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# Human Gait Recognition Based on Deep Learning: A Review

**Diler Atrushi [1], Adnan Mohsin Abdulazeez [2]**
diler.ahmed@auas.edu.krd, adnan.mohsin@dpu.edu.krd
[1] Technical College of Informatics-Akre- Department of Information Technology, Akre University for Applied Science, Duhok, Kurdistan Region, Iraq.
Department of Computer Science, University of Duhok, Duhok, Kurdistan Region, Iraq.
[2] Technical College of Engineering-Duhok, Duhok Polytechnique University

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**Abstract**

Human gait recognition as a branch of biometric identification, has witnessed remarkable progress in recent years, thanks to the integration of deep learning techniques. This paper presents a comprehensive review of the latest advancements in the field, specifically focusing on the transformative role of deep learning methodologies. Recent research papers highlight novel approaches in gait recognition, including deferent models proposed that is consisted of using more than one approach together to increase the accuracy. Subsequently, we undertake a comprehensive investigation of the most relevant literature and present an analysis of gait recognition techniques employing deep learning. We discuss the models, systems, accuracy, applications, and datasets utilized in these studies, aiming to outline and structure the research landscape and literature in this domain. Methods for acquiring gait data are distinguished between capturing video frame, radar signals, or from wearable sensors as well as from the available online datasets that are large-scale and significantly contributed to the advancement of deep learning models. The study also shows the verity applications that can utilize human gait recognition to achieve certain goalss.

## A. Introduction

Gait refers to the repetitive motion of the legs, arms, body, and joints in both the upper and lower limbs of the body that is known as walking pattern[1]. Human gait patterns can be used to identify and assess an individual's identity and psychological condition[2]. Gait recognition is a highly important technology for identifying individuals across great distances and does not require the person collaboration[3], [4]. Human gait recognition is highly significant in the field of surveillance[5] because of its ability to provide remote access and address security issues. HGR, or Human Gesture Recognition, is a commonly utilized approach to recognizing human behavior and movements in everyday situations. Nevertheless, a number of frequent scenarios, such as changing clothes and viewing angles, reduce the efficiency of the system[6].

Currently, sophisticated systems that provide artificial intelligence characteristics frequently depend on machine learning. Machine learning refers to the ability of computers to acquire knowledge from training data that is specific to a certain problem. This knowledge is then used to automatically construct analytical models and solve related tasks[7]. Machine learning including deep learning models are extensively utilized for many forms of inference and decision-making[8]. Deep learning is highly advantageous in computer vision applications[9].

Deep learning is highly used in the field of personnel authentication. Biometrics utilizes methods for determining a human's physical characteristics (such as iris diaphragm, the geometry of our hands, the fingerprint, retinas, and facial figures[10], [11]) or behavioral elements (such as signature, voice, and keystroke rhythms). AI-driven biometrics use technologies like facial recognition, speech recognition, and computer vision to achieve identification, authentication, and security goals in various settings such as computing devices, workplaces, and home security systems[12]. Among the biometric identification methods, Human Gait recognition has gained a position because of its capability to recognize people from a distance[13]. It is good mentioning that the history of gait analysis is back to 384–322 BCE[14].

## B. Applications

Gait as a biometric can have many applications such as, 1) Surveillance and Security: Utilizing gait recognition for surveillance purposes as a method in video surveillance to accurately identify and monitor individuals in public spaces, airports, and vital infrastructure locations. [15], [16], [17] and 2) Law enforcement: through threat detections to increase the public safety incorporating from various threats, including acts of terrorism, incidents of mass shootings, and instances of suicide bomb[18], [19], [20]. 3) Healthcare: HGR is widely used in the field of the healthcare especially to discover gait abnormalities and fall detection of patients and elderly people [21], [22], [23]. 4) Gait recognition can be used for gender recognition [24], [25]. 5)Automated emotion recognition and neurological disorders prediction [26], [27]. 6) Gait recognition for Smart homes and Internet of Things (IOT) for personalized automation in smart homes, adjusting settings based on recognized residents [28], [29]. 7) Biometric Identification and Authentication: Utilizing gait patterns as a biometric identifier for access control systems and secure authentication [30]. 8) Sports and physical activities: Examining the stride patterns of athletes to improve their performance, reduce the risk of injuries, and optimize their training regimens[31], [32].

## C. Advantages

Gait recognition has many advantages over the other types of biometrics and can be summarized to the following points:

- can be identified from a significant distance, unlike biometric methods such as fingerprints or retina scans, which require the individual to be in close proximity to a biometric data collector.
- Gait recognition can evaluate individuals even in low-quality photos or resolutions, while biometrics like face recognition necessitate high-quality resolution.
- recognition is a method of identifying an individual's walking pattern utilizing different devices such as cameras, floor sensors, or radar.
- Gait recognition does not require the individual's cooperation, unlike biometric technologies such as fingerprint recognition which rely on the individual's entire cooperation.

## D. Gait Phases

To know the process of gait recognition, a good understanding of the biomechanics of the human gaits must be obtained. The gait cycle refers to the period of time between two continuous events of the heel making contact with the ground during walking or running[33]. The process involves a sequence of instructions originating in the brain and transferred via the spinal cord to stimulate the lower neural center. This, in turn, leads to the activation of specific muscular contraction patterns, which are regulated by sensory input from joints, muscles, and other receptors to govern movement. This will cause the feet to repeatedly make contact with the ground surface in order to move the trunk and lower limbs in a synchronized manner, resulting in a shift in the location of the body's center of mass[34]. Examining an individual's walking pattern in phases allows for a more precise understanding of the functional importance of the various movements taking place at each joint. The stages of gait serve as a method for establishing a connection between the coordinated movements of the individual joints and the overall functioning of the limb. Consequently, both the timing and joint angle hold great importance. Each of the eight gait phases serves a specific purpose and requires a precise pattern of coordinated movements to achieve its intended effect. The successive integration of stages also allows the limb to achieve three fundamental objectives which are the weight acceptance (WA), the single limb support (SLS), and lastly the swing limb advancement (SLA) [35] (Figure1).

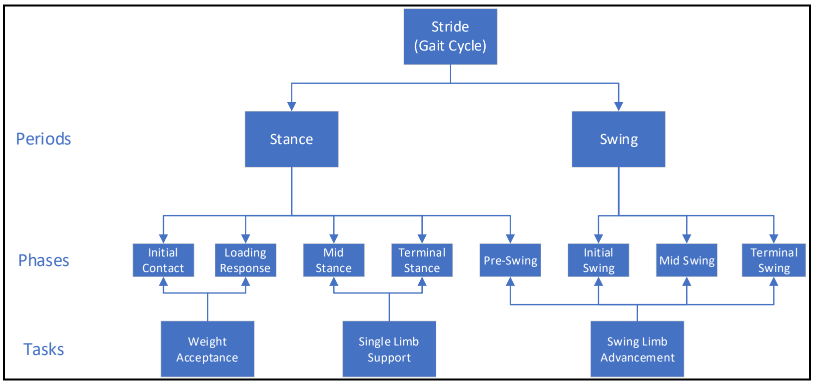


**Figure 1.** Division of the gait cycle

During a single gait cycle, each foot undergoes one instance of ground contact, known as the stance phase, which lasts around 60%–62% of the complete gait cycle. The swing phase, which refers to the period when the foot is raised off the ground, comprises approximately 38%–40% of the gait cycle. Unlike sprinting, when both feet are never simultaneously in contact with the ground, walking involves two instances of double contact. During the initial and last 10% of the walking stance phase, both feet remain in contact with the ground. The precise time and composition of the gait cycle is contingent upon factors such as walking speed, current symptoms, and the type of footwear being worn[36], (Figure 2).

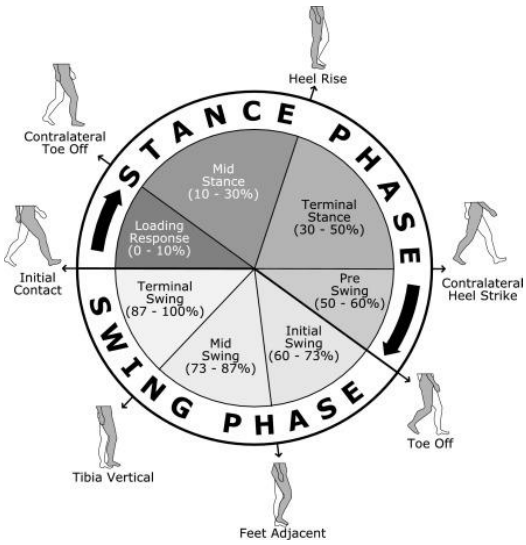


**Figure 2.** The gait cycle[37]

## E. Related Works

Many researchers have worked on human gait recognition using different methodologies. This section will include a summary of the recent works related to human gait recognition that are utilizing deep learning.

In their study, both Gurbuz and Amin explored the potential of deep learning (DL) in radar applications for residential monitoring and smart home applications.

Specifically, they focused on the classification of daily human activities, detection of falls, and monitoring of gait abnormalities. The significant performance improvements provided by deep learning (DL) have been demonstrated through a case study involving a 12-activity class. In this study, the accuracy of different deep neural networks (DNNs) was compared to that of traditional classification methods that rely on manually designed features and other data-driven techniques. One specific obstacle in utilizing deep learning for radar applications has been the limited quantity of actual data accessible for training purposes[38].

A framework for human gait recognition using deep learning and an improved ant colony optimization algorithm is proposed in [39]. The framework contains four main steps: preprocessing the dataset, extracting features from modified ResNet101 and InceptionV3 models using transfer learning, optimizing the extracted features using IACO, and classifying the optimized features using Cubic SVM. The experiments were conducted on three view angles of the CASIA B dataset. The proposed method achieved accuracy of 95.2%, 93.9%, and 98.2% for 0, 18, and 180 degree view angles respectively, outperforming existing techniques in terms accuracy and computational time.

[40]This research presents a framework that utilizes deep learning and Bayesian optimization for the purpose of human gait recognition. The method employs optical flow to extract regions of motion from video frames for the purpose of training an EfficientNet model. Additionally, enhanced video frames are utilized for individual training of the identical model. Bayesian optimization is utilized for training instead of fixed hyperparameters. The features obtained from both models are combined via parallel fusion and then refined using an enhanced tiger optimization technique. The framework undergoes testing on two datasets and attains an average accuracy of 92.04% and 94.97%. It surpasses other deep learning techniques in terms of performance.

Within the boundaries of their written work, [41]presents a novel framework for identifying human walking patterns by employing deep learning and feature selection methodologies. The method utilizes transfer learning on pre-trained models to extract features from the CASIA B dataset. The retrieved features are combined using a modified mean absolute deviation extended serial fusion technique. The utilization of an enhanced whale optimization method is employed to systematically determine the most optimal features through a three-step process. The suggested method is assessed using the complete CASIA B dataset and demonstrated to attain superior accuracy in comparison to hi-tech techniques. The research limitations lie in that there is a possibility of diminishing certain crucial features, which could subsequently lead to a decrease in the accuracy of classification. Additionally, the fusion of features using the threshold function based on Mean Absolute Deviation (MAD) might miss significant features.

[42]This study presents a method for identifying and analyzing human gait recognition by utilizing deep learning. The proposed approach specifically focuses on utilizing smartphones as the primary data collection and processing device. Accelerometers and gyroscopes, which are inertial sensors found in smartphones, are utilized to record gait dynamics. A novel hybrid deep neural network, which integrates both convolutional neural network (CNN) and recurrent neural network (LSTM), is suggested for the purpose of extracting spatial and temporal gait

features. An advanced convolutional neural network was introduced to separate the inertial data into walking and non-walking sessions. Additionally, hierarchical convolutional features were combined to achieve precise semantic segmentation. The performance of person identification and authentication is evaluated using two datasets obtained from 118 subjects. The proposed method achieves an accuracy of over 93.5% for identification and over 93.7% for authentication.

According to [43] that presents an approach for gait recognition that employs hierarchical convolutional neural networks. The hierarchical structure is specifically devised to capture and depict both local and global characteristics in gait patterns. The model seeks to enhance its capacity to distinguish individuals based on their gait by structuring the convolutional layers hierarchically, allowing it to acquire discriminative features at various levels of abstraction. The suggested method presumably entails creating a Convolutional Neural Network (CNN) structure that includes several layers of convolution, with each layer responsible for extracting distinct elements from the input gait sequences. The network's hierarchical structure enables it to accurately capture detailed features and spatial correlations in the gait data, leading to enhanced performance in gait identification. For a comprehensive grasp of the methodology, experimental setting, and performance evaluation criteria employed by the authors, it is advisable to refer to the original work.

[44]The publication introduces a technique known as 3D local convolutional neural networks (3D local CNNs) for the purpose of gait recognition. The proposed model utilizes 3D local CNNs to analyze each body part individually. This is achieved by localizing adaptive 3D volumes around specific parts such as the head, arms, and legs, and extracting features from these volumes. The method attains exceptional performance on widely used gait datasets by effectively capturing part-specific spatial and temporal patterns, surpassing existing approaches.

In[45], The authors provide a resilient deep learning model called “Time-based Graph Long Short-Term Memory” denoted by (TGLSTM). The objective is to offer the capability to dynamically acquire knowledge of graphs that may undergo changes over time, such as in gait and action recognition. Each MSR-Action3D consists of 20 nodes junctions, with each node being represented by a 4-tuple. The 4-tuple provides the coordinates of the junction node, the depth (d), and the belief value (c). The dataset classifies the actions into five distinct settings: “office, kitchen, bedroom, bathroom, and living room”. The suggested methodology focuses on the analysis of activity recognition on a frame-by-frame basis. It takes into account a 3D size of frames with orders of graphs.

[46]This research presents an innovative deep learning model aimed at enhancing the accuracy of human gait identification. The process involves extracting features from gait photos using two distinct phases - an appearance-based model and a model-based model. During the initial stage, silhouette images are retrieved from films and fed into a Convolutional Neural Network (CNN). During the second step, 3D poses and static/dynamic features are derived from the poses and then fed into a fully linked network. The features obtained from both phases are combined and fed into another network for the purpose of recognition. The model undergoes testing using CASIA gait datasets and attains an accuracy

ranging from 99.6% to 99.8%, surpassing the performance of alternative approaches.

This work[47] presents a machine learning approach that utilizes inertial measurement unit (IMU) sensors to analyze gait and identify individuals. A novel learning model is created, which utilizes deep feature learning to extract sophisticated representations from IMU gait data. These representations are then integrated with a clustering technique that is multi-layered. The model is assessed using a gait dataset that includes measurements of gender, height, age, and weight from 90 individuals. The experimental results demonstrate that the proposed clustering model outperforms existing models in terms of identification accuracy for all target variables. Specifically, the model obtains accuracies of 75.6% for gender identification, 76.7% for age identification, and 92.2% for height identification. Utilizing retrieved latent features improves the model's ability to handle fluctuations in gait.

The objective of the study [48] is to introduce a sophisticated neural network, named DCapsNet, which utilizes smartphone sensors to accurately recognize and classify human activities and walking patterns. The approach utilizes convolutional layers to extract temporal information from sensor data, while including a capsule network to maintain spatial relationships and equivariance. The model attains the highest level of recognition accuracy on four datasets for activity and gait recognition, surpassing all other models.

The researchers in [49] presents the WiFOG technique, which utilizes WiFi signals and deep learning algorithms to accurately identify freezing of gait (FOG) in individuals diagnosed with Parkinson's disease. Data in its original form was gathered for a range of activities, including sitting, walking at different speeds, intentional pausing, and episodes of freezing of gait (FOG). Signal processing and feature extraction were conducted by employing discrete wavelet transforms and Hilbert-Huang transforms as part of feature engineering. Dimensionality reduction was performed using a hybrid approach that included whale optimization with recursive feature elimination. The researchers employed a deep gated recurrent network (DGRU) model to classify activities and detect freezing of gait (FOG). The results demonstrated enhanced accuracy in comparison to current methods. The main characteristics of the reviewed articles are summarized in table 1.

**Table 1.** Reviewed articles summarization

| Ref. | Year | Model | System | Accuracy | Application | Dataset | Pros | Cons |
|---|---|---|---|---|---|---|---|---|
| [49] | 2024 | proposed DGRU model (*WiFOG*) | WiFi signals | 98% in detection of FOG | Medical | Data are collected from signals using wearable sensors (IOT) | • Using WiFi sensing for detecting freezing of gait (FOG).<br>Performance Improvement. | • IOT Sensors accuracy limitation<br>And the system is proposed for indoor environment |
| [47] | 2024 | DNN and a clustering-based learning model | Inertial Measurement Unit (IMU) sensors (gait analysis sensor | 75.6% for gender identification; 76.7% for age identification; and 92.2% for | Individuals Identification | Sensor data; Gait dataset comprising measurements of gender, age, height and | • Novelty.<br>• New Dataset.<br>Performance | Gait patterns variety can limit the effectiveness of IMU-based gait analysis across diverse |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | system) | height identification | | weight from 90 individuals. | Improvement. | demographics. |
| [48] | 2024 | Proposed DCapsNet | Smartphone Sensors | 97.92% for UCI-HAR; 99.30% forWISDM | Human Activity | UCI-HAR; and WISDM | High recognition accuracy. | • N/A |
| [46] | 2023 | CNN | Video Frames | 99.6-99.8% | Human Authentication | CASIA gait Datasets | •Novel approach combines model-based and model-free. •Real-time authentication | •Limited dataset evaluation |
| [40] | 2023 | Fine-tuned deep model through Bayesian Optimization | Video Frames | According to dataset CASIA B =92.04%; CASIA C = 94.97% | Biometric | CASIA B[50] and CASIA C[50] | •Combines deep learning and Bayesian optimization. •Improved feature selection. | •Limited dataset evaluation. |
| [39] | 2022 | Improved ant colony optimization (IACO) | Video Frames | According to an angle 0°=95.2 %; 18°=93.9%; 180°=98.2% | Biometric | CASIA B[50] | •Accurate recognition. •Comparative analysis. | •Lack of validation on diverse datasets. •limitations of gait recognition. |
| [41] | 2021 | Deep learning and a proposed feature selection method | Video Frames | According to an angle And feature selection method, between (70.53.% and 88.73%) | Biometric | CASIA B[50] | •Feature Optimization and Fusion. | •Generalizability. •Lack of Real-World Application Validation. |
| [44] | 2021 | 3D local CNNs | Video Frames | Reached 97.5 on CASIA-B dataset | Biometric | CASIA-B and OU-MVLP [51] | •Adaptive •localization integration of global and local features. | •Lack of comparison. •Datasets dependency. |
| [43] | 2020 | CNN | Video Frames | 93.2% and 92.6% | Biometric | CASIA-B and OU-LP-Bag [52] | •Discriminative feature learning. | • Problems in gait occlusion and dress change. |
| [38] | 2019 | DNN | Indoor Radar Signals | 94.2% | Smart Home | Radar readings for 12 classes | •Comparison with other approaches. • Discuss wide range of applications. | •Limited scope. •Small amount of training data. |
| [45] | 2018 | Proposed TGLSTM model | Video Frames | 95.2% with 3D dataset; 94.4% with CAD-60; 87.8 % for CASIA; | Human activity recognition and gait analysis | MSR Action 3D[53], CAD-60, CASIA Gait B, TUM Gait[54] | •Novel approach. •Dynamic graph learning. | •Lack of real-world evaluation. Generalizability to other datasets or domains. |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | 98.4% for TUM Gait dataset. | | | | |
| [42] | 2018 | CNN and LSTM | Outdoor, Smartphone, walking sensors | 93.5% for identification and over 93.7% for authentication | Smart Phone | 2 datasets are collected using smartphone for (118,20) subjects walking data taken from smartphone sensors. | •Robust feature representation. High accuracy | •Dataset limitations. |

## F. Discussion

The paper provides an in-depth review of deep learning methods used in human gait recognition. The text explores the significant impact of deep learning techniques in this domain and emphasizes the progress achieved in gait identification through the application of deep learning. The research also examines different models, systems, levels of accuracy, applications, and datasets employed in these experiments.

Artificial neural networks, namely Convolutional Neural Networks (CNNs), are commonly utilized and consistently outperform other learning models in terms of important metrics. Moreover, apart from examining video frames, the research also evaluates radar signals, WiFi signals, smartphone walking sensors, and other Internet of Things (IoT) sensors employed for obtaining gait measurements. The publication highlights the presence of online datasets that have greatly helped to the progress of deep learning models in gait identification. Notable gait recognition datasets include CASIA Gait Database, OU-ISIR Gait Database, and USF HumanID Gait Database. Nevertheless, some proposed techniques have made significant contributions to enhancing accuracy and resilience to variations. However, it is worth noting that some of these systems have been trained and tested on identical datasets or on limited amounts of data, without experimentation in real-life environments. Diving into the findings from the studies based on the similarities, we can group them into the following categories:

1. Sensor Modalities:
    - WiFi signals: Study [49] proposes a model using WiFi signals for gait analysis.
    - Inertial Measurement Unit (IMU) sensors: Study [47] utilizes IMU sensors for gait analysis.
    - Smartphone sensors: Studies [48] and [42] use smartphone sensors for activity recognition, identification, and authentication.
    - Radar signals: Study [38] employs radar signals for smart home applications.
2. Deep Learning Techniques:
    - CNN-based approaches: Studies [46], [43], and [44] utilize CNNs for biometric recognition and authentication.
    - DNN-based approaches: Studies [46], [38], and [43] employ DNNs for

gait analysis, smart home applications, and biometric recognition.
- LSTM-based approaches: Studies [42] and [45] use LSTMs for identification, authentication, and gait analysis.
- Capsule Network: Study [48] proposes a DCapsNet for activity recognition.

3. Application Areas:
    - Medical: Study [49] focus on gait analysis for medical purposes.
    - Biometric and authentication: Studies [46], [40], [39] , [41], [44], [47], and [43] explore biometric recognition using gait or video frames.
    - Human Activity Recognition: Studies [48] and [45] address human activity recognition using different sensor modalities.
    - Smart Home Applications: Studies [38] and [42] investigate smart home applications using radar and smartphone sensors.
4. Performance Evaluation:
    - Accuracy Metrics: Most studies report accuracy as an evaluation metric, ranging from moderate to high accuracy levels depending on the specific study.
5. Dataset Usage:
    - CASIA datasets: Studies [39] ,[40], [41], [44], [43], [45] and [46] utilize the CASIA dataset for biometric recognition.
    - Other studies use various datasets specific to their application areas.

The finding highlights the similarities among the studies in terms of the sensor modalities used, the deep learning techniques employed, the application areas addressed, the performance evaluation metrics, and the datasets utilized.

## G. Conclusion

This article reviews the latest advancements in the field, focusing on novel approaches in gait recognition and the use of multiple approaches together to increase accuracy. The authors conduct a comprehensive investigation of relevant literature, analyzing gait recognition techniques that employ deep learning. They discuss various models, systems, accuracy measures, applications, and datasets used in these studies.

The paper also highlights the diverse applications of gait recognition. The advantages of gait recognition over other biometric methods are discussed. To understand gait recognition, the document explains the biomechanics of human gaits and the phases of the gait cycle. It also mentions related works in the field of human gait recognition utilizing deep learning.

Overall, the document provides a comprehensive overview of the advancements, applications, advantages, and related works in the field of human gait recognition based on deep learning techniques.

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