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Real-time gait biometrics for surveillance applications: A review

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A R T I C L E I N F O

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A B S T R A C T

Deep learning (DL) pipelines have evolved for over a decade now and are efficient at solving many challenging problems of image and signal processing applications. Designing deep learning pipelines for a particular application requires a good understanding of deep learning and various intermediate layers available. To develop a DL pipeline, one uses available dataset(s) suitable for an application, and the pipeline is refined by iterating over intermediate layers. A large amount of time and extensive thinking goes into these selections and validating the performance of each configuration. Thus, it is hard to choose the correct and robust DL pipeline that performs well on all relevant datasets. This review aims to aid researchers in understanding different gait sensing technologies and provide foundational knowledge of the deep learning concepts for faster solutions for a given problem. Gait recognition is more recent since it hasn't yet been used in a real-world situation. This article provides a comprehensive overview of gait biometrics suited to real-time surveillance applications. All the important parameters of deep learning pipelines are explained, along with their selection and implication for a given problem. Authors have reviewed important research articles recently on deep learning models and how these perform across different application datasets. The benefits and drawbacks of the approaches are elucidated to help arrive at the optimized pipeline derived from a fusion of available pipelines to achieve faster but accurate results for a given problem.

1. Introduction

The rise in popularity of automated identification over the past few years has increased the focus of professionals working in computer vision and kinematics on gait recognition in real-time settings. This is because automated identification entries are becoming increasingly common. A person's gait, which can be recognized from a great distance and does not need cooperation from the target, is one of the most important biometric qualities humans possess. In vision-based techniques, it is likely that videos from low-resolution cameras will be

Abbreviations: DL, Deep Learning; BCE, Binary Cross Entropy; CCE, Categorical Cross Entropy; SGD, Stochastic Gradient Decent; MSE, Mean Square Error; WD, Weight Decay; LR, Learning Rate; M, Momentum; BP, Back Propagation; SNE, Stochastic Neighbor Embedding; SD, Standard Deviation; ED, Euclidean Distance; LRL, Logistic Regression Loss; PSO, Particle Swarm Optimization; RMSP, Root Mean Square Propagation; GA, Genetic Algorithm; CGI, Chrono Gait Image; IMU, Inertial Measurement Unit; BN, Batch Normalization; LRN, Local Response Normalization; NAC, Normalized Auto Correlation; SNR, Spectral Norm Regularization; NN, Nearest Neighbor; KNN, K Nearest Neighbor; NC, Nearest Centroid; SVM, Support Vector Machine; SNN, Spiking Neural Networks; CNN, Convolution Neural Network; MLP, Multilayer Perceptron; HMM, Hidden Markov Model; DCNN, Deep Convolutional Neural Network; DNN, Deep Neural Network; PReLU, Parametric Rectification; ReLU, Rectified Linear Unit; LReLU, Leaky Rectified Linear Unit; LSTM, Long Short-Term Memory; FCL, Focal Convolution Layer; LDA, Linear Discriminant Analysis; PCA, Principal Component Analysis; DCT, Discrete Cosine Transform; GAN, Generative Adversarial Network; BS, Background Subtraction; GEI, Gait Energy Image; OF, Optical Flow; SSA, Stacked Sparse Autoencoder; SSM, Silhouette Stereo Map; CFA, Canonical Feature Aggregation; PFA, Pose Feature Aggregation; GMM, Gaussian Mixture Model; FCNN, Fully Connected Neural Network; DCRNN, Deep Convolutional and Recurrent Neural Network; NDNN, Non-Linear Deep Neural Network; COG, Centre of Gravity; RNN, Recurrent Neural Network; DRN, Deep Recurrent Network; MB, Model Based; PB, Pose Based; SNN, Siamese Neural Network; ANN, Artificial Neural Network.

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carried out. Other biometric identification methods (in Fig. 1) have absolutely no possibility of functioning correctly in such stated scenarios [76]. Thanks to this capability of gait, it is now possible to employ it in a real-time environment. Because gait patterns are challenging to replicate and substantially more difficult to hide than facial characteristics, they are regarded as more secure forms of biometric identification [77].

Deep learning has emerged as a promising method for recognizing humans through gait [80]. Starting gait recognition with deep learning might be difficult since researchers don't know which deep learning pipeline to use or what results to anticipate. There are presently just a few review publications discussing deep learning techniques for gait identification, including deep pipeline parameters. A few surveys on gait analysis have been conducted [70–75], but the majority of survey publications concentrated on model-free gait recognition systems, ignoring model-based strategies. Despite the aforementioned benefits, gait identification real-time performance suffers because of factors like gait characteristics analyzed from various deep learning architectures and datasets. Researchers have focused on finding a method to develop a reliable gait recognition system in response to these problems [78,79]. This survey article aims to analyze in-depth the most recent developments in gait recognition research.

1.1. Contribution

The following are the important contributions of the paper.

1)The paper presented essential deep learning approaches in gait identification with a comprehensive emphasis on the architecture of gait recognition.
2)Outline the methodologies that are used the majority of the time throughout the various deep learning pipelines that have been reported, along with an explanation and assessment of these approaches.
3)The performance of gait recognition in a real-world setting is thoroughly investigated in this work.
4)The paper focuses on the future prospects that should be taken into account for the real-time use of gait recognition.

1.2. Organization

The paper is organized as follows. The first section provides an outline of the topics, including motivation, contribution, and organization. In Section 2, an examination of numerous factors reported in studies resulted in the development of a deep learning pipeline for gait.-Section 3 discusses and highlights the benefits and shortcomings of pipeline components along with gait sensing technology. The accuracy

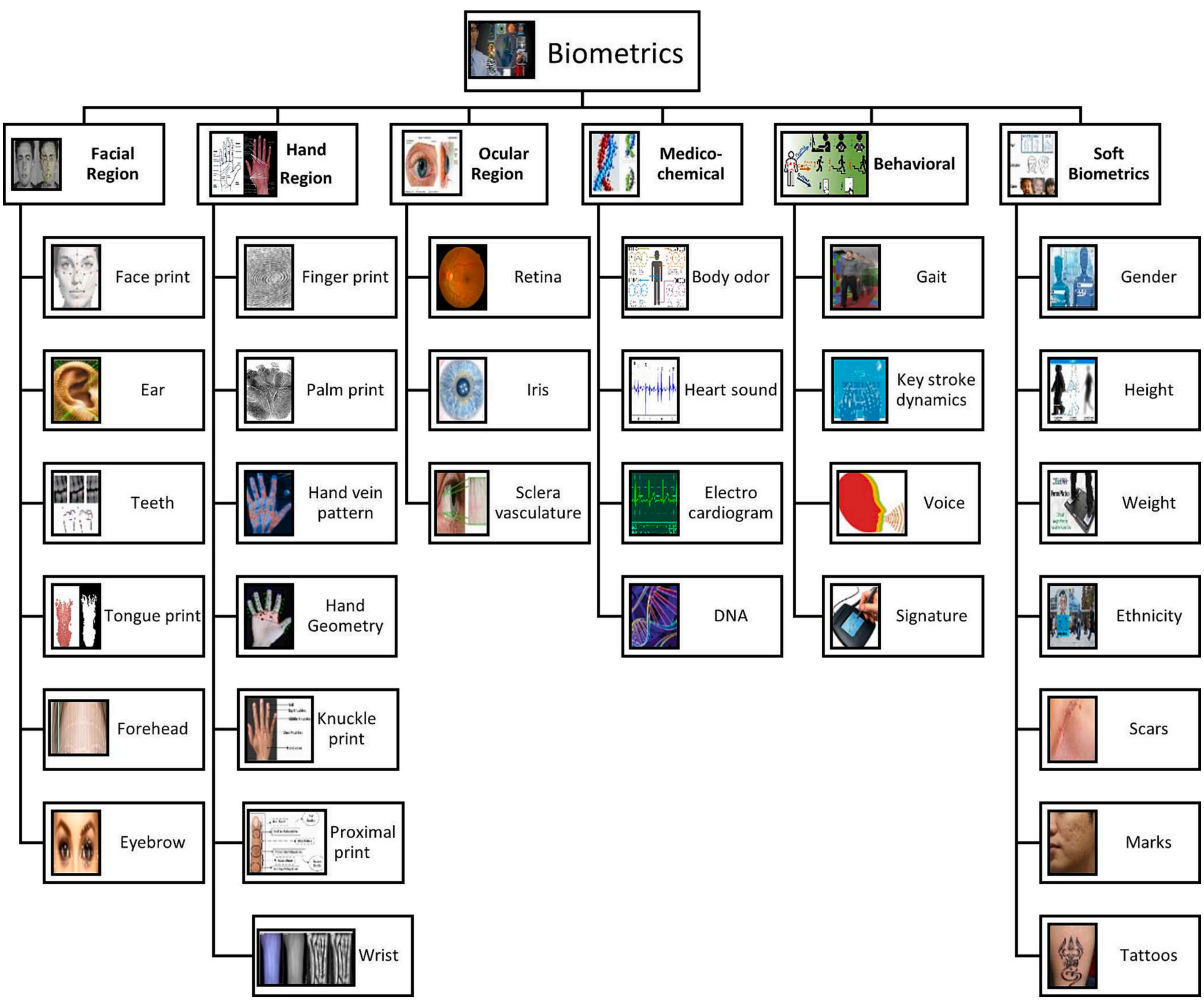


Fig. 1. Various types of biometric approaches that are used for recognition.

and dataset utilized in research publications compare major features of deep learning pipelines. Section 4 is the conclusion. We list the acronyms used in this article in the abbreviations section.

An overview of deep learning techniques for covariate conditions in gait recognition is presented in this work. A thorough examination of the recent literature published in reputable journals (Scopus or Web of Science), conferences, and Google Scholar was carried out. “Gait recognition”, “Sensor-based”, “gait identification”, “model-based gait recognition”, “pose-based”, “gait-datasets”, “gait surveillance”, “biometrics”, and other similar terms were used to search for papers. The chosen search yielded roughly 1200 papers. A total of 200 unique publications related to gait identification were chosen after analyzing the title, abstract, and keywords. After reading through the publications and considering their relevance to this survey, 69 references were finalized, which focused on gait recognition. Fig. 2 depicts a systematic review methodology adopted.

2. Various deep learning parameters to recognizing gait

Gait recognition is a challenging task in computer vision and deep learning. Here are some of the key parameters that are commonly used in deep learning models for recognizing gait:

Convolutional Neural Network (CNN): CNN is a popular deep learning architecture used for gait recognition. It consists of several convolutional layers that can extract meaningful features from the input image.

Recurrent Neural Network (RNN): RNN is another deep learning architecture that is used for gait recognition. It is especially useful for handling sequential data, such as video frames.

Transfer Learning: Transfer learning is a technique where a pre-trained model is used as a starting point for a new model. This technique can be used for gait recognition by fine-tuning a pre-trained model on a gait recognition dataset.

Data Augmentation: Data augmentation is a technique used to artificially increase the size of a dataset by creating new training examples through various transformations such as rotation, flipping, or cropping.

Learning Rate: The learning rate is a hyperparameter that controls how much the model’s weights are updated during training. A higher learning rate can help the model converge faster, but it may also cause the model to overshoot the optimal weights.

Batch Size: The batch size is a hyperparameter that determines how many samples are used in each iteration of training. A larger batch size can increase the training speed but can also lead to overfitting.

Dropout: Dropout is a regularization technique used to prevent overfitting. It randomly drops out a percentage of the neurons in the network during training.

Activation Function: The activation function is a non-linear function applied to the output of each neuron in a neural network. Common activation functions used in gait recognition models include ReLU and Sigmoid.

Loss Function: The loss function is a function that measures how well the model is performing on the training data. Common loss functions used in gait recognition include binary cross-entropy and mean squared error.

Optimization Algorithm: The optimization algorithm is responsible for updating the model’s weights during training. Common optimization algorithms used in gait recognition include stochastic gradient descent (SGD), Adam, and RMSprop.

2.1. Data collection

The gathering of gait datasets using a variety of methods is the initial step of gait detection (sensing technologies). The quality of the data used has a significant impact on how well the deep learning model performs and how accurate it is. Fig. 3 illustrates various gait sensing devices like displacement sensors, accelerometers, strain gauges, tiltmeters, depth cameras, Microsoft Kinetic, lidar, and radar for gait collection. List of data collection techniques used in deep learning-based gait papers are listed in Table 1.

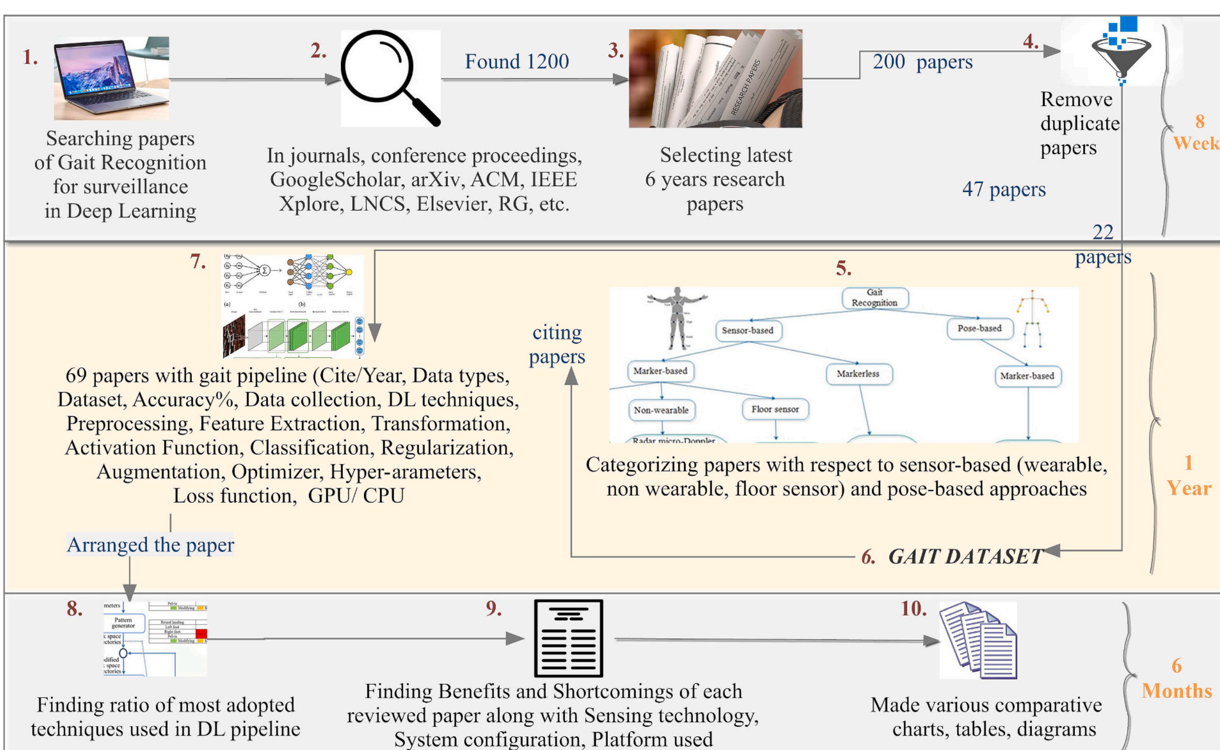


Fig. 2. Systematic review methodology adopted for searching papers and categorizing them.

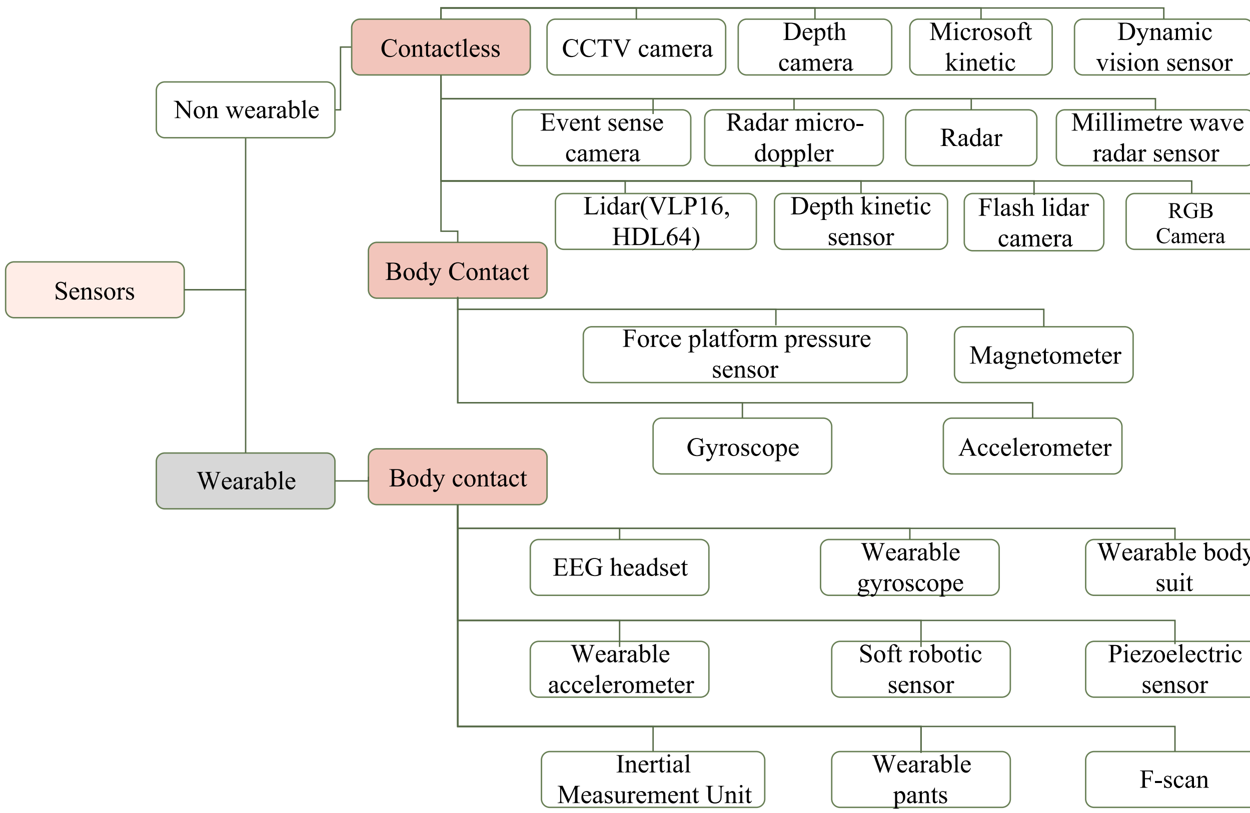


Fig. 3. Different gait sensing devices through which gait dataset can be prepared.

2.2. *Data types*

Sensors may be used to collect data as inputs to the gait process. A deep learning pipeline or CNN receives a dataset as input. Gait recognition systems are used to recognize individuals based on their walking patterns, which serve as a representation of a person's gait. They guess the identification of a probing sample from a gallery of samples the system has collected[44]. Low-resolution frames are captured from video surveillance using closed-circuit television (CCTV) [30,31,43]. In a conventional preprocessing step, most of the existing works on RGB images will first calculate silhouettes based on the images. RGB gait image silhouettes must be utilized, although extracting the gait may cause color loss in any locations where the gait is identical to the backdrop color [39–41,45,46,84]. A Kinect sensor was employed in an indoor setting to capture gait and depth data. Using depth data to model gait characteristics based on model-based data [24,37]. The effectiveness of 2D posture motion analysis systems for 2D posture gait analysis is well recognized. It does not need as much expertise as 3D systems, and the necessary technology is readily accessible and affordable. Due to high processing costs, 3D efforts in monitoring and research have been restricted so far [6].

For a single silhouette frame, a human skeleton was created. After that, the raw gait signature is produced by recognizing skeletons in each frame of the video feed [47]. GEI is a large descriptor that comprises a vast quantity of data, which diminishes the quality of distinguishing characteristics. It encompasses both linear and angular kinematics, which explain the trajectories and angular positions of body segments as they move through time [2]. The gait cycle is the time period or series of events or activities that occur during locomotion from the moment one foot makes contact with the ground to the time the same foot makes contact with the ground again, and it includes the center of gravity's propulsion in the direction of motion [4,13]. Shapelets are subsequences of time series data that may distinguish across classes [17]. Shapelets are the most emblematic of their kind. Grayscale R-D maps, which take grayscale input pictures and map them [19]. List of data types used in deep learning-based gait papers are listed in Table 1.

2.3. *Preprocessing*

After the input is taken in the gait pipeline, it is passed to the next gait pipeline stage for preprocessing and feature selection. Table 2 shows the various techniques used by the researchers for data preprocessing and feature selection.

2.4. *DL techniques*

To distinguish gait, a variety of deep learning approaches are applied. We provide a summary of deep learning methods and succinct explanations of each strategy used to identify gait. CNN, or Convolutional Neural Networks, were created to transform image input into parameters. List of deep learning techniques used in gait papers are listed in Table 3. They have proven to be so successful that they are now the solution of choice for any kind of prediction problem that takes visual data as input [2,4,5,8,10,12,14,17–22,25–27,29,30,33,35,38–42,46]. A generative adversarial network (GAN) is based on "indirect" training through a discriminator that is also dynamically updated. This means that the generator is trained to fool the discriminator rather than lessen the distance to a certain image. This enables the model to learn without supervision [37]. The Encoder-Decoder is a recurrent neural network created to deal with sequence-to-sequence (seq2seq) problems. Sequence-to-sequence prediction tasks are challenging when the number of items in the input and output sequences differs [7,28]. Autoencoders are an unsupervised artificial neural network that learns efficient data coding. An autoencoder trains the network to eliminate signal "noise," generally for dimensionality reduction, in order to learn a representation (encoding) for a set of data, [45]. An artificial recurrent neural network with deep learning is designed for long short-term memory. LSTM has feedback connections as opposed to traditional feedforward neural networks. It can

Table 1
List of parameters used in deep learning-based gait papers.

Cite	Year	Data types	Dataset	Data collection
[1]	2017	Sensor data	eGaIT – embedded	Wearable sensors
[2]	2017	Gait segments	10 subjects	Wearable Accelerometer
[3]	2020	EEG, gait signals	EID-M EEG	EEG Headset; Accelerometer, Gyroscope, Magnetometer
[4]	2018	Gait cycle	ZJU-gaitAcc	Wearable Accelerometer
[5]	2019	Sensor data	OU-IS	Wearable Accelerometer Gyroscope Sensor
[6]	2019	3D skeleton view	CASIA B	Wireless body suit; Camera; Magnetometer
[7]	2019	Signals	Calibration dataset	Wearable pants
[8]	2020	Input samples	SBHAR, UniMiB, REALDISP	Wearable sensors
[9]	2020	Foot–ankle	PART VI - 3D motion	soft robotic sensors
[10]	2016	Sensor data	Raw data form ankle-IMU	Accelerometer, gyroscope, IMU
[11]	2017	Raw input sensor data	GoogleNet	Accelerometer gyroscope
[12]	2017	Sensor data	OULP	Accelerometer Gyroscopes
[13]	2017	Gait cycles	ZJU-GaitAcc	Accelerometer
[14]	2017	Gait detection	McGill dataset; OU-IS	Accelerometer gyroscope
[15]	2018	micro-D signature	22 subjects Treadmill	Radar micro-Doppler
[16]	2018	Acceleration data	ZJU-GaitAcc	Accelerometer
[17]	2018	Time series data-image	34 participants	Accelerometer
[18]	2018	Sensor data	McGill University	Accelerometer gyroscope
[19]	2018	Grayscale R-D maps	Grayscale R-D maps	Radar sensor
[20]	2019	Long sequence of angle	original dataset	IMU Gyroscope
[21]	2019	Gait spectrograms data	own dataset	Accelerometer Gyroscope
[22]	2019	Raw I/Q Radar Data	No dataset	Radar
[23]	2019	Signals	OU-IS	Gyroscope, Accelerometer
[24]	2019	Image depth intensity	TigerCub 3D Flash lidar camera	RGB camera
[25]	2020	Raw Input accelerometer based	DFNAPAS; SisFall; UniMiB-SHAR; ASLH	Accelerometer
[26]	2020	Raw gait signals	CNU; OU-IS	Accelerometer Gyroscope
[27]	2020	Sensor data	Identification	Accelerometer Gyroscope
[28]	2019	Sensor data inputs	UIR; HHAR	Accelerometer Gyroscope
[29]	2020	Sensor data	Signals of a walking	Accelerometer
[30]	2020	Frames	mmWave - radar waves	mmWave sensor
[31]	2020	Frames	12 people data	Millimetre wave radar
[32]	2019	Individual footprints	12 participants	F-scan
[33]	2020	Sensor data input	treadmill - pressure data	Force platform pressure SENSOR
[34]	2019	Footstep signals	Floor Sensor System	Piezoelectric sensors
[35]	2017	GEI descriptor	SZTAKI-LGA-DB	Lidar (VLP16, HDL64)
[36]	2019	Raw event stream	DVS128-Gait + EV-CASIA-B	Dynamic Vision Sensor
[37]	2020	Depth image	3D walking	Microsoft Kinect sensor
[38]	2020	Joint angles	SIIT-CN-A, B, D, F, G; C; E	Kinect sensor
[39]	2018	RGB Gait image	CASIA B nm;bg; CL	RGB camera
[40]	2020	RGB Gait image	CASIA B NM BG CL	RGB camera
[41]	2020	Silhouette sequences OF	CASIA B 92.95; TUM GAID, OU-LPPS	RGB camera
[42]	2019	RGB gait image	CASIA A	RGB camera
[43]	2020	Shapes	CMU Mobo; CASIA B -Bag; Coat; KY4D	RGB camera
[44]	2020	Gait video	CASIA A; CASIA B NM, BG, CL	RGB camera
[45]	2020	RGB Gait image	TUM GAIT	RGB camera
[46]	2020	RGB frames	CASIA B/ NM; BG; CL	RGB camera
[47]	2020	Skeleton	3D SKELETON	RGB camera

manage whole data sequences as well as individual data points [3,6,9,25,27,31,32,37,40,45,47]. A residual neural network is a kind of artificial neural network based on cerebral cortex pyramidal cells. Skip connections, or shortcuts, are used by residual neural networks to avoid specific layers [15,33,39].

A pose estimation network is a computer vision technique that predicts and tracks the position of a person or object. This is performed by looking at a person's or object's posture and orientation. Skeleton in 2D Pose Estimate makes advantage of GPU acceleration to deliver low-latency joint real-time object identification and high-accuracy 2D key point pose estimate [24]. A recurrent neural network is a kind of artificial neural network in which node connections form a directed graph over time. It is possible to display temporal dynamic behaviour as a result of this [3,23,27,31,44,47]. The RCNN algorithm creates a set of boxes in the picture and examines them to determine whether any of them contain any objects. RCNN uses selective search to extract these boxes from a picture [4]. LeNet-5 is a large-scale image processing feedforward neural network containing artificial neurons that can respond to a fraction of the cells in its coverage region [19]. High-order sequences may be stored, learned, inferred, and recalled using Hierarchical Temporal Memory. HTM is different from most machine learning algorithms because it constantly learns time-based patterns in unlabeled data. HTM is quiet and can hold a lot of things [43]. Radial basis function (RBF) networks are a form of artificial neural network that is often employed for function approximation challenges [16]. A neural network is a collection of algorithms that attempts to detect underlying connections in a batch of data by simulating how the human brain works [31]. In most circumstances, an artificial neural network (ANN) is employed when something that occurred in the past is repeated nearly identically in the same manner [9]. A deep neural network is a machine learning system that uses numerous layers of nodes to extract high-level functions from input data. It involves transforming data into a more ethereal and imaginative element [1,13,36].

2.5. *Feature extraction*

When dealing with massive amounts of raw data, feature extraction refers to the process of transforming raw data into numerical characteristics that may be analysed while retaining the information in the original data set. A large number of variables in these large data sets involve using a large number of computer resources to process them. Table 2 provides a detailed overview of the various methods used in

Table 2
List of deep learning parameters used in gait papers.

Cite	Year	Gait Pipeline	Pre-processing/ Feature Extraction
[1]	2017	Deep neural network	CNN
[2]	2017	DCNN	CNN
[3]	2020	RNN; LSTM	Encoder-decoder
[4]	2018	RCNN	Cycles extraction, normalization/ CNN
[5]	2019	Deep learning based end-to-end approach	CNN
[6]	2019	3D CNN; LSTM	CNN
[7]	2019	Encoder, decoder	Encoder
[8]	2020	CNN	CNN
[9]	2020	ANN-LSTM	CNN
[10]	2016	CNN	CNN
[11]	2017	DCNN	CNN
[12]	2017	CNN	CNN
[13]	2017	Deep neural network	Cycles extraction, normalised/ CNN
[14]	2017	CNN	Angle embedded dynamic Image/ CNN
[15]	2018	50-layer deep residual network	Convolutional autoencoder
[16]	2018	constant RBF network + F19:F39F17F19:F39	Quasi-periodic signals
[17]	2018	CNN	CNN
[18]	2018	CNN-based authentication	Discriminant, class-invariant features/CNN
[19]	2018	DCNN - LeNet-5	CNN
[20]	2019	LSTM-CNN	CNN
[21]	2019	CNN	CNN
[22]	2019	Deep learning	CNN
[23]	2019	Recurrent Neural Network	CNN
[24]	2019	2D skeleton detector	3D Joint location estim-ator, outlier detection
[25]	2020	CNN + LSTM	CNN
[26]	2020	CNN	Gait Cycle Segmentation/ CNN
[27]	2020	CNN RNN- LSTM	Gait Cycle Segmentation/ CNN
[28]	2019	Encoder Decoder	CNN
[29]	2020	CNN	Scattering transform
[30]	2020	CNN-f ResNet18	CNN
[31]	2020	DRN- NN + LSTM	Kalman filter/ CNN
[32]	2019	Deep learning - LSTM	CNN
[33]	2020	CNN - Resnet	Low-pass filtered at 30 Hz; down sampled to 50 Hz/CNN
[34]	2019	Deep Residual Network Model	Spatial Temporal/ CNN
[35]	2017	CNN	CNN/ LGEI LiDAR
[36]	2019	Deep neural network	event noise cancellation/ CNN with Residual Block
[37]	2020	GAN - LSTM	CNN
[38]	2020	CNN	CNN
[39]	2018	CNN; ResNet;LSTM	3D Pose estimation/ CNN, LSTM
[40]	2020	CNN	CNN
[41]	2020	DCNN	Motion map computation/ OF, average pooling
[42]	2019	CNN	Morphological filters/ CNN
[43]	2020	Hierarchical Temporal Memory	Synthesized 3D gait model/ 3D Gait Estimation
[44]	2020	RNN network	Normalised 2D Pose/ Spatio temporal feature extraction
[45]	2020	LSTM - Autoencoder	Reconstructed trajectories and encoded features embeddings
[46]	2020	CNN	CNN
[47]	2020	RNN-LSTM	CNN

deep learning frameworks with different feature extraction and representation techniques explored.

2.6. Hardware and software details

A tiny computer devoted to one specific activity is known as a graphics processing unit (GPU). It is distinct from a CPU that does several tasks concurrently. GPUs have their own processors, motherboards, vRAMs, and a suitable thermal design for cooling and ventilation. Gait recognition algorithms are performed on CPUs in 65% of the listed publications, whereas GPUs are utilized in 35% of them. The platforms that authors have utilized to execute their gait recognition algorithms are listed in Table 3.

3. Comparative analysis of most adopted deep learning approach

The most often used data types are shown in Fig. 4 (a). The most often used deep learning methods are shown in Fig. 4 (b). shows the most popular deep learning approaches. CNN is the most adopted deep learning technique followed by LSTM.

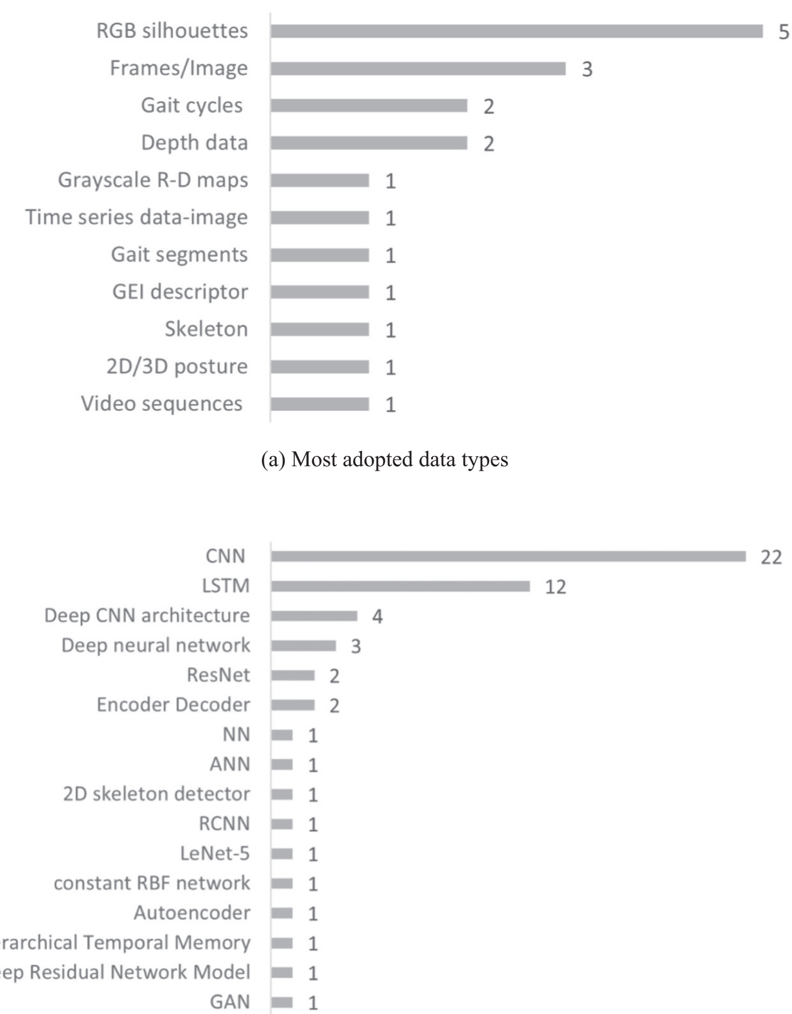
3.1. Potential future directions

There are open issues and challenges in surveillance application of gait analysis that have not been fully explored or addressed:

1. The inability of DL models to be interpreted when used in conjunction with applications that take into account variables
2. The restriction of computing resources and the risk of compromising the confidentiality of data when using a variety of gait sensing methods to identify gait.
3. Various real-time gait datasets are missing due to which performance of deep learning pipeline cannot be evaluated properly.
4. Wearable sensing devices have greater accuracy than non wearable devices but wearable devices are not feasible every place and intervene with the subject during surveillance.
5. Various gait covariates need to be addressed like perturbation, speed, and other environment factors.
6. The majority of the efforts on gait recognition concentrate on observing a single person in the scenario while they are conducted in controlled situations. However, situations that really occur in real life often demand solutions that can withstand uncontrolled conditions in which more than one person is present.

Table 3
System configuration, GPU detail, language used and framework details.

Cite	System configuration	Platform (CPU/ GPU)	Language	Framework
[1]				tensorflow
[2]			MATLAB	
[5]	PC with Titan X Pascal GPU	Titan X Pascal GPU		
[7]			Python	PyTorch
[8]	PC with GPU (NVIDIA RTX 2080Ti)	GPU (NVIDIA RTX 2080Ti)		
[11]		GPU	Python	keras
[12]	CPU Core i5 7400, 16 GB RAM, GPU Geforce GTX 1060 (6 GB RAM)	GPU Geforce GTX 1060 (6 GB RAM)	Python	tensorflow
[13]	System with NVIDIA GTX1050 GPU	NVIDIA GTX1050 GPU.	Python	Caffe
[14]	PC with an i7-5500U 2.40 GHz CPU and 16 GB RAM	CPU		Tensorflow
[15]	PC with NIVIDIA Titan X GPU	NIVIDIA Titan X GPU		
[16]	Intel Corei5 3.5 GHz computer with 4 GB RAM	CPU		
[17]	PC whose CPU is i7-7820HQ, 2.90 GHz CPU and with 16 GB RAM	CPU		
[25]	Xeon E5-2698 16 core processors, with 256 GB of RAM and a NVidia Titan X, operating at 2.3 GHz. Ubuntu 16.04	NVidia Titan X,	Python	Keras and Tensorflow
[30]				Pytorch
[31]			Python	Keras library and a Tensorflow backend
[33]		GPU computing	Python, Matlab	Tensorflow and Keras on Python 3.6
[34]			MATLAB R2018a	
[36]	Ubuntu 16.04, single NVIDIA 1080Ti GPU	1080Ti GPU		
[37]		GPU		
[41]	NVIDIA GTX 1070 GPU	NVIDIA GTX 1070 GPU		OpenCV
[46]	PC WITH 2 NVIDIA 1080TI GPUS	2 NVIDIA 1080TI GPUs		
[47]	Intel(R) Core (Tm) I7-7700 k CPU, 8.00 Gb Ram, Nvidia Geforce 1050-Ti			Tensorflow



(a) Most adopted data types

(b) Most used deep learning techniques

Fig. 4. Most adopted deep learning approaches.

7. Lots of gait recognition algorithms performs below average on few datasets due to wrong model selection or less training.

Before we wrap up our study, we would want to emphasise that gait-based recognition is a very new topic that is fraught with difficulties and offers a wealth of possibilities that have not yet been fully explored. In these early years of study, a number of approaches have been developed and are producing promising findings; nevertheless, they have only been tested on datasets whose properties differ greatly from one another. The absence of a reference dataset that can test the algorithms with a large range of conceivable situations has, up to this point, rendered it impossible to provide an accurate comparison between different techniques [85–95]. We anticipate significant progress in the years to come as a result of recent developments including the availability of massive datasets, improved sensors, and end-to-end training methods such as deep learning.

4. Conclusion

While the gait recognition system is still in its early stages compared to other biometrics like fingerprint, face, voice, and iris identification, its non-intrusiveness makes it more desirable than other approaches for many applications. However, running deep learning methods in real-time has made it impossible to utilize this biometric effectively in any circumstance and is thus its limitation as applications move to the edge for privacy and security in real time gait applications. In this study, a large number of deep learning pipeline parameters for recognizing gaits were determined. We evaluated a set of datasets suitable for training deep learning pipelines to handle a range of confounders in addition to evaluating the methods' accuracy. Furthermore, we analyzed the most current deep learning models for each parameter and highlighted those that delivered remarkable results. There is a variety of possible advantages and disadvantages associated with deep learning techniques, which have been thoroughly addressed. Deep learning approaches have also been discussed in terms of potential advantages and limitations. We examined the deep learning approaches to gait identification that has been most widely used. In order to identify the gait recognition gaps that need to be addressed, comparisons of accuracy attained and datasets utilized are also summarized.

CRediT authorship contribution statement

Anubha Parashar: Conceptualization, Investigation, Visualization, Writing-original-draft. **Apoorva Parashar:** Funding-acquisition, Investigation, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

My manuscript has no associated data.

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