



A review on Gait Recognition, Classification methods and Databases used

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Abstract

Vulnerability to human authentication is a major problem in today's digital society in real-time settings such as airports, hospitals, metro stations, etc. Video surveillance security solutions have grown in popularity as a result of this problem. Due to its subtle and imperceptible character, behavioural biometric feature gait has become a viable candidate for a surveillance monitoring system in recent years. One benefit of even more human gait is that it may be observed in low-resolution footage and from a distance. Lastly, it is challenging to mimic gait characteristics. In this paper we cover gait recognition system and its types. The paper delves further into different classification methods which are mainly used for gait recognition. Additionally, the paper covers description of databases that can be used for research, divided into two groups: sensor-based and Vision Based. We look closely at the variables that influence gait recognition; recent work was done to address these variables. Furthermore, after reviewing the most recent research in the field, this paper suggests CNN based architecture which has recognition the person with high accuracy as compare to other discussed methods. Finally, we also provided a brief overview of the suggested workflow.

Keywords: Gait Recognition, CNN

1. Introduction

In the modern digital world, a reliable and safe method of verifying an individual's identity in real-time situations like computer security, border crossings, airport parking, and metro stations is necessary. Conventional authentication methods, such as passwords and tokens, are highly vulnerable to hackers, password forgetting, theft and other problems. In order to address these problems, human body characters or traits such as the face, ear shape, fingerprint, gait, etc. have come to be recognised as biometrics and are crucial to an individual's identity throughout time. There are two categories that can be used to classify biometric modalities: physiological (which includes things like the face, fingerprints, and iris, among other things) and behavioural (which includes things like voice, gait, signature, and so on). All of the many types of biometric modalities come with their own set of benefits and drawbacks [1, 2]. In this paper section II, explains the detailed working of the gait recognition system, outlining all processes involved in gait identification. We additionally delineate feature selection and categorization

methodologies. Section III discusses gait categorization approaches mostly based on machine learning and distant learning. In part IV, we examine the gait VB and SB datasets and delineate the architecture of the CASIA dataset. In section V, discuss the conclusion.

2. Gait Recognition System

Researchers curiosity is excited by the significant and broad research scope of gait-based human authentication. Applications for gait recognition include video surveillance monitoring, gender recognition [3]–[5], age classification [6], [7] and gait-based clinical disease diagnosis [8][9] A type of pattern recognition technique known as "gait-based authentication" gathers each subject's gait patterns for analysis and assessment. Model Based (MB) and model Free (MF) feature representation techniques are the two groups into which gait recognition techniques fall. For Model Based techniques to produce gait characteristics, modelling was necessary beforehand. The authors [10] were the pioneers in employing light display reflectors on specific body

joints to illustrate the Model Based approach and provide gait data for individual validation. Conversely, Model Free utilizes silhouette frames to directly extract features. The first group to extract spatiotemporal features for recognition, Niyogi et al. [11] achieved 81% accuracy. Comprehensive elucidation of the methodologies (Model Based (MB) and Model Free (MF)). The general gait recognition system contains two distinct phases: the training phase and the testing phase, as illustrated in Figure 1.

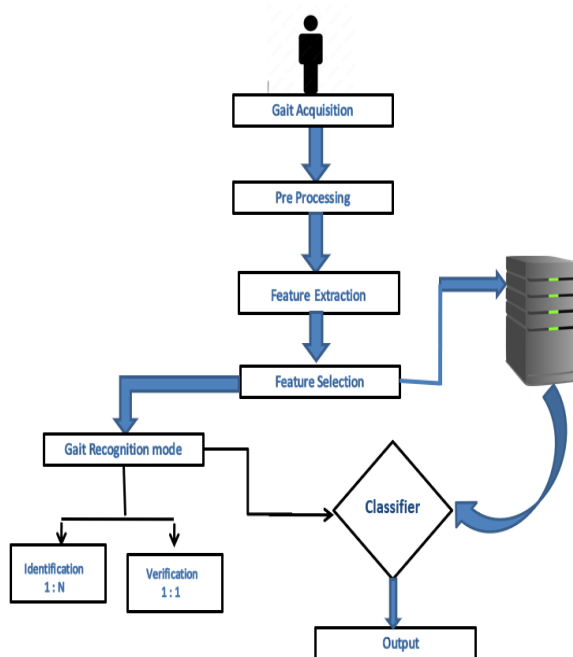


Figure 1 General Work Flow of Gait Recognition System

Each phase undergoes a sequence of stages. The performance of a gait recognition system or the similarity between trained and test data can be evaluated through two methods: verification and identification [12], [13]. The performance of the gait system was illustrated using the receiver operating characteristic (ROC) in verification mode, utilizing two error metrics: the false acceptance rate (FAR) and the false rejection rate (FRR). Conversely, in the identification mode, the cumulative match characteristics (CMC) score was represented using rank order [1]. Using various modalities (sensing technologies), the first stage of gait identification is

primarily focused on gathering gait datasets. The obtained data samples have a significant impact on the model's correctness and success. According to the taxonomy displayed in Figure 2, the gait acquisition technologies is categories in two major parts : Vision Based and sensor based.

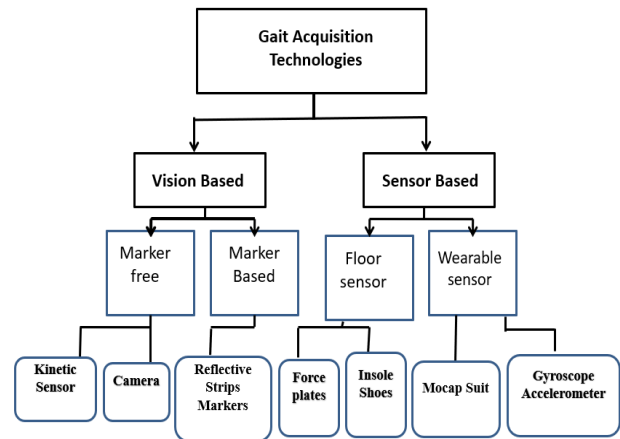


Figure 2 Taxonomy of Gait Acquisition Technologies

2.1.Sensor Based

The data is collected by sensors and different devices is come under the category of sensor-based data and devices are used to generate the data is called sensor devices. There are two categories of sensor devices: wearable sensors and floor sensors. In wearable sensor According to Bachlin et al.[14], A wearable device for detecting the start of frozen gait in individuals people with Parkinson's disease. They utilised on-body acceleration. sensors to gauge the patient's walking pattern. based on clothes Bergmann et al.'s [15] proposed sensor system. Senses were put into the fabric to measure the characteristics of the knee joints for clinical examination. Muaz and Mayrhofer's [16] smartphone-based gait recognition system was proposed to achieve a zero-effort and minimally effortful walk in real-world conditions. They created an Android app which collected data on gait movement using an accelerometer sensor built into a smartphone. More complex equipment is needed for the sensor based (SB) gait acquisition. for data sensing. Nevertheless, they offer precise



quantitative data for examination. These methods of acquisition are frequently employed in clinical diagnosis, such as Parkinson's knee osteoarthritis [17], illness [14], and other illnesses connected to gait. According to Bachlin et al. [14], a wearable aid for identifying the sign of freezing gait in people with Parkinson's disease. They utilised on-body acceleration. sensors to gauge the patient's walking pattern. based on clothes Bergmann et al.'s proposed sensor system[15]. Senses were put into the fabric to measure the characteristics of the knee joints for clinical examination. Muaaz and Mayrhofer's[16] smartphone-based gait recognition system was suggested in opposition to Achieve a zero-effort and live minimal-effort walk under actual situation. They created an Android app. Which collected data on gait movement using an accelerometer sensor built into a smartphone. More complex equipment is needed for the SB gait acquisition. for data sensing. Nevertheless, they offer precise quantitative data for examination. These methods of acquisition are frequently employed in clinical diagnosis, such as Parkinson's knee osteoarthritis [17], illness [18] and other illnesses connected to gait. On the other hand, in floor sensor Pressure sensors are used, which are positioned on a certain floor, and when someone walks over it, they produce pressure signals [19], [20]Weiss and associates used two Kistler force plates in [19] to gather kinetic parameters (ground reaction forces) for 50 sick and 37 healthy people on a 10-meter-long pathway. In a similar vein, Kotti et al. used two Kistler force plates in order to get 47 patients' ground reaction forces for osteoarthritis in their knee's diagnosis. The creation of a cumulative foot pressure picture database Zheng et al.'s work[21]. The RScan USB foot sensor was utilised to record ground reaction force data, taking into account two factors, namely walking pace and the use of different shoes. A total of 121 subjects provided a total of 3000 photos. When it comes to wearable sensors, the devices are affixed to specific parts of the human body in order to record dynamic characteristics. (such position, acceleration, speed, etc.), which can be utilised to analyse gait [14]. Tereso and associates [5] used using an inertial sensor

to gather spatiotemporal characteristics of osteoarthritis patients in their knees

2.2. Vision Based

A visual camera is required for this sensing modality to capture gait information and assess the gait cycle. There are two further classifications for this category: marker-based and marker-free. Marker-based reflective approaches involve the application of tapes or markers on a human body to capture dynamic information for analysis, including kinematic parameters, joint angle movements, and distance [22], [23]. Mahyuddin et al. [24] developed a dataset on gait using LED markers, which can be employed for clinical diagnosis and rehabilitation purposes. The optical 2D motion analyzer system was developed by collecting kinematic and Kinect characteristics from a dataset consisting of 212 people. Ishikawa et al. [25] utilised eight optical cameras equipped with plug-in-gait markers to gather data on knee patients for diagnostic purposes. The employment of this sensory modality may be advantageous in clinical diagnostics. Visual cameras can be used as a method to capture gait patterns for recognition without the necessity for markers. Nowadays, Kinect sensors (depth cameras) are used to find gait joints without attaching any of the previously described sensors. The number 28 is enclosed in square brackets[29].

Wang et al. [30] employed a Kinect sensor to generate a dataset for gait detection, utilising a 3D skeleton framework. To obtain both static and dynamic information for recognition purposes, a human model was developed. Research on gait recognition over the last couple decades has been based on video datasets. One or more cameras installed anywhere can be sufficient to record human gait patterns for identification in these databases. As a result, gait can be used in real-time scenarios. The detailed explanation of feature extraction techniques based on the video gait database covered in Figure

3. Gait Classification Techniques

Classification, the final phase in gait recognition, is employed to compare test and trained feature vectors to evaluate their similarity and assess the accuracy of the proposed model. A taxonomy system has been created, which describes the classifiers that have been

used recently to recognise gaits, separated into two groups: machine learning based and distance based. Machine learning based, as depicted in Figure 3. In this section, we examine the distance-based and core machine learning classifier in brief. measures that are often employed in the identification of VB gaits based. Table 1 displays an ML classifier based on categorization benefits and drawbacks.

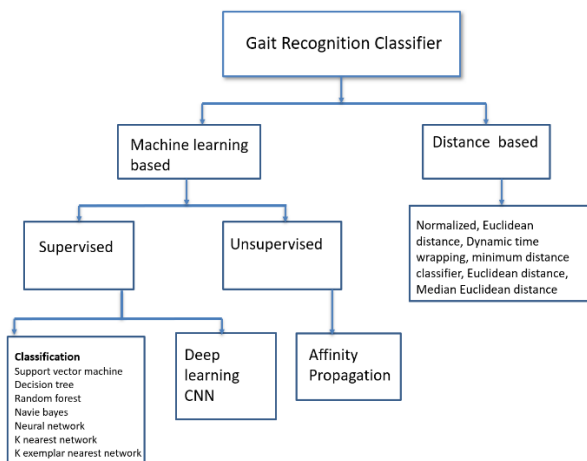


Figure 3 Classifier in Gait recognition

The majority of machine learning classifiers in gait recognition have been developed, with the analysis based on the sources cited in this article. K-NN is the preeminent classifier, owing to its simplicity of application. Neural networks are extensively utilized in gait recognition. Currently, supervised machine learning, particularly deep learning, is focusing gait identification experts' attention towards its implementation in real-time environments [35, 36].

3.1.Distance Based Classification

The distance classifier is a typical statistical method employed in gait recognition to assess the degree of similarity between the stored gallery gait data set and the probing feature set based on a predefined threshold. The standard representation method for behavioural biometric gait identification is Euclidean distance (ED) where we calculate the distance between pixel values and then match it with stored values for identifications. Jia et al. [50] proposed a view-invariant gait identification method that utilized

the Euclidean distance between the Lucas-Kanade gait for similarity assessment. Bouchrika et al. [51] used Euclidean distance to figure out the difference in performance between the labeled features and the recovered joint features. Also, Kusakunniran et al. [48] used Euclidean distance to see how similar gait traits they got from a view transformation model (VTM) were to each other. Wang et al. [52] noted that the Normalized Euclidean Distance (NED) between two consecutive projection centroids (C1 and C2) can be used to make the matching more similar.

3.2.Machine Learning Based Classification

A branch of artificial intelligence called machine learning (ML) improves data-driven model building methods. In this context, data refers to information like pictures, movies, etc., while a model is the result of machine learning. ML has shown itself to be a potent method in recent years that improves gait recognition ability [31], [51]. This section presents a quick look at the machine learning approaches that are most often used in gait classification. These are SVM, k-NN, NN, and Deep Learning.

3.2.1. Support Vector Machine

The support vector machine (SVM) is a type of supervised machine learning that can be used to sort data in gait recognition. SVM is a good non-linear mapping function that can be used to fix problems with regression and classification. The goal of support vector machines (SVM) is to make a hyperplane that splits all training feature vectors into two groups. SVMs can be taught to correctly sort things into two or more groups. Using a binary SVM classifier, divide the data set into two groups (1 and -1) based on whether each item is in a class or not. Li et al.'s study [42] applied gait analysis to gender classification. They classified gait patterns using SVM into two classes—male and female—and attained a 98% accuracy rate. Similar work is done by Sudha and Bhavani [53], who use spatiotemporal aspects of gait to do gender classification. For classification, they employed two classifiers, SVM and PNN, and achieved 82.5% accuracy for each. Nandy et al. As part of their study into how clothes affect GENI, [35] used three classifiers—SVM, k-NN, and MDC (minimum distance classifier)—to check

how accurate their results were. They got a precision that was 80% higher in SVM and MDC than in k-NN.

Table 1 A Summary of the Machine Learning Classification Methods for Recognising GAITs

S no	Learning method	Types of learning	Sub category	Merits	Demerits	Reference
1	Support Vector Machine (SVM)	Supervised	Classification	1) Fewer parameters should be considered. 2) Avoid overfitting.	1) More learning time 2) Use complete data	[31],[32] [33]
2	Decent Tree (DT)			1) Use white box model 2) Deal with hard data	1) Work with 1 quantitatively data 2) Frequently wrong	[34],[35]
3	Random forest			1) No need to normalize the feature 2) More accurate 3) Can operate on large dataset	1) Difficult to understand. 2) Overfitting issue	[1] [36]
4	Navie Bayes (NB)			1) Simple to install 2) Needs little training data	1) More inaccurate	[21], [37], [38]
5	Neural Network			1) Capability to tolerate faults 2) Is able to manage noisy data	1) Expensive computation 2) Require a lot of data 3) Avoid hostile situations	[39]–[42]
6	Convoluti onal Neural Network			1) Improved output 2) Effective extractors of features	1) The cost of computation is significant 2) Extensive intricacy 3) Unable to deal with a tiny dataset	[41]–[43][18], [41]–[43]
7	K nearest neighbour	Supervised	Instance based	1) Simple and straightforward execution 2) Does not assume anything about the data	1) Slow algorithm 2) Extremely susceptible to anomalies	[43]–[47]
8	Affinity Propagation	Unsupervised	Clustering	1) Clarity and Low Error Rates 2) Needs less processing time	1) Difficult to ascertain ideal parameters	[48], [49]



3.2.2. K-Nearest Neighbour (KNN)

In recent years, KNN has become the most common method to describe gait recognition because it is simple and easy to use. When KNN figures out how far apart its training and test vectors are, it chooses the k vector that is closest to them for the average calculation. It costs a lot for the k-NN classification to sort an unknown test pattern into a category. It also takes a lot of work to make the training set bigger, because the distance between the k close neighbors has to be calculated a lot of times. A study by Tafazzoli et al. [42] used a k-NN predictor to make sure that the genetic algorithm-extracted optimized features were correct. With 1500 people and 46 specific traits, they got 87% accuracy with k-NN. With an 81% success rate. Wang et al. [52] used k-NN to find the Procrustes distance and figure out the walking style of 20 patients by looking at their Procrustes statistical shape features. A study by Mahfouf et al. [54] used optical foot tracking to figure out how people walked and a k-NN classifier to sort 1000 movies with 100 people into groups. The group groups were correctly sorted 97% of the time. Author Portillo et al. [55] tested how well k-NN classifier could recognize walking patterns in 11 different views using the CASIA-B dataset with 124 subjects. About 99% of the time, they were right. Table 1 shows A Summary of the Machine Learning Classification Methods for Recognising GAITS

3.2.3. Artificial Neural Network (ANN)

Based on the idea that the human brain is made up of multiple neuron connections, artificial neural networks (ANNs) are a popular supervised machine learning model for gait identification. Three parts make up the basic artificial neural network (ANN): input, hidden layer, and output. Bhowmick et al. [56] suggested a method for speed-invariant gait recognition. For classification, they used a multilayer perceptron (MLP) neural network and a Bayes-based probabilistic model. Tan sigmoid was employed as the activation function in MLP, while gradient decent was used to minimise errors. The vision transformation model (VTM) was trained by Kusakunniran et al [49] using a multilayer perceptron (MLP) regression model to figure out aspects of

walking from a specific area of interest (ROI) in order to recognize it. Zeng et al. [41] applied deterministic learning and radial basis function (RBF) neural networks to accurately identify human gait in the sagittal plane, achieving an accuracy rate of 91%. In another study, Zeng and Wang [57] applied a radial basis function (RBF) neural network to accommodate for varying speeds and deliver precise approximations. Three gait datasets CAISA-C, CMU MoBo, and OUISIR were used to evaluate their methods concerning variations in walking speed. Similarly, RBF was used by Mansur et al [58] to train the subject matrices for the purpose of mapping manifolds to image space. Yang et al. [59] provided a way to recognize gait that was about 90% accurate by using a back-propagation neural network (BPN) which is applied on SOTON gait database and the stick figure model as a base. Krzeszowski et al. [40] used multilayer perceptron (MLP) and naïve bayes (NB) as classifiers to identify gait. MLP was 90% accurate, while NB was only 85% accurate. A probabilistic neural network (PNN) was used by Sudha and Bhavani [53] to classify genders based on gait characteristics. With nine feature estimates, they attained 100% accuracy.

3.2.4. Convolutional Neural Network (CNN)

Deep learning, a type of machine learning, is currently making the identification more accurate. Deep learning adds more levels to a multilayer neural network, which has at least two hidden layers. Pattern recognition, computer vision [18], and other related areas can use CNN, a type of deep learning, to solve problems. CNN gives network layout designers a lot of freedom by letting them change inputs, outputs, and loss functions like cross-entropy, Hinge, Huber, and others. By looking at cutting-edge research, CNN has been used to solve the problems described above with recognizing gait and make it better than traditional methods [60]. Alotaibi and Mahmood conducted the first study on CNN-based gait recognition [62] to estimate non-linear and high-resolution gait data. They used the CNN architecture with the input of Gait Energy Images with different feature they develop a architecture with four convolutional layers in their model with four

subsampling layers is there, the architecture achieves a 92% accuracy. In an additional study, Alotaibi and Mahmood [61] suggested a thorough an examination of behavioural Biometric Gait Recognition. CNN design that took into account differences in gait recognition across views.

4. Survey of Gait Recognition Datasets

A database is necessary for the creation of a new application. Sufficiently sized data samples are required for the training and testing of the gait recognition system, taking into account various circumstances like carrying a weight, changing views, clothes, occlusion, etc. During the span of the past year, there has been a significant advancement in the creation of technologies that collect gait data. Additionally, various factors that influence the performance of gait recognition have been added for the purpose of investigation. In Sect. IV.1, we also provide a brief overview of the environmental setup of the CASIA dataset, a well-known organisation that produced the VB gait dataset and is extensively utilised in the gait recognition research field.

4.1.VB Datasets

We know that the dataset used in the VB gait recognition system was selected to make the system work well in real-time settings, here VB dataset w further divided into marker-based where data is stored by direct calculation or physically touch method as foot print or kinetic energy and marker-free situations where data is stored by camera or from distance. By few years analysis it is observed that only few of the methods use markers data set, while most of the methods uses marker free data set. For researchers, the most important things were carrying load, different viewpoints, and clothing style.

4.2.Standard Gait Database

The Chinese Academy of Sciences Institute of Automation (CASIA) offers the CASIA Gait Database to researchers in the field of gait identification and related studies, with the aim of fostering research in this area. The CASIA Gait Database has three separate datasets: Dataset A, Dataset B (a multi-view dataset), and Dataset C (an infrared dataset). Figure 4 illustrates the databases with their respective creation years.

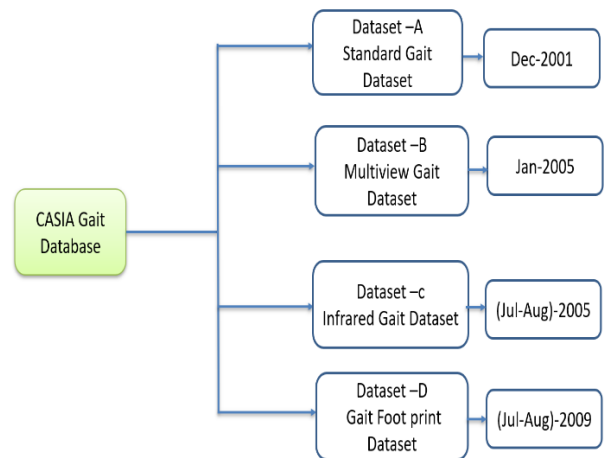


Figure 4 The CASIA Database's Subsets Along with The Year They Were Created

4.2.1. Dataset A

Using spatiotemporal motion patterns, this dataset was created for the purpose of identifying gaits in silhouette frames [98]. Dataset recorded outside at 25 frames per second with a resolution of 352 x 240 using a Panasonic NV-DX100EN digital camera. All subjects in this dataset traverse a linear path in three distinct viewing angles: horizontally which are taken by 0° angle, diagonally which are taken by 45°, and from the front which are taken by 90°. Four of the twenty subjects are present in the dataset. Figure 4 shows The CASIA Database's Subsets Along with The Year They Were Created

4.2.2. Dataset B

Multiview Gait Database [99] the 11 view variants at an 18° difference, including clothes, comprise the CASIA dataset B, which was designed for gait detection and classification under various walking variations and transporting circumstances. Eleven USB cameras (Model: Fametech 318SC) were positioned around the left in this dataset the subject's left-hand side as they were walking. The data was collected from 124 volunteers of both genders (93 males) in an indoor setting with 31 females) at a frame rate of 25 frames per second at a 320 by 240 frame size; example frames are displayed in Fig. 10d.

4.2.3. Dataset C (Database of the Infrared Gait)

Infrared Gait Database when other biometrics cannot



be used to identify a person at a distance, gait is a helpful behavioural biometric attribute that can. Over the past ten years, the majority of work on gait identification has been visible spectrum-oriented, ignoring night time recognition, which is highly demanded in real life. In July and August of 2005, the infrared gait database, or CASIA dataset C, was built in order to function in low light. There are 153 participants in this data set: 23 girls and 130 males. The human night gait data was recorded at a frame rate of 25 frames per second using a thermal infrared camera with a resolution of 320 x 240. This particular dataset contains information on four different walking scenarios: a regular walk, an easy walk, a quick walk, and a regular walk while carrying a bag.

Conclusion

Biometric behavioral modality denotes a technique for identifying individuals through their distinctive behavioral traits. Gait has received heightened attention in recent years due to its nuanced and undetectable characteristics. Nonetheless, regarding development, gait remains at a nascent phase relative to other biometric modalities such as iris, facial recognition, and fingerprints. This study presents the entire framework of the gait recognition system and an extensive review of the research undertaken in VB gait recognition over the last ten years. We employed classification strategies and concluded that the k-NN machine learning method is the most prevalent classifier due to its straightforward installation and capacity for unsupervised operation. Recently, CNN has been employed in gait detection, leading to an enhanced gait recognition rate. This research meticulously analyzed the methodologies employed by several authors to get information from gait patterns for recognition objectives. The appearance-based methodology in gait recognition has predominantly employed the Gait Energy Image (GEI) technique, which constitutes 62% of the citations referenced in the article. Nonetheless, covariate effects adversely influence the efficacy of appearance-based gait recognition. Additionally, we conducted a survey of VB and SB gait databases that are specifically intended for research purposes. Our findings indicate that 42% of the publications

analysed in our survey utilised the CASIA-B dataset for their analysis. This dataset was chosen because to its vast sample size and its ability to account for various covariate situations. The OU-ISIR organisation possesses the most extensive compilation of gait samples, taking into account many characteristics such as speed, carrying objects, and gait variability.

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