Advancements in Artificial Intelligence for Biometrics: A Deep Dive into Model-based Gait Recognition Techniques

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ABSTRACT

Over the past decade, Deep Learning (DL) pipelines have undergone significant evolution and demonstrated effectiveness in addressing complex challenges within artificial intelligence domains. The construction of tailored DL pipelines for specific applications necessitates a solid grasp of deep learning principles and the range of intermediary layers at one's disposal. Crafting a DL pipeline involves leveraging appropriate datasets for the intended application and iteratively refining the pipeline by navigating through intermediary layers. The process of selecting and validating configurations demands substantial time and meticulous consideration, making it intricate to identify an optimal and resilient DL pipeline that excels across pertinent datasets. This article seeks to support researchers in comprehending diverse gait sensing technologies while establishing a foundational understanding of deep learning concepts to expedite problem-solving. A comprehensive overview of gait biometrics tailored for surveillance applications is presented herein. The fundamental aspects of deep learning pipelines are expounded upon, encompassing their selection criteria and implications for specific problems. Recent pivotal research on deep learning models is surveyed, encompassing their performance across varying application datasets. By elucidating the merits and limitations of these approaches, this work guides the derivation of an optimized pipeline achieved through a fusion of existing alternatives. The ultimate objective is to attain swifter yet precise outcomes for a given problem.

1. Introduction

Gait recognition is a biometric technique that uses a unique way of walking to identify and classify people. Face recognition and finger prints are examples of biometric technologies [76]. The advantage of gait recognition over other biometrics is that users may interact with the individuals without getting permission. The target data may be distant or at poor resolution. Additionally, it might be difficult to conceal one's gait. For instance, thieves often wear gloves, dark sunglasses, and masks to conceal their fingerprints, eyes, and features. In these situations, one of the ways to identify someone is through their gait. The shape of human and walking style have a significant impact on gait recognition as well [77]. Over the last ten years, a plethora of techniques for determining gait have been proposed. Model-based techniques [1 - 84] and model-free approaches [85 - 94] are two categories into which these might be divided.

The main goal of model-based approaches is to determine the subject's stride characteristics, which use the anatomy of the human body to describe the gait [78]. Most of the time, model-based techniques make it harder to provide a reliable approximation. High-resolution images are required, yet they are challenging to design. Model-free methods focus on how the human body moves and often work by directly extracting silhouette-based gait parameters from them [79]. It is challenging to create a system for gait identification that is efficient. The scope of our review is for surveillance or authentication based application in gait recognition. Model-based techniques are further classified as sensor-based and pose-based. Points on the human body are indicated via marker-based approaches (for example, pose-based technique as shown in figure 1 with a stick diagram with 15 points on it). Direct silhouettes are extracted and recognized using markerless approaches. Deep learning approaches successfully complete a variety of classification

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tasks and provide fresh perspectives on challenging covariate situations (clothing, carrying condition, speed change, occlusion). Deep learning systems often have the drawback of behaving as a "black box" in the majority of situations; for instance, if pre-trained models are employed if hyper tuning is not performed, they seldom reveal the reasoning behind a given a choice.

Deep learning has emerged as a promising approach for human identification based on gait patterns [80]. However, starting gait recognition with deep learning can be challenging due to the lack of guidance regarding suitable deep learning pipelines and expected outcomes. Currently, there are limited review publications that delve into deep learning techniques for gait identification, including the parameters of deep pipelines. While several surveys on gait analysis have been conducted [70, 71, 72, 73, 74, 75], the majority of them primarily focus on model-free gait recognition systems, often overlooking model-based strategies.

1.1. Contribution

The following are the important contributions of the paper.

1) The most common model-based strategies for gait detection using deep learning are broken down and explained in this literature review. A comprehensive explanation is provided for all of the sensors that can identify gait, along with a discussion of the benefits and drawbacks associated with using each sensor.

2) Provide an overview of the predominant methodologies frequently employed across a range of reported deep learning pipelines. This overview will include a detailed explanation and evaluation of these methods.

3) Pay attention to the parameters of deep learning for the many gait covariate conditions that lead to an enhanced recognition rate. Describes the benefits as well as the drawbacks of using solutions that are based on deep learning.

4) Compile the datasets that are used by deep learning algorithms and demonstrate the level of accuracy that can be reached on a particular dataset.

1.2. Organization

The paper's structure is as follows: The first section presents an overview of various topics, encompassing motivation, contributions, and organization. Section 2 delves into an analysis of several factors found in existing studies, leading to the development of a deep learning pipeline for gait recognition. Within this section, we explore the structure of a deep learning-based gait recognition system and examine the advantages and disadvantages of each approach. Section 3 emphasizes the strengths and weaknesses of pipeline components, as well as gait sensing technology. It also includes a comparative analysis of the accuracy and datasets used in prior research publications. Finally, Section 4 provides the conclusion.

2. Various Deep Learning Methods for Recognizing Gaits

Approaches that are model-based may be divided into two categories: sensor-based [1-38] and pose-based [39-47] methodologies. After developing the whole of the human body, model-based feature representation models would often use distance or joint angle on the human body for the purpose of gait recognition. The objective is to determine crucial locations as precisely and effectively as possible. Because these techniques require to calculate important points in every frame, the majority of the methods are difficult to implement and expensive to compute. The quality of the video is more important than the quantity of the attributes being modelled since model-based representation is not dependent on these factors. They are able to deal with the multiple intraclass variances that are caused by the several variables that have an effect on the look of the products, such as attire, carrying, and viewing angle. The computational cost of these approaches is quite high due to the fact that it is not an easy task to calculate the important spots in each frame. The deep learning pipeline for recognizing gaits is shown in Figure 1, together with all of its potential parameters.

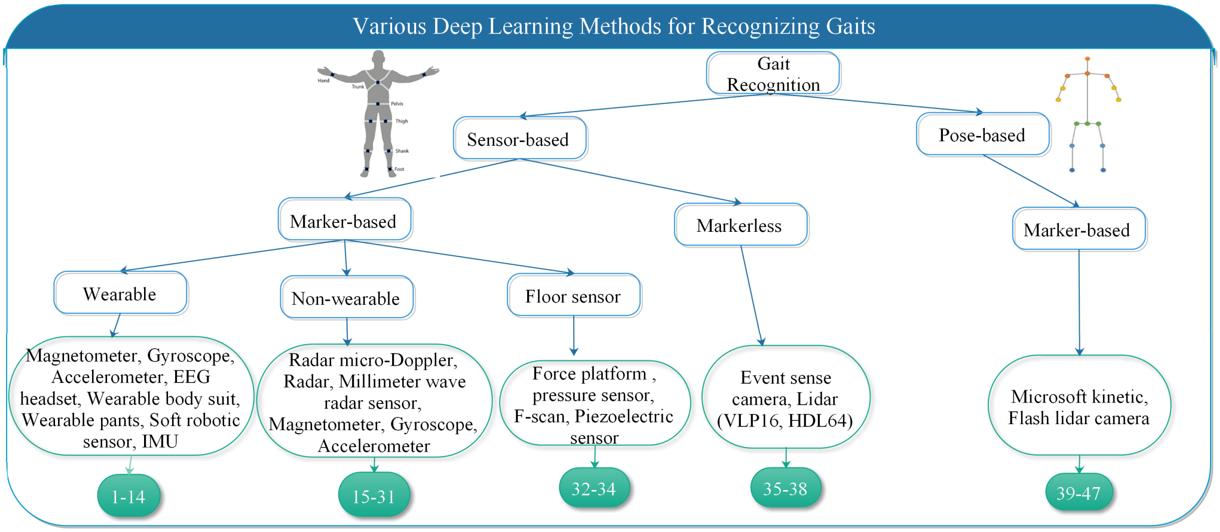
2.1. Sensor-based

Techniques based on sensors, signal processing, and data gathering all play an important part in authenticating the user by utilizing their gait characteristic.

2.1.1. Wearable

A wearable gait sensor is a device designed to monitor and analyze a person's walking pattern or gait. These sensors are typically worn on the body, often on the legs or feet, and they use various technologies to collect data on how a person moves while walking. This information can be valuable for a wide range of applications, including healthcare,

Figure 1: Structural arrangement of paper for gait recognition approaches



sports performance analysis, rehabilitation, and research. Table 1 depicts the gait analysis pipeline, encompassing preprocessing and feature extraction stages.

Here are some key features and components commonly found in wearable gait sensors:

- Accelerometers: These sensors measure acceleration and can detect changes in velocity and direction of movement. They are often used to track the movement of different body segments during walking.
- Gyroscopes: Gyroscopes measure angular velocity and help capture rotational movements, which can be important for analyzing gait abnormalities.
- Magnetometers: Magnetometers measure changes in magnetic fields and can be used for orientation and direction tracking.
- Pressure Sensors: Placed in shoe insoles or on the soles of shoes, pressure sensors can provide information about foot pressure distribution, which is useful for analyzing foot strikes and balance.
- Stride Length Measurement: Some gait sensors use algorithms to calculate stride length based on the data collected from accelerometers and gyroscopes. This is important for understanding walking speed and cadence.
- Wireless Connectivity: Many wearable gait sensors are equipped with Bluetooth or other wireless communication technologies to transmit data to smartphones, tablets, or computers for real-time monitoring or data analysis.
- Data Processing Software: Data collected by the sensors is typically processed using specialized software or mobile apps, which can provide detailed gait analysis reports and insights.

To extract the characteristics from the wearable sensor, Hannink et al. [1] presented a deep CNN approach. Their method is incredibly adaptable and may be used in a variety of situations. It takes a long time and is often impossible for them to obtain representative training data. Feature collection by handcrafted or manual means is sometimes complex, cumbersome, and error-prone. Also, the inertial sensors limit the generalization capabilities as the motion data collected from them are arranged in a complicated manner. They proposed a deep CNN based on time and frequency. Dehzangi et al. [2] proposed a model that takes 2D gait cycles as input and extracts discriminative features. Their model works effectively and captures data from multiple nodes using inertial sensors. Their model does not work on unlabelled data (signals) for detecting a subject as the interface of a human robot is dependent on the user and is usually noisy.

Fingerprint films, contact lenses, vocoders, and anti-surveillance masks are biometric tools that trick traditional biometric systems such as iris, voice, face recognition, fingerprint, and retina. They proposed a multimodal biometric

Table 1
Gait analysis pipeline encompassing preprocessing and feature extraction stages for wearable sensor

Cite	Gait Pipeline	Pre-processing/ Feature Extraction
[1]	Deep neural network	CNN
[2]	DCNN	CNN
[3]	RNN; LSTM	Encoder-decoder
[4]	RCNN	Cycles extraction, normalization / CNN
[5]	Deep learning based end-to-end approach	CNN
[6]	3D CNN; LSTM	CNN
[7]	Encoder, decoder	Encoder
[8]	CNN	CNN
[9]	ANN-LSTM	CNN
[10]	CNN	CNN
[11]	DCNN	CNN
[12]	CNN	CNN
[13]	Deep neural network	Cycles extraction, normalised / CNN
[14]	CNN	Angle embedded dynamic Image/ CNN

system for authentication called Deepkey. The model designed by the authors [3] works on gait signals as well as Electroencephalography (EEG). The model Deepkey consists of an identification model based on attention-based RNN and an invalid ID filter model. The former is used to identify Gait IDs and EEG IDs of the subject, while the latter is used to block unauthorized subjects. Their model has used both EEG and camera-based systems for fake resistance. There is a need for extensive evaluation using more subjects as the number of participants is less in the dataset used. The analysis of seamless authentication is prone to errors and is a challenging task. There is a need for authentication systems to dynamically adapt to new requirements and conditions of today's biometric systems. Giorgi et al. [4] proposed an authentication system for gait biometrics. They used recurrent CNN to classify gait readings taken by body sensors based on selective iterating and data augmentation. No additional sensors are required for authenticating gait. Instead, the task of identifying is integrated with personal items. The approach used by the authors is very effective in recognizing users where smartwatch and smartphone sensors are used. The authors did not perform the case where the classification and training were in real-time with the framework installed in the user's smartphone.

Using inertial sensors for gait identification in places where computer vision-based systems are unavailable is robust. Using deep learning approaches and handcrafted features is more prevalent in prior literature. Delgado et al. [5] proposed a method that automatically applies inertial data to learn the best-pre-processed features. Their approach takes multiple labels per sensor in multi-task learning and uses the fusion of information from various inertial sensors. Their method takes advantage of information from various sensors as they have applied an early fusion scheme. In comparison with the approach of a single task, their proposed methodology is a bit slow. Multimodal fusion and some other factors make gait data acquisition challenges. The authors [6] have proposed a fusion-based decision method for gait acquisition. They have used visible light cameras and motion sensors to record gait. Their results are very accurate, and the methodology used is robust and can be further explored for biometric systems. The authors have not applied or compared any other algorithms using fusion tuning.

The wearable sensor methods currently require a lot of data to calibrate and have design constraints. The devices must be attached to the subject to record the gait data, which leaves the system impractical. Kim et al. [7] have proposed a semi-supervised model for data calibration. They have used two microfluidic sensors for generating gait. Their methodology is more practical and functional; therefore, it can be used to improve soft wearable robots. There is a requirement to improve the model to give real-time results. Two of the most challenging tasks in mobile computing are user recognition (UR) and Activity recognition (AR) with the help of wearable sensors. Chen et al. [8] proposed a model called METIER to transfer knowledge and solve joint UR and AR tasks. They trained activity and user recognition models to deal with the changes. The performance of their model is not very good. To improve the performance of their model, they must incorporate sensor placement and direction recognition tasks.

Investigating a gait cycle's foot and ankle kinematics using wearable soft robotic sensors. Davarzani et al. [9]

proposed model collected the data on a sloppy and flat surface for 20 individuals. They used linear regression, LSTM, and ANN for 3D motion capture of data to find the SRS foot-ankle model power. Their model is very reliable for analyzing gait movements in SRS. Their training data is very less, and their model is computationally expensive as they used LSTM. Designing and applying various structures to derive a well-suited structure for every subject was problematic for the authors due to the complex nature of LSTM.

A gyroscope and accelerometer are used to collect gait data which can be further used for the authorization of subjects. Gadaleta et al. [10] proposed a wearable sensor technology worn on the ankle. IMU is used to directly collect motion data. This data is then processed to train. They used CNN to extract features. They achieved excellent results within 5 step count of user walk. Their algorithm shows less than 1% results in false negative/positive rates. They did not test their algorithm on any existing standard datasets. Adversarial perturbations are vulnerable. Prabhu et al. [11] proposed a method that can deal with adversarial perturbations using deep learning models with an efficient gradient method. With minor perturbations, they have seen a precipitous decrease in precision of almost 40%. Their proposed method is not very accurate. A cost-effective, easily integrable, and user-friendly device is highly in demand. Such a device can be used for authentication purposes and gait measurement systems. Nguyen et al. [12] suggested a new way to authenticate people using wearable sensors with accelerometers and gyroscopes and in gait recognition. The proposed gait recognition algorithm has a high level of accuracy. It does not take different contexts/covariates into consideration. Wearable sensors provide authentic and seamless results. Their capabilities extend beyond general gait identification; they can be used in wearable or cellular devices to identify the user. Giorgi et al. [13] proposed model uses CNN to collect features of 175 subjects using inertial body sensors. Their model is optimized and can recognize the subjects within ten steps of the walk compared to other models that require a minimum of 25 minutes of walking. They are not validating results on any standard dataset.

The inbuilt-inertial sensors in smartphones are a breakthrough technology in gait pattern analysis; however, these sensors fail to provide reliability in the extraction of discriminative features to recognize the gait pattern. Thus, optimum data collection via these sensors is challenging and unreliable. Zhao et al. [14] proposed a CNN model which does not need to collect discriminative features manually. They gathered invariant features from inertial sensors, effectively using linear transformations on the input sensor data. Their model is sensor placement sensitive despite being robust and invariant in translation and orientation scenarios. AE-GDI is sensitive toward sensor placement despite being invariant to translation and its orientation for data time series for the inertial sensor.

2.1.2. Non-wearable

Non-wearable gait sensors refer to gait analysis systems or devices that do not require the individual to wear any sensors or equipment on their body. These sensors are typically placed in the environment or on the ground to capture and analyze a person's walking pattern or gait as they move naturally without any additional equipment. Non-wearable gait sensors are commonly used in various applications, including healthcare, biomechanical research, and security. Table 2 depicts the gait analysis pipeline, encompassing preprocessing and feature extraction stages.

Detailed and accurate information about the walking style of gait can be captured precisely with a smart sensing system. The radar micro-Doppler analysis can be used as a proven metric to obtain smart surveillance of human locomotion. Abdulatif et al. [15] use D signatures to examine the results of human body characteristics on human identification. Non-wearable sensors like radar are considered more efficient as they can overcome the shortcomings of other vision-based systems. They did not compare their results with any other standard dataset. Zeng et al. [16] proposed model-based gait recognition approach using an accelerometer. Their model consists of two stages. The authors proposed dynamical estimators through the small error principle, which can gather gait inertial data more efficiently. Their model did not focus on the discriminative power and gait data collectability from several positions.

One of the most critical concerns of contemporary society is mobile- assurance. The authors proposed a periodogram-based sequential method for gait separation, authentication, and a classification-based CNN algorithm. Yuan et al. [17] implemented the method proposed in the paper. Data collection is done via the in-built accelerometer in the mobile phone. The gait separation algorithm based on the periodogram separates the gait of individuals from the time series and calculates the walking periodicities of phone users. Identification of specific gait types can be difficult as some people take steps using 1s while some use 1.2 s to take steps. After transforming the periodicity variance into an image, the focus can be put on the aM itself and how steps are formed in a time series. The authors did not compare their results with any other dataset. Their data is 100 HZ, which may result in extra heating of mobile phones due to high energy consumption.

Gadaleta et al. [18] proposed IDNet, an authentication framework for smartphone users with acquired motion signals. The main goal is to use the gyroscope and accelerometer signals to recognize the target users. The authors did not compare their work with existing methods. Radar sensors can analyze frequency shifts in velocity dimension micro-Doppler and range (micro-Range). Doppler and Range signatures will be unique for different target classifications. This classification can be helpful in fields like surveillance, gait recognition, and safety. Abdulatif et al. [19] have used Range-Doppler ($R - D$) maps to analyze real-time classification problems. The authors have also compared deep learning approaches, conventional classical learning approaches, and ensemble classifiers. The gradient boosting method used by the authors gives better results for comparisons and investigations. The authors have addressed the classification in the radar area for a single moving target. However, authors should also consider detecting a static human via radar cross-sections or vital signs.

There is more emphasis on the detection of specific gait patterns. Abnormalities like cross threshold, tiptoe, and hemiplegic gait are prevalent in research. Gao et al. [20] proposed a method for classifying and diagnosing abnormal gait by using LCWSnet (LSTM and CNN). They used parameters and Euler angle information of leg to optimize the functions. They carried feature extraction from multiple angles and considered all the features for decision sampling. The authors did not compare their work with existing methods or standard datasets. Human Gait is an essential behavioral trait in biometrics for personal authentication and identification. Jung et al. [21] proposed a neural network gait classification approach using wearable inertial sensors. The results obtained are not understood easily as their method follows a black-box model. There are some other problems associated with reproducibility and generalizability.

Deep learning has fascinated researchers for all sorts of applications. Some emerging deep learning applications are secure and smart home systems, easy medical diagnosis, indoor monitoring, and target classification. Gurbuz et al. [22] discussed various recent classification enhancements and challenges in deep learning. Fernandez et al. [23] proposed an algorithm that extracts gait cycles from processed signals and generates feature vectors by providing the extracted signal to the Recurrent Neural Network (RNN). The authors have presented a novel gait recognition approach using RNN for smartphones. The authors have not used hyperparameters in their proposed methodology. Gait recognition methods that use skeletal data have fast processing and can select better features. Models that use features from a fitted skeleton model have better scale-invariant properties and views. Sadeghzadehyazdi et al. [24] proposed correction of features and 3D estimation of the skeleton for lidar data of flash. Their methodology computes feature moments in a gait cycle, thus, outperforming the methods that use temporal information. Their model is computationally expensive and only performs well with a low number of subjects. Gait as a biometric is unobstructed and is difficult to hide. Gyroscopes and accelerometers are used to capture the dynamic gait of the subjects. These sensors are widely used in smartphones. Delgado et al. [25] proposed a deep learning model independent of the dataset. The inertial data of subjects can be collected without the information regarding the walk of the user. The task of identification and detecting user fall are both handled in the method proposed by the authors. Their model has an overfitting problem as they have used more LSTM layers and produced many outputs.

There are many inertial sensor-based gait models, but these models are not robust due to the scarcity of data. Tran et al. [26] proposed a method to augment gait data based on the inertial sensor. They proposed Stochastic Magnitude Perturbation (SMP) and Arbitrary Time Deformation (ATD) to generate more gait training data. Their proposed model can be used to augment data in gait models. The authors did not use a large dataset. Gait as a biometric is unobstructed and is difficult to hide. Gyroscopes and accelerometers are used to capture the dynamic gait of the subjects. These sensors are widely used in smartphones. Zou et al. [27] proposed a method to collect the unconstraint inertial gait data without the knowledge of how, where, and when the user walks. Their proposed method provides very discriminative features to authenticate and identify a person. Gyroscope data has a better performance than accelerometer data. Human identification through mobile sensing information is very difficult and is affected by the interference of human actions.

Lee et al. [28] proposed DeepIdentifier, a novel deep learning approach to reconstruct input data signals and recognize the user in the training phase. They designed a convolutional funnel block to accurately recognize the identity of a user in different contexts and have used the concept of multi-task in their proposed model. Their model does not have very good accuracy as they have increased the path number, decreasing the channel number for every convolution. The classical approach to handling gait pattern recognition involves floor-embedded piezoelectric sensors and video recordings. Kitic et al. [29] proposed a shallow scattering-based feature extraction method and gait recognition and identification method using measurements obtained by geophone sensors and a microphone. Their proposed method is robust to ambient noise and is specially tailored to extract features from shallow scattering networks. Also, they have shown that the fusion of two modalities (microphone and a geophone sensor data) improves identification. Their model uses scattering feature extraction for identification. Their recognition model is relevant only to training data of

Table 2
Gait analysis pipeline encompassing preprocessing and feature extraction stages for non-wearable sensor

Cite	Gait Pipeline	Pre-processing/ Feature Extraction
[15]	50-layer deep residual network	Convolutional autoencoder
[16]	constant RBF network+F19:F39F17F19:F39	Quasi-periodic signals
[17]	CNN	CNN
[18]	CNN-based authentication	Discriminant, class-invariant features/CNN
[19]	DCNN - LeNet-5	CNN
[20]	LSTM-CNN	CNN
[21]	CNN	CNN
[22]	Deep learning	CNN
[23]	Recurrent Neural Network	CNN
[24]	2D skeleton detector	3D Joint location estim-ator, outlier detection
[25]	CNN+LSTM	CNN
[26]	CNN	Gait Cycle Segmentation / CNN
[27]	CNN RNN- LSTM	Gait Cycle Segmentation / CNN
[28]	Encoder Decoder	CNN
[29]	CNN	Scattering transform
[30]	CNN-f ResNet18	CNN
[31]	DRN- NN+LSTM	Kalman filter / CNN

small size.

The mm wave-based gait recognition is the most recent technology for surveillance compared to camera-based surveillance. Meng et al. [30] proposed a deep learning-based method which is known as mmGaitNet. They collected the data of 95 people from two-millimeter wave RADARs for 30 hours, which contains two sequences. They used a deep learning approach for identifying subjects. This method retains the privacy of the users and can work well under the scenarios of dim or weak light and when the subject is not in the line of sight. They are not able to collect and identify multiple people at a time. Radar waves can damage tissues of the human body if exposed at a very high frequency. Also, their algorithm has a high computational cost. 3D space generates a lot of extra spatial data. Hence, mID is very slow; therefore, it needs 500ms to return a gait recognition result when it is running on GPU. It is crucial to know how much privacy a customer needs to provide personalized facilities. Although surveillance is a very good option, some people are wary of using cameras in their homes or workplaces. Zhao et al. [31] proposed a millimeter-wave radar-based tracking and recognition system that can combat the above-stated problem, i.e., it can easily track people without breaching their identity. They used a low-cost radar-based system that can obtain a sparse matrix from the trajectories (feature) obtained from radar. Then they applied DRN to identify each person individually. Their proposed methodology is capable of tracking multiple people simultaneously. Therefore, it can be easily applied in smart homes without breaching the privacy of people as it is not using any vision-based techniques. They did not validate their results on standard datasets. Moreover, they used RADAR waves in their methodology. These waves are very harmful to the human body and can damage human tissues if exposed regularly at a high frequency.

2.1.3. Floor Sensor

A floor sensor for gait recognition is a type of non-wearable gait sensor that is embedded in the floor or ground to monitor and analyze an individual's walking pattern or gait as they walk over it. These sensors can be used in various settings, such as healthcare facilities, research labs, and security applications. They typically use different technologies to capture and analyze gait patterns. Table 3 depicts the gait analysis pipeline, encompassing preprocessing and feature extraction stages.

Terrier et al. [33] showed that COP trajectory is less expensive and could accurately identify people as a stand-alone approach. The authors have used a very limited number of subjects and did not apply the proposed method in real-life conditions. The accuracy of their method falls when people carry a heavy load (carrying condition). Also, their method can only be applied on force platforms that use 3D gait recognition. The pressure in the shoes of 12 participants was

Table 3: Gait analysis pipeline encompassing preprocessing and feature extraction stages for floor sensor

Cite	Gait Pipeline	Pre-processing/ Feature Extraction
[32]	Deep learning - LSTM	CNN
[33]	CNN - Resnet	CNN
[34]	Deep Residual Network Model	Spatial Temporal / CNN

measured [32]; each of them had their gait varied purposely by changing shoes. The data was gathered at 100 Hz over 2520 data channels and analyzed using deep learning architecture and LSTM networks. They have not mentioned the rate by which they have applied gait recognition. A novel technique for the view-invariant encoding of gait in cross-view situations was suggested by Reyes et al. [34]. Their approach is able to capture both spatiotemporal and kinematic aspects of human gait. The speed of their suggested solution is made possible by the elimination of the need for any preprocessing processes, such as the identification and segmentation of gait cycles. It is able to determine human gait from a video database directly. Because it has to be compatible with a significant number of frames, prediction requires a high level of computational complexity.

2.1.4. Marker-less

Marker-less gait recognition is a technology used to identify and analyze an individual's walking pattern or gait without the need for any physical markers, attachments, or wearable devices. Instead, it relies on computer vision and machine learning techniques to extract unique characteristics from a person's natural walking motion. Table 4 depicts the gait analysis pipeline, encompassing preprocessing and feature extraction stages.

Table 4: Gait analysis pipeline encompassing preprocessing and feature extraction stages for marker-less sensor

Cite	Gait Pipeline	Pre-processing/ Feature Extraction
[35]	CNN	CNN / LGEI LiDAR
[36]	Deep neural network	event noise cancellation / CNN with Residual Block
[37]	GAN - LSTM	CNN
[38]	CNN	CNN

In previous approaches like Velodyne HDL-64E LiDAR sensor was in use for outdoor surveillance in re-identification, but the sensor was very costly and heavy. Thus, not feasible for wide applications of surveillance. Gálai et al. [35] offer a comparison of activity analysis on gait for distinct resolutions with the help of LIDAR scanners. Their proposed method takes GEI descriptors for gait recognition. The proposed gait recognition algorithm is less costly, less heavy, and able to achieve better accuracy than the Velodyne HDL-64E sensor. As the proposed accuracy is better than the overall accuracy of their method, it is not good. Despite having many unique advantages, the Dynamic Vision Sensors or the event cameras produce asynchronous events in intensity variations with added noise.

Wang et al. [36] proposed a gait recognition system using deep neural networks based on the new event approach. Using DVS sensors is advantageous as they are ideal for wireless monitoring due to their low bandwidth footprint. Secondly, DVS sensors can work under challenging conditions without the control of illumination as they have a high dynamic range. Lastly, DVS sensors can independently produce an asynchronous stream of events and capture intensity changes in microseconds. Their model does not give good accuracy results as RGB-based image processing methods cannot be applied in their approach. They have used a DVS camera, which does not capture human motion frames; instead, it generates noisy and asynchronous events.

Abnormal gait behavior recognition (AGBR) based on the visual approach is limited in virtual sample generation (VSG) and has difficulties in the 2D approach and the small size of the sample. Luo et al. [37] used a structured light sensor to obtain unstructured gait point cloud data. To fit the point cloud data in posture and shape, they used a 3D parametric body model. Their proposed method uses the 3D gait estimation to abstract the higher-order abnormal gait point cloud data. The computational complexity of their proposed model is very high. Gait recognition is fascinating to the researchers as it is possible to recognize the gait of an individual unobtrusively from a distance with the intervention of a subject. Limcharoen et al. [38] proposed a CNN-based Joint Replacement (JRC-CNN) technique to preprocess data by rotation so that the view angle problem vanishes. Their method concentrated more on the movement of non-connected joints instead of the local movement. Their proposed method suggests that monitoring local joint moments and identifying any subject is a better option as non-connected joints do not contain a relevant piece of information. Their proposed method did not consider the entire body. They must consider the movement of the entire body.

2.2. Pose-based

An innovative development improves the precision of gait identification as part of developing computer vision for it. Pose-based techniques help in gait identification by gathering characteristics based on joint angles. The rate of gait recognition is lowered by variations in viewing angles, attire, and carrying circumstances. Model-based methods are quite effective at managing these variances. Table 5 depicts the gait analysis pipeline, encompassing preprocessing and feature extraction stages. A three-dimensional convolution neural network and LSTM network were suggested by Weizhi et al. [39] to collect spatial and temporal data from two-dimensional pictures. Their model does a decent job of capturing both temporal and spatial information. Compared to two-dimensional pose-based approaches, the three-dimensional pose-based method can extract characteristics from view variation more accurately. Their model's accuracy is really poor. The majority of the early methods for identifying gait were focused on appearance. The criteria used in appearance-based approaches were derived from silhouettes. The silhouettes are simple to calculate and have decent identification accuracy, but variables have a significant impact. Model-based techniques, in contrast to appearance-based approaches, are less impacted by variables, but they have a high processing cost and poor identification accuracy with low-resolution pictures.

A model based on posture characteristics that use CNN for gait identification of 3-dimensional human stance was suggested by Liao et al. [40]. Their model is invariant to changes in view angles and other variables since it employs 3-dimensional posture estimations. Additionally, the accuracy of the model is increased by adopting a three-dimensional posture for spatial and temporal information. Their suggested model well captures gait characteristics and resilience to fluctuations in covariate conditions. Their model translates two-dimensional joint points to three-dimensional ones, which results in extremely poor accuracy and huge computing costs. When the angle between the train and test set is 90 degrees, there is significant variability in accuracy.

Table 5: Gait analysis pipeline encompassing preprocessing and feature extraction stages for pose-based

Cite	Gait Pipeline	Pre-processing/ Feature Extraction
[39]	CNN; ResNet;LSTM	3D Pose estimation/ CNN, LSTM
[40]	CNN	CNN
[41]	DCNN	Motion map computation / OF, average pooling
[42]	CNN	morphological filters / CNN
[43]	Hierarchical Temporal Memory	synthesized 3D gait model / 3D Gait Estimation
[44]	RNN network	Normalised 2D Pose / Spatio temporal feature extraction
[45]	LSTM - Autoencoder	Reconstructed trajectories and encoded features embeddings
[46]	CNN	CNN
[47]	RNN-LSTM	CNN

The accuracy of identification suffers since early approaches do not take the subject's complete height into account. Sokolova et al. [41] took into account both the joint angle points and the whole height. They suggested a cutting-edge pose-based CNN method that takes joint angles and the whole height of a silhouette into account. Covariates, particularly viewing angles, have little impact on their technique. Instead of taking into account the full silhouette, they take into account the entire height and the joint angle points, which increases the identification accuracy. Because they just utilise motion and ignore all color information, their model has a lower recognition rate. The PifPaf approach, which extracts characteristics from noisy environments using sounds, was proposed by Tavares et al. [42]. They are obtaining the greatest posture characteristics by employing photographs from high-resolution cameras. Their approach has produced subpar outcomes and is not very accurate. They also did not take into account covariate circumstances. Due to the need for high-resolution cameras, which are not installed, their suggested model is expensive. Luo et al. [43] suggested a hierarchical temporal memory network employing a convolution neural network and recurrent neural network to address challenges in actual three-dimensional structured data. Their suggested solution employs an estimating methodology to identify virtual clothing, body-parsing photos, and body shapes. As a result of the use of all these methods, their model functions effectively in object and attire variations. Their approach takes more time since it gathers both spatial and temporal data. Only huge datasets can support this algorithm's performance. A RNN-based approach was presented by Hossen et al. [44]. The temporal dynamics posture sequence of the human body may be captured by recurrent neural networks with gated recurrent units architecture, which are particularly effective at performing recognition. The scientists also created a low-dimensional gait feature descriptor based on 2D coordinates of human posture data that has been shown to be successful in capturing the dynamics of different gait patterns while remaining invariant to a variety of covariate variables. They discovered useful gait characteristics for the view variation environment, which led to reliable outcomes. However, they did not take into account the cross-view situations.

The accuracy of current skeleton-based approaches has decreased since they must deal with both normal and noisy data while detecting gait. A skeleton-based technique based on the siamese network and autoencoder networks was suggested [45]. For factors including differences in attire, time, and carrying goods, their model performs well. Additionally, using photos with side view angles, their system is capable of accurately recognizing gaits and reconstructing typical trajectories. They are not addressing the cross-view issue. To capture geographical and temporal data, Li et al. [46] suggested a methodology based on a joint connection mapping pyramid. Their method has a very high computational cost. With the use of an autoencoder based on RNN, Kooksung et al. [47] created a novel method for automatically extracting the features. Principal component analysis and singular value decomposition are not as effective at capturing recurrent neural network properties as their suggested approach. Their poor recurrent neural network performance is a result of the fact that they ignored sequential data when dimensionality was reduced.

2.3. Dataset

In recent years, data collection technology has advanced further, and new gait identification-related training variables have been included (see Table 1). The gait datasets that have been utilized in the mentioned research and are currently available are examined in this section. The OU-ISIR large population dataset, as described in reference [48], involves subjects walking on a ground surface while being recorded by two surrounding cameras. Additionally, the OU-ISIR multi-view large population dataset, detailed in reference [49], encompasses a wide range of 10,307 subjects, spanning ages from 2 to 87 years. These subjects' walking patterns were captured from 14 different viewing angles, producing images with dimensions of 1280 by 980 pixels. The image acquisition process employed seven cameras positioned at 15-degree intervals, operating at a frame rate of 25fps.

Furthermore, the OU-ISIR multi-view large population dataset with pose sequence, which extends the OU-MVLP dataset, was created using seven network cameras, each capturing the gait sequences of 10,307 subjects. These RGB format images also measured 1280 by 980 pixels, with a frame rate of 25 fps, as mentioned in reference [50]. In the OU-ISIR inertial sensor dataset, detailed in reference [50], sensors were affixed around the waist of 744 subjects, covering age groups ranging from 2 to 78 years. Data collection took place on both flat and inclined surfaces. Table 6 provides a comprehensive list of datasets utilized in research papers focused on deep learning-based gait analysis.

The CASIA gait database A, as referenced in [51], comprises 12 image sequences featuring 20 subjects, each offering four images captured from different view angles (0, 45, 90). In total, this dataset includes 19,139 images. CASIA gait database B, detailed in [52], introduces variations in clothing, carrying conditions, and view angles. It encompasses 11 view angles and was constructed by recording video sequences from 124 subjects.

The TUM gait from an audio, image, and depth database (GAID), as described in [53], offers RGB video footage of 305 subjects in three distinct variations, accommodating spatial-temporal covariate conditions. The CMU motion of body (MoBo) database, outlined in [54], features treadmill gait data from 25 subjects, encompassing covariates like carrying, cross-view perspectives, and different walking speeds. Subjects were instructed to walk at varying paces, and image capture involved six cameras. Lastly, the KY4D gait database A, detailed in [55], includes images and 3D models of 42 subjects walking along a straight path, incorporating variations in clothing and pose. Sixteen cameras were strategically positioned along the path to capture additional reconstructed images using a visual hull approach.

Dataset eGaIT [56] constitutes gait parameter validation of 101 subjects walking on a straight course. They used a wearable sensor on the lateral side of the shoes. Googlenet dataset [57] is a 22 layers deep CNN. It uses inception modules, giving the network freedom to select multiple filter sizes of convolution for every block. SZTAKI-LGA database [58] is used for activity recognition and person identification based on the gait. The dataset constitutes data from 54 subjects and ten outdoor sequences. ZJU-GaitAcc dataset [59] constitutes gait sequences of 175 subjects

Table 6: Gait datasets

Cite	Dataset	Type of Data
[48]	OU-ISIR	RGB camera
[49]	OU-ISIR Multiview	RGB camera
[50]	OU-ISIR with pose	RGB camera
[50]	OU-ISIR inertial sensor	Wearable Accelerometer and Gyroscope Sensor
[51]	CASIA A	Image sequences
[52]	CASIA B NM BG CL	RGB camera
[53]	TUM GAID	RGB camera
[54]	CMU Mobo	RGB camera
[55]	KY4D	RGB camera
[56]	eGaIT – embedded	Wearable sensors
[57]	GoogleNet	Accelerometer, Gyroscope
[58]	SZTAKI-LGA-DB	Lidar (VLP16, HDL64)
[59]	ZJU-gaitAcc	Wearable Accelerometer
[60]	McGill	Accelerometer gyroscope
[61]	EID-M EEG	EEG Headset; Accelerometer, Gyroscope, Magnetometer
[62]	DVS128-Gait+ EV-CASIA-B	Dynamic Vision Sensor
[63]	GPJATK dataset	3D video camera
[64]	TigerCub 3D Flash lidar camera	RGB camera
[65]	SisFall	Accelerometer
[66]	UniMiB-SHAR	Accelerometer
[67]	ASLH	Accelerometer
[68]	CNU	Accelerometer, Gyroscope
[69]	SIIT-CN-A, B, D, F, G; C; E	Kinect sensor

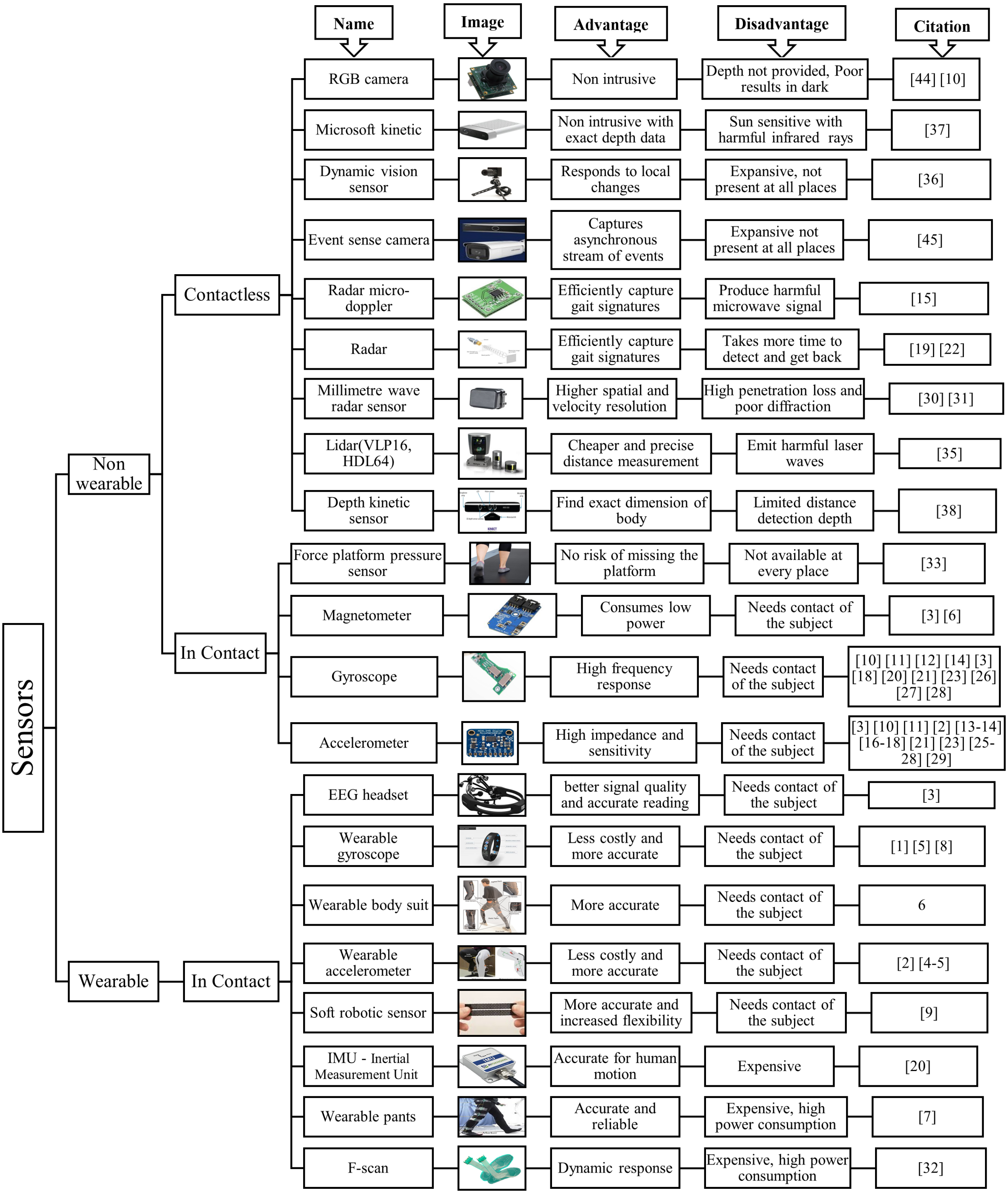
between the age group of 16 to 40. The dataset covers pose covariate for gait recognition. McGill dataset [60] contains raw sensor data gathered from 20 subjects that carried their phone in their pockets.

EID-M EEG dataset [61] is a sensor-based dataset with 7000 samples. These samples are collected from eight subjects with their eyes in a rest state on 14 electrodes with the help of EPOC+ at 128Hz for a duration of 54s. DVS128-Gait+ EV dataset [62] is a sensor-based dataset having 21 subjects and 100 sequences. GPJATK dataset [63] is a 3D dataset that constitutes 166 sequences of 32 subjects captured with the help of 10 mocap cameras and four video cameras. 3D flash lidar camera gait dataset [64] constitutes 16,300 people and 166 gait sequences. The Data was captured indoors and covered temporal and noisy image covariates. SisFall database [65] constitutes of 19 people and 38 gait sequences. The Data was captured indoors and covered temporal covariate. UniMiB SHAR database [66] consists of acceleration samples obtained from cellular devices of 30 subjects. ASLH database is a temporal sensor-based dataset [67] constitutes 378 gait sequences of 63 subjects captured indoors. CNU database [68] considers sensor-based covariates and constitutes 495 subjects with four gait sequences of each subject captured indoors. SIIT-CN [69] considers sensor-based covariates and contains real-time data captured indoors.

3. Prominent Characteristics, Benefits, and Drawbacks of Deep Learning

Deep learning algorithms avoid handcrafting feature extraction techniques by identifying discriminating regularities in raw data, which is a trend in several pattern recognition fields. Early gait recognition systems depend on video and machine learning to provide less accurate findings than deep learning. Deep learning has begun to pervade the gait recognition field in each major modality. Our solution consistently outperformed the other alternatives assessed

Figure 2: Potential sensors used in gait recognition to gather data along with their advantage and disadvantage.



in the study in every covariate condition. This paper provides a comprehensive review of deep learning parameters for gait recognition. Figure 2 mentions the sensors used in capturing the gait of a person with their advantage and disadvantage. Deep learning algorithms avoid handcrafting feature extraction techniques by identifying discriminating regularities in raw data, which is a trend in several pattern recognition fields. Table 7 summarises the advantages and limitations of the recommended technique in the context of the publications we analyzed.

Table 7: Benifits and drawbacks of each listed paper

Ref	Advantage	Disadvantage
[1]	Recognizing subject within 5 step counts	Not validating results on standard dataset
[2]	Better performance	Does not work on different covariates
[3]	Effective feature collection	Sensitive to sensor placement
[4]	Better performing classifier	Not performing good in presence of covariates
[5]	Consider all the view angles	Not compared their work with existing methods
[6]	DVS Sensor has high range	Generates noisy and asynchronous image
[7]	Performs well with smart phone	Did not use hyperparameters
[8]	Less computationally expensive	Do not perform well in real-time
[9]	Robust algorithm against noise	They do not train with large data
[10]	Effective used of autoencoder	Low performance
[11]	Generalized and flexible framework	Time-consuming
[12]	Less costly	Low accuracy
[13]	Captures data from multiple nodes	Not work on unlabeled data
[14]	Recognize the subjects within 10 steps of walk	Not validating results on standard dataset
[15]	Multimodal system	Not suitable for large datasets
[16]	Better performance	Not validating results on standard dataset
[17]	Good performance	Did not focus on data collectability
[18]	Tackles variable gait length	Unstable gait cycle is assumed as stable
[19]	Better performing classier	Not compared their work with existing methods
[20]	Additional sensors not required. Performs well on phone.	Not compared their work with existing methods
[21]	Information fusion from multiple sensors	Low accuracy
[22]	High accuracy	Not compared their work with existing methods
[23]	Developing high sensitive personalized devices	Not performing well on smaller datasets
[24]	Robust with test data	Accuracy is not given
[25]	Effciently executed distance-based features	Computationally expensive
[26]	Multi modal system	Overftting
[27]	Supports multiple sensors	Not tested on large dataset
[28]	Extracted discriminative features	Does not perform well on gyroscope data
[29]	Better performing 3D gait model	Computationally expensive
[30]	Captures relevant features	Not considering entire body so less accurate

Table 8: Benifits and drawbacks of each listed paper

Ref	Advantage	Disadvantage
[31]	Preserve privacy of subject	Not identifying multiple person
[32]	Collects deformation patterns to reduce calibration data	Do not perform well in real-time
[33]	Multi-task learning model	Achieve low accuracy with the increase in paths
[34]	Detect gait directly from a video	High computational complexity
[35]	High performance when attacked by adversarial	Accuracy of their authenticating system is inadequate
[36]	Works in real-time	Not generalized and non scalable
[37]	Dynamic model	Low accuracy
[38]	High performance	Computationally expensive
[39]	Effective detection due to multimodal strategy	Recognition rate is low
[40]	Efficiently captures the spatial features	High computational cost, low accuracy
[41]	Capsule network is efficient than simple CNN	Low accuracy
[42]	Good generalization capability on various datasets	Less effective on smaller datasets, real-time data
[43]	Intra-subject changes very small	Not consider inter-subject deformation
[44]	Method effectively deceived the GaitSet network	Imposter attack could be done
[45]	Reconstructed the images to increase the quality	Accuracy of a model depends on image resolution
[46]	Achieved good imperceptibility	Limited capacity of trained generators
[47]	Improved gait classifer's performance	Not evaluated on large datasets

3.1. Comparative Analysis of Obtained Results in Covariate Conditions using Deep Learning

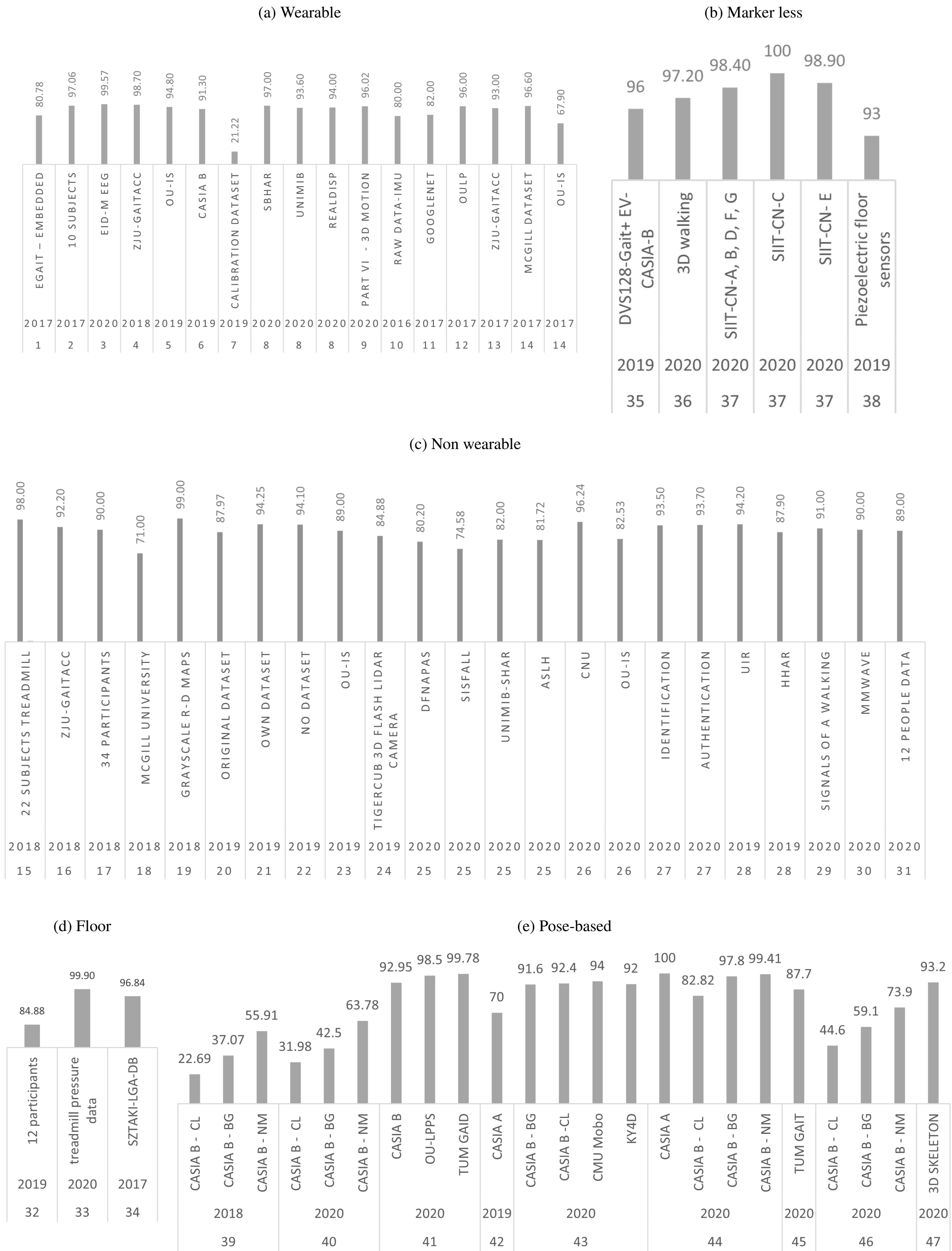
Deep learning possesses the ability to autonomously acquire features, eliminating the necessity for predefined feature extractors guided by expert knowledge. However, deep learning methodologies do come with significant limitations. Foremost among these limitations is the requirement for ample high-quality data, as deep learning is inherently data-dependent. The capability to generalize outcomes can be impeded if this prerequisite is not met. Moreover, any biases present within the dataset, such as capture bias, selection bias, negative set bias, or variety bias, can adversely impact the quality of results generated by the deep learning model.

To effectively train robust deep networks, authoritative, comprehensive, and reliable benchmarks are essential. It's worth noting that deep learning techniques are inherently opaque, often referred to as 'black boxes.' To gain a better understanding of the learning process of a specific network, efforts have been directed toward visualizing the outputs of various layers. Figure 3 provides a detailed breakdown of dataset accuracy within each paper, categorized according to sensor-based (wearable, nonwearable, floor sensor) and pose-based approaches.

Considerable research has been conducted in both sensor-based and pose-based approaches for gait recognition. Wearable sensors have demonstrated generally satisfactory results. Figure 3(a) illustrates the highest accuracy achieved for the EID-M EEG dataset. Notably, datasets like the Calibration dataset and eGaIT – embedded require substantial effort and refinement. Conversely, minimal research has been dedicated to underfloor (marker-based) and markerless gait recognition systems. Floor-based and markerless systems exhibit lower accuracy, with the markerless system performing best on the SIIT-CN-C dataset (Figure 3(b)). However, the accuracy of Piezoelectric floor sensors on the DVS128-Gait+ EV-CASIA-B dataset remains suboptimal. Consequently, researchers should consider leveraging datasets like DVS128-Gait+ EV-CASIA-B when developing deep learning solutions. The architecture should be designed to accommodate various datasets effectively.

Figure 3(c) presents nonwearable results, where Grayscale R-D maps yield the best performance, while OU-IS exhibits lower accuracy. Further research is required on the OU-IS dataset, given its size and complexity. The true

Figure 3: Description of accuracy achieved in various conditions with respect to dataset used



potential of deep learning emerges when training with larger datasets, such as OU-IS, and subsequently fine-tuning parameters to enhance accuracy. In Figure 3(d), the best results are shown for the treadmill-pressure data and SZTAKI-LGA-DB datasets. However, results for the 12 participants on this dataset are considered unsatisfactory.

Figure 3(e) displays pose-based results. Datasets like CASIA A and CASIA B excel under spatial and temporal constraints, as demonstrated in reference [44], provided there are no covariates present. However, when covariates, such as clothing and carrying, are introduced, results become less acceptable. Datasets like CASIA B - CL and CASIA B - BG have not yielded satisfactory outcomes, necessitating further research and improvement in deep learning methodologies.

3.2. Possible Avenues for Future Exploration

Numerous unexplored challenges and open issues exist within the realm of gait analysis for surveillance applications:

Interpretability of DL Models: The integration of deep learning (DL) models with applications that consider various variables remains a challenge, as these DL models can be difficult to interpret in such contexts.

Resource Limitations and Data Confidentiality: The use of diverse gait sensing methods for identification purposes poses resource constraints and risks compromising data confidentiality.

Insufficient Real-Time Gait Datasets: The lack of comprehensive real-time gait datasets hinders the proper evaluation of deep learning pipelines.

Wearable vs. Non-Wearable Devices: While wearable sensing devices offer higher accuracy, they are not universally practical and can interfere with subjects during surveillance.

Gait Covariates: Various gait covariates, including perturbation, speed, and environmental factors, need to be addressed.

Real-Life Scenarios: Gait recognition efforts often focus on single individuals in controlled settings. However, real-life situations frequently demand solutions that can withstand uncontrolled conditions with multiple individuals present.

Dataset-Specific Performance: Many gait recognition algorithms underperform on specific datasets due to incorrect model selection or inadequate training.

Hyperparameter Tuning: The critical concept of hyperparameter tuning is sometimes overlooked in research.

Model-Based Techniques: Model-based techniques show promise but are sensitive to data quality and resource-intensive. Combining model-based and model-free approaches may offer a more robust solution.

Multimodal Fusion: Combining multiple characteristics is an intriguing avenue; however, challenges remain in selecting features, determining the best fusion approach, and adapting modalities adaptively to avoid accuracy loss due to redundant or noisy data.

Gait-based recognition is a relatively new and complex field with untapped potential. While promising approaches have emerged, they have often been tested on highly diverse datasets, making accurate comparisons challenging. The absence of a standardized reference dataset has hindered comprehensive evaluations. The future holds promise with the availability of larger datasets, improved sensors, and advanced training techniques like deep learning, paving the way for significant progress in this domain.

4. Conclusion

While gait recognition is still an emerging technology compared to established biometrics like fingerprint, face, voice, and iris identification, its non-intrusive nature renders it highly appealing for numerous applications. However, the real-time execution of deep learning methods has posed challenges, limiting the effective utilization of this biometric in various scenarios, particularly as applications migrate to edge devices for enhanced privacy and security.

In this study, we meticulously explored a multitude of parameters within deep learning pipelines designed for gait recognition. Our evaluation encompassed diverse datasets capable of training deep learning models to handle a wide array of confounding factors, alongside an in-depth assessment of method accuracy. Moreover, we conducted a comprehensive analysis of the latest deep learning models associated with each parameter, highlighting noteworthy outcomes. We also conducted an extensive examination of the potential advantages and disadvantages inherent in deep learning techniques, providing a thorough overview of their applicability. Furthermore, we discussed the prevalent deep learning approaches employed in gait identification and compared their achieved accuracy and dataset utilization, with the aim of identifying existing gaps in gait recognition research that warrant further exploration.

CRediT authorship contribution statement

Anubha Parashar: Conceptualization, Data acquisition, Analysis and interpretation of data, Investigation, Visualization, Writing - original draft. **Apoorva Parashar:** Data acquisition, Analysis and interpretation of data, Investigation, Visualization. **Mohammad Shabaz:** Finalizing this paper. **Deepak Gupta:** Finalizing this paper. **Aditya Kumar Sahu:** Finalizing this paper.

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