information from gait videos or sequences that can be used to represent an individual's walking style. Researchers have proposed various methods for gait feature extraction, including using motion information, silhouette information, and texture information. Some studies have used motion-based features, such as joint angles and velocities, to describe gait patterns. Silhouette-based methods use the shape and contour of the person's body in motion to extract features. Gait representation is the process of converting the extracted features into a compact and descriptive representation that can be used for comparison and classification purposes. Researchers have proposed various representations, including gait energy images, gait silhouette sequences, and gait templates.

Evolution of Gait Recognition Methods

Initial gait recognition methods used handcrafted descriptors, such as silhouette templates, gait energy images, contour statistics, spatiotemporal moments, and manually selected kinematic variables. These methods were computationally efficient and interpretable. However, their performance degraded substantially under appearance variation, sequence noise, and cross-view conditions. Thus, the field has gradually shifted to representation learning approaches that can discover discriminative features directly from data. This transition was accelerated by deep learning that allowed end-to-end learning from gait sequences, silhouettes, skeleton graphs, or sensor time series. For silhouette-based recognition, CNN-based approaches dominated, while graph neural networks and recurrent or temporal models extended the applicability of gait analysis to skeleton and inertial modalities. More recently, neural architecture search and attention-based designs have further improved the ability to capture subtle local and global motion patterns.

As shown in Figure 10, the historical evolution should be presented as an evolution in representation power and not as a simple chronology.

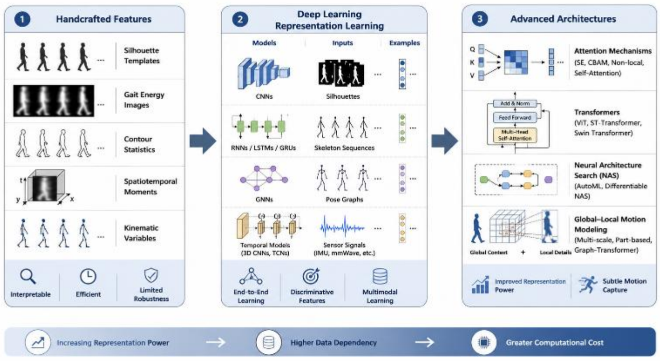


Figure 10. Evolution of gait recognition methodologies from handcrafted feature engineering to deep learning–based representation learning and advanced attention-driven architectures

Advancements in Gait Recognition Technologies

Gait recognition has seen significant improvements with new techniques that address long-standing challenges. The Gait Period Set (GPS) and its enhanced version, the Improved Gait Period Set (IGPS), have emerged as key methodologies in this domain. These approaches leverage Convolutional Neural Networks (CNNs) and Modified Generative Adversarial Networks (M-GANs) to extract and classify gait patterns with high precision (Zhang et al., 2019; Huang et al., 2021). They achieve robust performance by considering sequence consistency and employing generative models, even under conditions of low-resolution or noisy frames. Furthermore, Bayesian optimization has been integrated with advanced deep learning frameworks such as HGRBOL2, which utilizes Sq-Parallel Fusion and Extreme Learning Machine (ELM) classifiers. This integration optimizes hyperparameters and ensures optimal feature selection, resulting in robust classification performance across diverse datasets.

Ensemble Techniques for Comprehensive Gait Analysis

The use of ensemble methods has revolutionized the field of gait recognition by exploiting the strengths of multiple heterogeneous classifiers. Approaches that combine Naive Bayes, Artificial Neural Networks (ANNs), and K-Nearest Neighbors (KNNs) can capture complex gait features that a single model might not (Derlatka & Borowska, 2023). Ensemble techniques combine multiple views of decision-making and improve the generalizability and reliability of gait recognition systems and are thus suitable for real-world applications where variability is common. Such methods are particularly advantageous in cases where environmental elements, like lighting and background noise, add to the complexity, providing a balanced and adaptive solution to gait analysis.

Deep Learning and Multimodal Sensor Integration

Deep learning frameworks have changed gait recognition by allowing the fusion of multi-modal sensor data. For example, inertial sensors embedded in wearable devices provide continuous and reliable data that are not affected by external variables such as clothing, occlusions, or lighting changes (Shi et al., 2023). These sensors, along with advanced deep learning architectures, have shown remarkable robustness and accuracy. The multi-sensory input models extract gait features from multiple perspectives to reduce the effect of incomplete or noisy data. These frameworks also enable real-time analysis, opening the door to their deployment in healthcare, security, and personalized monitoring systems (Scott et al., 2022).

Skeleton Models and Lightweight Algorithms

In the study, it is seen that skeleton-based methods are now more popular by checking their effectiveness in human gait recognition tasks. Various methods like Principal Component Analysis (PCA) with ANN and Gaussian Bayes classifiers use the skeletal data for demonstrating gender classification and human gait identification in an efficient way (Alsaif et al., 2023). It is found that computationally, these methods are more efficient. Furthermore, skeleton-based methods are less intrusive and more privacy-friendly than video-based methods, which comply with ethics in the use of biometric data.

Public Datasets and Benchmarks:

Benchmark Gait datasets play a crucial role in gait recognition research. Various widely used datasets such as CASIA-B and OU-MVLP have enabled rapid progress by providing multi-view gait sequences under relatively clean conditions and have shown good results (Bansal et al., 2024). Gait3D similarly provides a large-scale benchmark with more natural scene variation and has become central in recent Open Gait evaluations.

Various datasets have been used to evaluate gait recognition systems. These datasets encompass a range of aspects relating to individual looks, surroundings, and acquisition angles. To properly train deep neural networks, big datasets are frequently requested and recommended, both in terms of the quantity and quality. Table 4 provides a summary of the key traits of well-known gait datasets. The kind and mode of the information, the number of individuals and sequences, the number of points of view, as well as the variations covered in each dataset are some examples of these characteristics. A dataset is a crucial and important aspect of every intelligent model to be trained well. Various research studies have also mentioned the dataset as one of the challenges in the path of gait analysis. Publicly available gait datasets are generally classified as indoor and outdoor in terms of environment.

A human gait dataset typically consists of data collected from sensors that measure the movements of the body during walking or running, including kinematic data (such as joint angles and limb movements), kinetic data (such as forces and moments), and electromyographic data (which measures muscle activity). This data can then be used to analyze and understand the mechanics of human gait and to identify patterns and trends in gait behavior.

Studies that have used human gait datasets have contributed to our understanding of various aspects of gait, including gait stability, the influence of ageing on gait, and the impact of gait disorders such as Parkinson's disease. For example, gait analysis has been used to study the effects of different types of footwear on gait, as well as the impact of various gait-training interventions on gait mechanics. Table 5 provides an overview of human gait datasets, including their objectives, data acquisition methods, primary data modalities, applications, and key contributions to the study of gait stability, aging-related changes, gait disorders, and the development of intelligent gait analysis systems.

Table 4. Summary of the key traits of well-known gait datasets

Dataset	Year	Subjects / Sequences	Environment	Description
UCSD ID	1998	6 / 42	Outdoor, wall background	Early outdoor gait dataset with simple background.
SOTON Large	2001	115 / 2,128	Indoor, outdoor, treadmill	View-angle variations and surface changes.
SOTON Small	2001	12 subjects	Indoor, green background	Carrying condition, clothing, shoe, and view variations.
MIT	2001	24 / 194	Indoor	View-angle variations.
HID-UMD dataset 2	2001	55 / 222	Outdoor, top-mounted camera	Different viewpoints (front, side) and time variations.
HID-UMD dataset 1	2001	25 / 100	Outdoor	Outdoor gait under varying conditions.
Georgia Tech	2001	15 / 268	Outdoor, magnetic tracker	Timespan (six months) and viewpoint variations.
CMU MoBo	2001	25 / 600	Indoor, treadmill	Different walking speeds, carrying conditions, and surface incline.
CASIA database A	2002	20 / 240	Outdoor	Three viewpoints; early multi-view gait dataset.
HumanID Gait Challenge	2002	122 / 1,870	Outdoor	Viewpoint, surface, shoe, carrying condition, and time variations.
CASIA database C	2005	153 / 1,530	Outdoor night, thermal camera	Speed and carrying-condition variations in infrared imagery.
CASIA database B	2005	124 / 13,640	Indoor	11 viewpoints; clothing and carrying-condition variations.
SOTON temporal	2012	25 / 2,280	Indoor	Time and view variations.
TUM-IITKGP	2010	35 / 840	Indoor hallway	Various carrying conditions and occlusions.

TUM-GAID (Audio, Image, Depth)	2014	305 / 3,370	Indoor, silent	RGB, depth, and audio recordings; includes age, gender, height, and shoe type.
OU-ISIR D	2007–2012	185 / 370	Indoor, treadmill	Gait fluctuations across time.
OU-ISIR B	2007–2012	68 / 1,350	Indoor, treadmill	Clothing variations.
OU-ISIR A	2007–2012	34 / 408	Indoor, treadmill	Walking speed variations.
OU-ISIR LP Bag	2017	62,528 / 187,584	Indoor	Seven different carrying-object conditions.
OU-MVLP	2018	10,307 / 259,013	Indoor	Normal walking from many viewpoints; large-scale multi-view benchmark.
OG RGB+D	2021	96 / 58,752	Indoor	Straight and curved walking; low, medium and high occlusion clothing; up to three people together.
GREW	2021	26,345 / 128,671 (+233,857 distractor)	Outdoor, in-the-wild	Large-scale in-the-wild benchmark with many cameras and rich covariates.
OU-MVLP Pose	2020	10,307 / 259,013	Indoor	Normal walking; multi-view pose sequences.
Gait3D	2022	~4,000 / >25,000	Unconstrained indoor multi-camera	Dense 3D SMPL representations; multi-view indoor scene with natural walking.
SUSTech1K	2023	1,050 / 25,239	Outdoor	LiDAR-based 3D gait data plus RGB and silhouettes for biometric identification.
GaitLU-1M	2023	>10,000 / >1,000,000 sequences	Indoor	Over one million silhouette sequences; large-scale indoor benchmark for deep gait models.
CASIA-E	2023	>1,000 / ~1M videos	Indoor and outdoor	Large-scale outdoor gait dataset with multiple scenes and views.

Here is a table summarizing some important information about human gait datasets:

Table 5. Summary of human gait dataset characteristics, applications, and contributions in gait analysis research

Information	Description
Purpose	To study and understand the mechanics of human gait, including gait stability, the influence of ageing, and the impact of gait disorders.
Data Collection	Data is collected using sensors that measure kinematic, kinetic, and electromyographic data during walking or running.
Data Types	Kinematic data (joint angles, limb movements), kinetic data (forces, moments), electromyographic data (muscle activity)
Applications	Used to study the effects of different types of footwear and gait-training interventions on gait mechanics, and to develop machine learning models and wearable technologies for gait analysis.
Key Contributions	Human gait datasets have contributed to our understanding of human gait, including gait stability, the influence of ageing, and the impact of gait disorders.

It is seen that CASIA is the most widely used dataset among researchers for testing the proposed model. Table 6, mentioned below, has surveyed the techniques used on that dataset in different scenarios.

Table 6. Methods and Accuracy achieved on the CASIA B dataset, since 2005

Year	Method	Dataset	Accuracy
2005(Lam et al., 2005)	SStS, PCA	CASIA	90%
2005 (Lu et al., 2005)	FastICA	CASIA (NLPR)	85%
2006 (Tan et al., 2006)	HTI	CASIA Infrared Night Gait Dataset	79.5%
2006 (Lu et al., 2006)	Wavelet Descriptors and Independent Component Analysis, NN and SVM Classifiers	CASIA (NLPR database) (20 persons, 3 views)	90%
2007 (Liu & Zheng, 2007)	Gait History Image (GHI)	CASIA Database	80%
2008 (Goffredo et al., n.d.)	Front-view Gait Recognition Method	CASIA-A dataset CASIA-B Gait Database	96.3%
2009 (Bashir et al., 2009b)	Fusion of MIIs and MDIs	CASIA-A, B, C Dataset	76.6%
2009 (Bashir et al., 2009a)	GEnI	CASIA-A, B, C Dataset	80.1%
2010 (E. Zhang et al., 2010)	AEI, two-dimensional locality preserving projections (2DLPP)	CASIA gait database (dataset B and C) d	B-87.50 C-89.43
2010 (Lee et al., 2010)	motion contour image (MCI), nearest neighbor	CASIA gait dataset A.	94%
2011 (Conference & Processing, 2011)	Robust View Transformation Model	CASIA gait dataset	65.8%
2012 (Arai & Andrie, 2012)	Gait Recognition Method Based on Wavelet Transformation: HG recognition method	CASIA gait dataset	95.97%
2013 (Jeevan et al., 2013)	Gait Pal and Pal Entropy Image (GPPE), SVM	CASIA-A, B, C Dataset	55%
2014 (Lishani et al., 2014)	HARALICK TEXTURE FEATURES EXTRACTED FROM GEI.	CASIA database	86%
2014 (Rida et al., 2014)	supervised feature selection method	CASIA database	85.21%
2015 (Rokanujjaman et al., 2015)	EnDFT	CASIA database	90%
2016 (Rida et al., 2016)	supervised feature extraction method	CASIA-B Dataset	81.40 %
2016 (Xing et al., 2016)	C3A	CASIA Dataset	85.37%
2017 (Yu et al., 2017)	Deep model based on autoencoder	CASIA B Dataset	71.72%

2018 (Wang et al., 2018)	Gabor wavelets	CASIA DATASET	93%
2019 (Battistone & Petrosino, 2019)	Time-based Graph Long Short-Term Memory	CASIA B GAIT Dataset	86.4%
2020 (Sharif et al., 2020)	MSVM Classifier	CASIA GAIT dataset	98.6% on CASIA-A, 93.5% on CASIA-B and 97.3% on CASIA-C
2021 (Yao et al., 2022)	HMP	CASIA	90.6%
2022 (Asif et al., 2022)	GEI, SVM, HOG	CASIA-B	87.9%
2023 (Khaliluzzaman et al., 2023)	Deep CNN variant (best CASIA-B in survey)	CASIA-B (overall performance evaluation)	98.07% (reported best in survey)
2023 (Fan et al., 2025)	GaitBase (OpenGait strong baseline)	CASIA-B* (reprocessed)	≈96–97% (rank-1, typical OpenGait results)
2024 (Burges et al., n.d.)	Hybrid LSTM–CNN + cGAN GEI generation	CASIA-A/B	≈95% (CASIA-A), ≈92% (CASIA-B)
2024 (Mehmood et al., 2024)	Two-stream deep neural network (appearance + motion)	CASIA-B (all views)	≈97% avg. across views
2024 (Thapar et al., n.d.)	GaitW (dynamic-info enhanced model)	CASIA-B (benchmark protocol)	96.9% (simultaneous SOTA across four datasets)
2025 (Khaliluzzaman et al., 2023)(Munusamy & Senthilkumar, 2024b)	Recent deep CNN/transformer variants (e.g., improved GaitSet/GaitPart)	CASIA-B	~96–99% range depending on protocol
2026 (D & T, 2026)	SPD-Net (Semantic Partitioned Transformer with Dynamic Graph)	CASIA-B	Strong performance on CASIA-B; emphasis extends to better generalization on larger and more challenging datasets such as Gait3D

OpenGait and Benchmark Reproducibility

One of the major practical advances in recent gait research is the emergence of unified open-source frameworks such as OpenGait (Fan et al., 2023). OpenGait provides standardized implementations, training pipelines, and benchmark protocols for multiple state-of-the-art gait recognition models across a range of datasets, including CASIA-B, OU-MVLP, GREW, Gait3D, and others. The OpenGait benchmark study also revealed an important insight: for example, specific local branches or multi-granularity pooling designs may help on indoor benchmarks and show little improvement in terms of utility in outdoor data as well.

Applications of Gait Recognition

Gait analysis can be done remotely either using camera-based vision systems or using ground reaction forces and pressure distribution sensors. In surveillance, human gait recognition has been used in many applications to identify persons in crowded or public areas where individuals don't always cooperate, a factor that makes it more advantageous than other biometric means such as fingerprint and iris scanning. In the medical field, gait analysis can be a critical diagnostic tool, used to determine whether a gait is normal or abnormal, and if the gait is abnormal, to detect the early signs of chronic diseases (Jarchi et al., 2018). Age plays a special role here, as the body's gait rhythm and gait pattern change as the body ages, and observation of this change can allow a clinician to take preventive measures to prevent a fall or injury when it occurs (Huang et al., 2021). Gait analysis is applied during sports to determine an athlete's flexibility and biomechanical preparedness, which can help when deciding team placement and injury prevention measures. For defense and military use, gait analysis is used to support trajectory prediction, pose estimation, and prediction of hand movements. It also has potential applications in robotics, as the study of human movement patterns aids in the development of more natural gaits for humanoid robots. In terms of implementation, both wearable and non-wearable devices are used to achieve consistent clinical results (Wan et al., 2018). Some scientists have gone one step further and are researching the possibilities of extracting energy from the heel strike itself. They use EMG sensors, QTM motion tracking systems, WinDaq, insole pressure sensors, and V3D to assess a participant's gait to gain insight into human locomotion and to develop techniques for harvesting energy generated by foot impact, which has real potential for powering wearable health monitoring devices in the field. These applications illustrate that gait recognition is not just a research item; it has practical managerial significance. Hospitals and rehab facilities have to consider the cost and integration involved in implementing gait-monitoring systems, while security agencies have to balance the impact on privacy and cost of implementation with the value of gait-based surveillance in their operations; and sports organizations have to determine the value of gait-based screening during athlete selection. The importance of the research gaps described below goes beyond the lab — these decisions rely heavily on the affordability, scalability, and ease of integration of the underlying technology.

Challenges and Research Gaps:

Although the gait models have made great strides, there are still some challenges that have not been solved for today's deep-learning-based gait models. The domain shift problem is still a significant challenge: Even though models learned on controlled sets often transfer poorly to unconstrained real-world scenes, this is caused by variations in resolution, background noise, pose, and image conditions. Another longstanding challenge is covariate sensitivity; for example, varying viewpoints, occlusion, shadow, or clothing can alter the silhouette and gait dynamics that a model is based on. Models are also very data-intensive, needing large, annotated datasets, which can be costly to collect, particularly if diversity and ecological realism are required. Most of the works that exist in the literature have also limited task scope, focusing on identity only and neglecting other signals such as age, gender, health status, mood, fatigue, or behavior, allowing multi-task and multimodal approaches. Lastly, privacy, ethical, and fairness issues are emerging, especially when it comes to capturing images remotely without consent, over-surveillance, and bias in terms of recognition accuracy.

Future Directions

Five major research directions will most likely be continued in the future of gait recognition: Cross-domain learning and domain adaptation are going to be critical to bridge the gap between the controlled benchmarks and real-world deployment in the first place (Guo et al., 2024). Second, transformer-based architectures could be better at learning features that capture long-range dependencies in gait sequences compared to traditional models. Third, multimodal fusion will be increasingly relevant; the idea of fusing silhouettes with pose data and inertial sensing, pressure signals, and contextual metadata holds promise of increased robustness for systems that lack one or more of these components. Fourth, privacy-preserving and lightweight models will be required to facilitate the deployment on mobile, edge, and clinical devices, which will have tighter computational resources and ethical constraints. Fifth, future systems should evolve towards a unified model of identity and abnormality and affective state, with gait becoming an overarching platform for human-centered intelligent sensing: not just identifying a person, but also how they are feeling.

Conclusion

Human gait analysis and recognition have evolved considerably, progressing from handcrafted motion descriptors to advanced deep learning frameworks capable of automatically learning discriminative spatiotemporal representations from gait silhouettes, skeletal data, and wearable sensor signals (Munusamy & Senthilkumar, 2024a; Shen et al., n.d.). Although they are impressive on standard benchmarks, recent large-scale studies and open benchmarking efforts have highlighted that it remains an open challenge to build robustness in real-world scenarios, ranging from clothing variations, viewpoint changes, occlusion, to cross-domain scenarios. Gait recognition is therefore a biometric method that needs to be further optimized to be able to be easily used in real-world applications without failure risk. This review covered the literature on various datasets and the technologies used on them. The most prominent one is occlusion, especially when subjects are holding bags or when they are inside a crowd, and this needs a more in-depth study to be tackled properly. Although modern methods achieve impressive performance on benchmark datasets, recent large-scale studies and open benchmarking initiatives have demonstrated that robust real-world gait recognition remains a significant challenge, particularly under variations in clothing, viewpoint, occlusion, and cross-domain conditions. Furthermore, the limited availability of large, diverse, and representative datasets continues to constrain the generalizability of existing models. Data augmentation techniques, such as Generative Adversarial Networks (GANs), offer a promising approach to generating realistic synthetic gait data and improving model robustness and accuracy. Despite substantial advances, several research gaps remain, highlighting important directions for future studies aimed at developing more robust, scalable, and generalizable gait recognition systems (Jeevan et al., 2013).

Conflicts of interest

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