Section A-Research paper
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Survey on Human Gait Analysis using Artificial Intelligence

Pushpalatha O[a,b], Pradeepa Palraj[c]

[a]Department of Electronics Engineering, Jain University, Bengaluru, Karnataka, India
[b]Department of E&CE, Jain Institute of Technology, Davanagere, Karnataka, India
[c]Department of Electrical and Electronics, Jain University, Bengaluru, Karnataka, India

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***Abstract*— Human biomechanics, as well as gait, are essential components of life. Human motion is an important spatiotemporal structure because it can determine human health and identification. Human gait demonstrates an individual's specific mobility pattern. The research of locomotion in people and animals is referred to as gait. It requires the synchronisation of many different parts of the human body, including the mind, vertebral column, nervous system, muscles, joints, and bones. Gait analysis has been extensively researched for a variety of applications such as healthcare, biometric authentication, games, and many others. The gait analysis is understood to include an enormous set of interrelated components, which would be difficult to use due to the high number of data and their links. The integration of Artificial Intelligence (AI) and biomechanics can optimize the gait analysis process. The paper details the gait analysis process step by step from data collection to AI model deployment. The steps present in between these processes are pre-processing, feature extraction, and selection. The focus of this survey is to inform emerging researchers about the important guidelines for using gait analysis with AI techniques. The entire survey is based on articles reviewed and implemented by numerous research scholars for gait analysis.**

Keywords— Gait, Stride, Artificial Intelligence, Feature Selection., Biometrics, Accuracy.

I. INTRODUCTION

Biometrics, a technology that uses physiological or behavioural features, can be used to authenticate or identify people [1]. The most common biometric applications are fingerprint and iris recognition. Medicine began by studying human gait. Doctors examined patients' gaits to determine whether they had any health issues. The researchers [2] revealed that almost everyone has a distinct walking style. As a result, someone speculated that gait may also be utilised to biologically identify a person. Human gait identification offers two advantages over fingerprint and iris-based identification: (1) it does not require user contact, and (2) it may be performed from a distance as long as the gait is visible. GAIT refers to how far a person's centre of mass travels while they move. Synchronizing lower limb and torso movements allows you to go from one posture to another [3]. The distinctiveness of each person's personality can be ascribed to a multitude of factors, including weight, gender, and age. In the discipline of gait analysis, descriptive studies have given way to more complicated approaches over the years. Aristotle (350 BC) was the first to study animal and human gait [4]. Rapid improvements in sensor systems that combine analytical computing technology have enabled more information to be extracted from a broader spectrum of sensors. It is also unclear if the intricacy of the gait can be represented by widely available, simple-to-use measurands, such as those used by diagnostics and classification systems. On the other hand, advancements in Machine Learning (ML) technology have produced Deep Learning (DL) models that could be deployed to complicated data without pre-processing and seem to produce quicker and more effective results. Models of DL, Data from multiple multi-sources and multi-sensor sources can now be used in unique ways for detection, fusion, and classification. Gait spatiotemporal features are gaining popularity as they have the potential to be employed in a variety of industries such as healthcare, sports, and security. There is no gold standard for sensing and processing data for gait analysis [5].

Changes in the usual gait pattern might be short-term or long-term depending on a variety of variables [6]. Factors can come in a variety of shapes and sizes. Some of the factors are terrain, shoes, clothes, and baggage are all examples of extrinsic factors to consider. Age, colour, and gender are all intrinsic factors. The physical factors are height and weight. Personality type, feelings, and thoughts are all psychological factors. Trauma, neurological ailments, musculoskeletal abnormalities, and psychiatric problems are all pathological factors. The gait analysis factors are as followed [7]:

1. Length of each step
2. Length of the stride
3. Cadence
4. Speed

5. Angle of Feet
6. Posture of Hips

Since advances in AI and computing have made it possible to recognise human gait from a distance, Gait Recognition has become the most widely used data-driven and artificial surveillance technique. The goal of this survey is to highlight the many gait analysis technologies that have been created. An individual's gait can be used as a soft biometric trait that can be used to identify him or her. Gait patterns are unique to each person, regardless of age or illness. Identification, re-identification, authentication, and gender recognition are some of the most common uses of gait recognition. Other uses include video surveillance, crowd sensing, crowd density estimation, crowd monitoring, and multi-player tracking and identification.

- Application-Oriented Systems: Protected locations such as the home, public safety, and so on necessitate the use of authentication. Processes of authentication [8] include knowledge-based (such as credentials, PIN, MPIN), object-based (such as bank cards, identification cards, etc.), and biometric-based (such as fingerprints). It is difficult to remember complex passwords in a knowledge-based authentication method. When the same password is used for several services, a security breach occurs. Accessing the services given by physical Keys is typically accomplished through a combination of object-based and knowledge-based methods. A person's thumb, retina, face, eye, palm, taste, body odour, and gait can all be used to identify him or her through biometric authentication. For a certain period, these characteristics are unique to each subject. It's difficult to replicate a person's personality traits. Gait will overcome all difficulties.
- Recognition of Patterns: Physical and behavioural characteristics make up the two main categories in biometrics. A person's physical characteristics include height, face structure, retina, and eye. A person's physical characteristics are universal and distinctive for a lengthy period. Walking, speaking, singing, and other forms of movement are all examples of behavioural characteristics. A person's uniqueness might be difficult to replicate, even if their conduct alters depending on their emotions. To confirm the similarity of the obtained image, a collection of biometric images is recorded [9]. Gait recognition is the most used biometric approach because of its high level of recognition accuracy in a variety of capturing modes.
- Biological and Medicinal Research: People with a variety of common gait disorders, including Parkinson's, heart problems, sclerosis, and stroke, can have their walking quality assessed using gait recognition [10]. It is important to study the gait sequences of patients with musculoskeletal and neurological problems to provide the most effective treatment. Gait analysis yields kinematic and kinetic data that assist doctors in interpreting, assessing, and evaluating each patient's unique gait issue. Before the examination, the patient will be videotaped so that data on muscle strength and tone, joint motion, bony anomalies and stubborn muscular contractions, as well as knee and ankle widths, the length between the right and left sacroiliac spines, may be collected.
- Animation: Kinematics, dynamics, and robotics are all heavily involved in the study of human gait animation [11]. Despite the difficulty of the techniques, the computer animation community is becoming increasingly interested in human gait animation. To illustrate the early sequential pictorial depiction of series, the 1st animation solution for humans was created in the 1970s. In the 1990s, researchers in the gaming, cinema, virtual avatars, graphics, ergonomics, and simulations industries impacted the development of the Humanoid animation standard. Human animation faces the problem of reproducing natural motion in virtual form. Extraction of motion sequences from joints like the shoulder, neck, elbow, wrist, knee and ankle in human skeletons is used in animation. The skeleton can be improved in quality by using surfaces to model it.

The paper is organised in the following ways: Section I details Gait's introduction and application. Section II shows the research flow of gait analysis. Section III and IV deal with data acquisition techniques and required data cleaning steps. Sections V and VI show the available methods for feature extraction to retrieve important features and feature selection to reduce dimensions from retrieved data. Section VII explains AI and its available types. Section VIII discusses the past work on gait analysis with full details like data, its pre-process, feature extraction and selection, AI model and its accuracy. Section IX shows the challenges in the gait analysis field. Section X concludes the survey with future scope.

II. Process Flow

The gait analysis is very much important to solve problems in many fields. The gait analysis is not done in a single step, it requires more process to reach the expected output. The initial step of the research is data acquisition. The data can be captured from sensors or websites. Pre-processing is the important stage of the research to get a better result. The colour conversion, background elimination, and noise rejection. The processed data passed through the feature extraction and selection process. This step is necessary for retrieving important features from the data. Next, the AI model is deployed to complete the required task. The research flow of the gait analysis using AI is shown in figure 1.

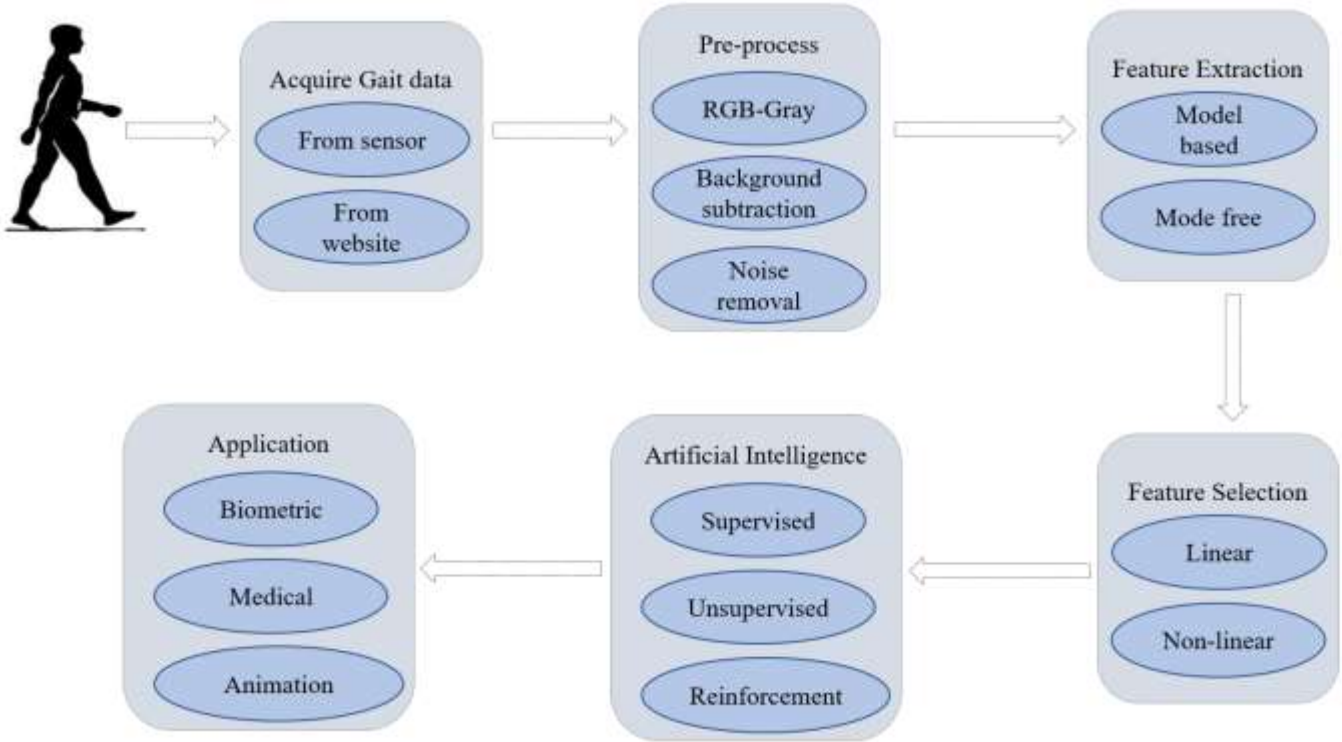

Fig. 1. Gait analysis using AI

III. DATA ACQUISITION

To deal with the ever-increasing number of data generated by biomechanics research, strong multivariate analysis and ML technologies are required. Researchers will be able to investigate fresh ideas on the biomechanical risk variables connected with gait-related musculoskeletal injury using novel data science technologies. The accuracy of gait analysis results is strongly dependent on the quality of the data used. There are two ways to collect gait data: create your own using sensors or access data from a website. This chapter provides an overview of the dataset that is publicly available. These data sets cover a wide range based on various factors of the participants' appearance, environment, and perspective. Large datasets are often necessary and recommended for AI to be successfully trained. Table 1 summarises the most important characteristics of popular gait datasets. Any dataset has characteristics such as data and environment type, number of subjects, sequences, and viewpoints. The data in Table 1 are organised in alphabet order.

Table 1: Gait dataset and its details

Dataset	Data type	Subject	Sequence	Views	Environment	Year
CASIA – A [12]	RGB; S	20	240	3	Outdoor	2005
CASIA – B [13]	RGB; S	124	13680	11	Indoor	2006
CASIA – C [14]	I; S	153	1530	1	Outdoor	2006
CASIA – E [15]	S	1014	Not Mentioned	15	Both	2020
CMU MoBo [16]	RGB; S	25	600	6	Indoor	2001
OU-ISIR [17]	S	4,007	31,368	4	Outdoor	2012
OU-MVLP [18]	S	10,307	259,013	14	Indoor	2018
SOTON [19]	RGB; S	115	2128	2	Both	2002

TUM GAID [20]	RGB; Depth; Audio	305	3,737	1	Indoor	2012
USF HumanID [21]	RGB	122	1,870	2	Outdoor	2005

IV. DATA PRE-PROCESSING

Pre-processing is the second step after data acquisition. It is done to make the data clean and make it ready for further process. The processed technique used for gait analysis is detailed below.

A. RGB to Gray

Grayscale images are often used in descriptor-based image recognition systems, although little is known about the process of transforming colour images to grayscale. This is because most academics consider colour-to-grayscale conversion to be unimportant. Grayscale representations are widely used instead of working directly with colour photographs since they simplify the procedure and reduce computational requirements. Many applications may not benefit from colour, and including unnecessary data may raise the quantity of training data needed to perform well [22].

B. Background Subtraction

The simple method is background subtraction using frame difference. Foreground pixels have a pixel value difference greater than the threshold T_h, which is computed by subtracting the current frame from the previous one [23].

$$|frame_i - frame_{i-1}| > T_h \qquad \text{----------- (1)}$$

To a large extent, the background estimate depends on the threshold value T_h. The hit-and-trial method was used to identify the threshold T_h.

C. Noise removal

The gait representation technique used may be influenced by silhouette noise. The noisy silhouettes are addressed by noise reduction algorithms, which efficiently remove two types of noise:

1.One method for removing salt noise (randomly distributed intensity errors) is to perform morphological processing on the silhouette by a 6*6 square structuring element. Following an erosion, the morphological open operation dilates using the same structuring element.

2.To remove faults in a binary silhouette that are connected by larger-than-necessary blobs of data, first, determine the number of associated components and afterwards filter every component depending on its region. As a result, only the most linked component (the silhouetted individual) remains and is filtered away.

V. FEATURE EXTRACTION

Gait is the rhythmic movement of the hands as well as legs. Gait analysis employs visual assessment as well as technologies such as cameras and sensors. It collects data on a human’s walking behaviours, which could be utilised to develop a variety of applications in the medical, security, and fitness industries. The entire gait contains several phases that define the overall walking pattern. It is vital to have a full understanding of how each step functions to accurately identify variations in normal gait. A gait cycle is an interval between two consecutive foot strikes throughout limb movements. Figure 2 depicts the entire gait cycle and it comprises two phases stance and swing.

A. Stance Phase:

During this time, the foot remains on the ground. This phase comprises 62% of the gait cycle. The stance phase consists of five stages.

- Initial Contact
- Loading Response
- Mid Stance
- Terminal Stance
- Pre-Swing

B. Swing Phase:

During this period, the foot makes no contact with the land. This phase comprises 38% of the gait cycle. The swing phase consists of three stages.

- Initial Swing
- Mid Swing
- Terminal Swing

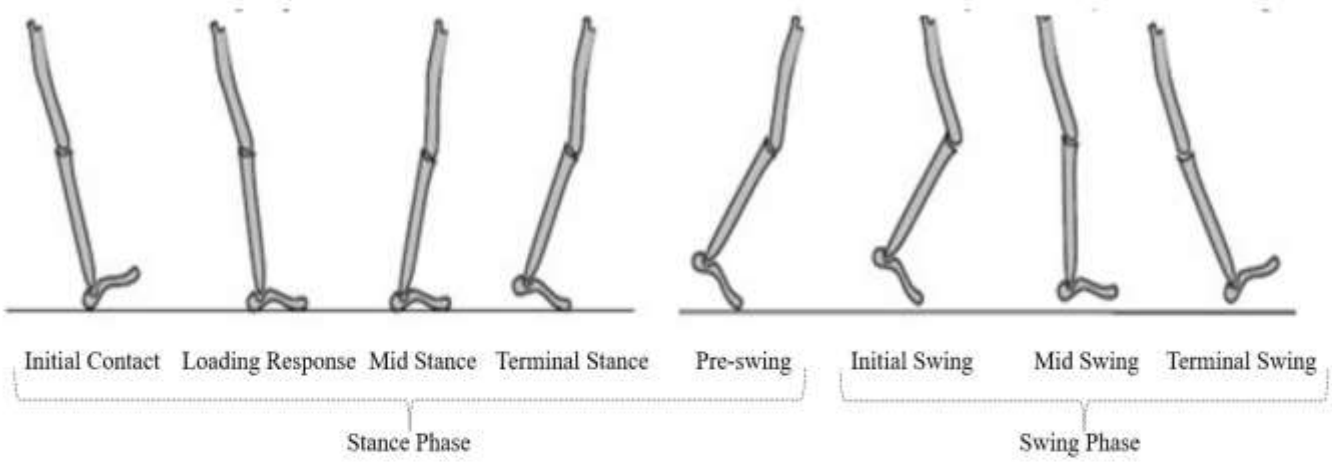

Fig. 2. Gait Phases in human walk [24]

A gait sequence can reveal step and stride length, speed, cadence, dynamic base, foot and hip angle, progression line, and squat efficiency. The information was processed, analysed, and used to identify the individual. The two primary categories of video-based human gait recognition are model-free and model-based.

A. Model-based approaches:

Various methodologies, including pendulum, leg tilt, stride, trajectories, joint angles, and 2D and 3D temporal frameworks [25], are employed to collect the model's structural pattern from the body using model-based approaches. Humans could be monitored using a variety of mathematical variables and the interactions connecting them. A model-based approach is used to deal with self-occlusions. A model-based approach has to cope with concerns such as viewpoint invariance, physiological changes such as age, height, and posture, and external impacts such as clothes and footwear, as well as environmental factors. Other aspects covered in the description are gait cycle duration, step length, Fourier amplitude, footstep, ground friction coefficient, and pressure mat qualities. The accuracy of the model-based method is influenced by the quality of the silhouette. In a model-free method, captured video or photos are used to extract gait features for classification and analysis without involving the person directly in the system. The model-based method is not affected by occlusion or noise. The model-based strategy has the disadvantage of requiring a significant investment in computational power [26].

B. Model-free approaches:

The majority of current gait recognition research employs the model-free technique. It is feasible to examine the motion of bodies without utilising models by employing a collection of measurements to characterise the forms and motions captured in a series of photographs [27]. This technique is characterised by insensitivity to silhouette standards, low calculation costs, and a lower quantity long. In many research papers, the model-free technique is applied. It shines in the low-quality video due to its lower computational cost and superior quality at lower resolutions. Backdrop subtraction is the process of removing the background from the foreground.

VI. Feature Selection

Dimensionality reduction techniques [28] were employed to improve processing capability while reducing complexity. It was divided into two categories: feature selection, which just changes the original set of features, and feature extraction, which uses mathematical transformations to transform the original features into new features. Recently, a huge amount of gait data from various places has been acquired utilising High Dimensions (HD). Over-fitting, spatial complexity, and temporal complexity are all issues that arise when attempting to analyse gait patterns using these high-definition data. To avoid these issues, DR is utilised before the classification section. DR can be used to transform HD to Low Dimension (LD) data without affecting its originality [29]. Data from LD experiments may be collected, analysed, and visualised effectively. Using the DR technique, it is also possible to retrieve important characteristics for gait pattern analysis. Using the DR strategy, it is feasible to improve prediction or classification results by eliminating noise, duplication, and irrelevant features [30]. Methods that employ DR can be split into two modules like linear and non-linear DR. The algorithms used for linear and non-linear DR are detailed in Figures 3 and 4.

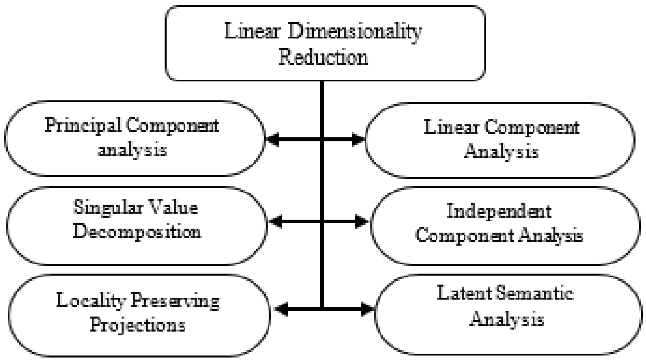

Fig. 3. Linear Dimensional Reduction

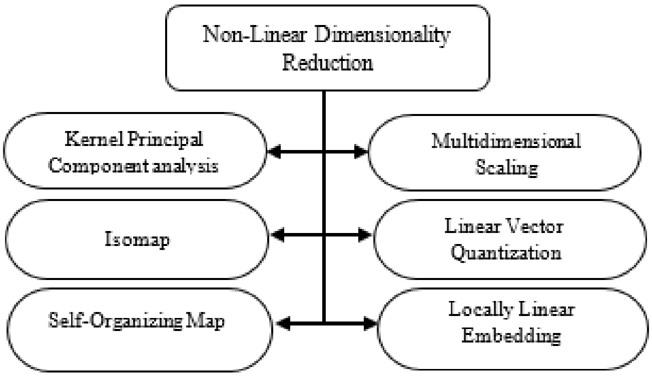

Fig. 4. Non-Linear Dimensional Reduction

VII. ARTIFICIAL INTELLIGENCE

Even though input data are distorted by noise, necessitating pre-processing, the development of ML for gait recognition $T(x)$ by discovering a correlation between input and output data [31]. The input is raw multidimensional arrays $\{ui, vi\}$, where ui represents several individuals and vi represents data attributes like kinetics or kinematics signals. The output can be used to classify gait occurrences, activities, and diseases. By splitting the input dataset into train, test, and validate sets, ML techniques are utilised to evaluate the biomechanical system $T(x)$. After selecting an acceptable ML approach, the model is trained and tested for correctness. Finally, the outcomes are compared to a previously unknown dataset. It's ideal to stop the method when the model parameters have been tuned and retrained to the appropriate level of accuracy; otherwise, the process will have to be repeated until they have. The number of parameters in a system can be lowered to reduce system complexity. Among the most common are supervised, unsupervised, and reinforcement approaches.

A. Supervised learning:

These data are utilised to generate feature vectors, to determine the function that best captures the relationship between the input feature vectors and their associated labels. Some of the approaches utilised in gait research include Support Vector Machine (SVM), Neural Networks (NN), Hidden Markov Models (HMM), Random Forest (RF), K-Nearest Neighbour (KNN), Ensemble Learning, and Decision Tree (DT). SVM was a popular choice for gait analysis because of its ability to generalise even in small samples. SVM contains kernels that can handle linear as well as nonlinear functions. The capacity to classify people into several groups can considerably improve gait research [32]. NNs with a single or multiple-layer perceptron are the most commonly utilised technique in gait analysis. Because of its usage of feed-forward and backward propagation methods, the NN frequently behaves like a black box. NN has been extensively employed in gait research to address the challenges of pattern recognition. The use of DT subclasses of RF was required due to the complex connections between variables. It is understandable; however, it does not provide the greatest solution. RF chooses the forecast although it is an ensemble of randomised DTs. Due to its distance metric, the KNN classification technique was frequently utilised in real-time applications because it makes no assumptions regarding the distribution of the dataset. Fuzzy techniques are employed in investigations of gait asymmetry to account for linguistic information that cannot be expressed analytically. Their usage in gait research is limited due to difficulties in defining language variables and choosing the most suitable membership functions.

B. Unsupervised learning:

In the case of unsupervised learning, the data was not labelled. This technique is responsible for establishing the relationship between the various inputs to arrive at the final result. The distance between all feature vectors is employed in most clustering approaches to determine which data points belong to which cluster. In gait research, defining learning objectives and dealing with a huge amount of feature vectors were time-consuming, which is why these techniques were not frequently adopted. Such tactics have been employed if the relationship among various observations is ambiguous. To handle huge data, classifiers can be used with dimensionality reduction techniques. Using these unsupervised methods, different patterns for various sorts of illnesses can be learned. An explanatory study can help decide whether distance measurements are appropriate for a certain problem. In addition to the distance metric, clustering could be utilised to classify individuals into subgroups.

C. Reinforcement learning

Exoskeletons and locomotive aid devices, require the ability to interact with changing environments to work. Several strategies for gait rehabilitation control have been developed. Because of their potential to better capture the variability of the participants and hence result in automation based on the subject's particular requests, rehabilitative devices were commonly used with RL and deep NN.

VIII. EXISTING TECHNIQUES

The previous work done on gait analysis using AI is detailed in table 2. The table helps to explain the research very clearly with the required details like data, pre-process, feature extraction and selection, AI approach, accuracy and application in a different field.

Table 2: Past research on gait analysis

Reference	Data	Pre-process	Feature Extraction	Feature Selection	Application	AI Technique	Accuracy
[33]	CASIA B	-	Model-free	-	Recognition	LeNet	normal - 98.3%, backpack -89.2%, Coat walking - 95.8%
[34]	Physionet	-	Model-based	-	Medical	Two-Dimensional Convolutional Neural Network (CNN)	R2 – 79%
[35]	Own dataset	Merging, Correction, Normalization, Generalization	Model based	-	Biometric	Random Forest	99%.
[36]	CASIA, AVAMG and Own dataset	Background subtraction	Model-free	Principal Component Analysis	Biometric	SVM + CNN	96%
[37]	CASIA	ROI	Model-free	Fisher Linear Discriminant Analysis	Biometric	Random Forest, Support Vector Machine, And Multilayer Perceptron	90.32%
[38]	CASIA A, B, OUISIR	Normalization	Model free	-	Recognition	Multichannel CNN	95%
[39]	CASIA B, OU-ISIR	-	Model free	two-branch CNN	Authentication	SVM	94%
[40]	Own dataset	-	Model-based	Linear Discriminant Analysis (LDA)	Medical	NN	98.44%
[41]	Own dataset, DBMHIDB	Background subtraction, Binarization, ROI	Model-free	CNN-Long Short-Term Memory (LSTM)	Recognition	Shallow CNN stacked with LSTM and deep CNN	99.71%
[42]	Own dataset	Resampling,	Model-	Power	Medical	Probabilistic	91.13%

		Denoising	based	Spectrum Density		Neural Network	

IX. CHALLENGES OF EXISTING WORK

DL algorithms for gait detection have been fairly successful, however, several difficulties remain that must be resolved. We highlight some exciting future ideas and open challenges on gait analysis in this section.

- Data count: Deep gait recognition systems necessitate a massive quantity of data for effective training and reliable evaluation. The bulk of deep gait detection systems utilised a large dataset. Data synthesis, such as employing GANs for deep gait recognition, can be used to obtain huge data or augmentation. Moreover, by employing fake data, synthesising datasets might alleviate concerns regarding subjects' privacy. Huge gait data, comprise solely conventional walking arrangements with zero distinctions in occlusion, carrying, dresses or circumstances. As a result, strategies trained on such data frequently fail to generalise when evaluated against varied surroundings and appearances. Existing datasets can be changed to include the required variations through domain adaptation, eliminating the requirement for new data collection [43,44]. As a result, anticipate the development of new supplementary gait datasets to make it possible to come up with stronger solutions as gait data synthesis and domain adaption methodologies evolve.

- Various training and testing datasets: To be helpful in real life, gait recognition algorithms must be able to generalise to previously unknown data. Although there are a few noteworthy solutions that use distinct gait datasets for training and testing in the literature, we are unaware of any work on cross-dataset gait identification utilising standard data. When compared to the training dataset, test data is frequently gathered in a range of diverse settings. Cross-dataset assessments can be used to test gait identification systems. A solution trained on one piece of data could be employed to retrieve features from another set of data. Classification could be used to identify a person's gait once the characteristics have been retrieved. Recognizing distinct sorts of walk patterns across diverse sets of data can be characterised as an out-of-distribution (OOD) testing issue. We anticipate that OOD tests [45] have become famous for assessing the generalisation of gait identification algorithms.

- Various perspectives: Many gait databases include many views of the same gait, allowing researchers to compare how a person moves from various vantage points. The most often utilised method in the research work is single-view gait analysis. Such techniques emphasise the links between particular points of view while neglecting the interplay between many points of view. When the challenge is presented as a Multiview problem, LSTM descriptors can be used to learn multiple views (Intra and inter) interactions. Furthermore, the majority of existing multi-view gait descriptors are employed with fixed camera placements. However, obtaining data in a real-world context can be problematic due to the camera moving or the view being skewed [46]. Pre-trained descriptor-based multi-view techniques fail to bridge the domain gap between training and runtime data. Future studies in this area will be influenced by the development of fresh ways of employing standard gait descriptions for multi-view.

- Disentanglement: When it comes to making complex gait data, the way a person looks, the order in which their body parts move, and the lighting sources that are used all play a role [47]. Complex relationships among these factors can make recognition more challenging. Other fields of study, such as face recognition and emotion detection, have lately seen an increase in the number of strategies aimed at learning disentangled characteristics by obtaining representations that distinguish the numerous explanatory elements in the high-dimensional domain of the data. As a result, the great majority of deep gait recognition approaches currently available cannot disentangle gait data and extract relevant disjoint variables in a meaningful way. Disentanglement approaches to gait identification have lately made progress, although there is still room for improvement.

X. CONCLUSION

People's assessments of their health and wellbeing are significantly impacted by interruptions to daily mobility. Gait and physical movement research are crucial for maintaining mobility. Numerous interdependent gait measures are hard to determine due to the massive amount of data gathered and the prolonged evaluation periods in gait laboratories. AI has been proposed as a possible solution to these problems. The field of gait analysis using AI is growing. It's because of the emerging use of AI algorithms in gait analysis, to retrieve basic functions using high-time and non-linear physiological data to generate a correct, robust, and rapid diagnosis. Because of their use in practical systems like non-invasive recognition and authentication of an individual, invader detection, clinical testing and treatment, enhanced fall prediction, and so on, gait analysis technologies are expected to be in the growing market. The field is projected to develop and increase in scope during the upcoming 10-15 years. The survey includes step-by-step instructions for performing gait analysis with AI. This study's key steps are summarised below. We'll begin with data collection and pre-processing. Following that the extraction of important features and selection of minimal features. Finally, the deployment of an AI model based on the gait application. The researchers will be able to better define their problem statements as a result of identifying several study gaps in previous studies. The survey paper is useful for beginning researchers who are unsure of how to proceed with their work. Hopefully, the results of this survey will provide them with a better sense of where to focus their investigation.

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