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Review Article

DL-Enhanced GAIT Analysis for Rehabilitation: A Comprehensive Survey

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Abstract - *Integrating DL techniques has revolutionized gait analysis, enhancing the accuracy and efficiency of detecting and characterizing gait abnormalities. This paper surveys recent studies employing Deep Learning algorithms (DL), such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to analyze gait patterns from diverse data sources with wearable sensors, video footage, and motion capture systems. The advantages of DL in handling complex, high-dimensional gait data and its potential to uncover subtle patterns indicative of disease or recovery status are discussed. Furthermore, the clinical applications of DL-based gait analysis, emphasizing its role in personalized rehabilitation programs and real-time monitoring, are explored. The paper also addresses the challenges of implementing DL in clinical settings, such as the need for large, annotated datasets, computational resources, and interdisciplinary collaboration. In conclusion, this survey highlights the transformative potential of DL methods in gait analysis for fracture and Parkinson's disease patients. By providing a detailed overview of current research and identifying key trends and challenges, this work seems to inform and inspire further advancements in this field, ultimately enhancing rehabilitation outcomes and quality of life for affected individuals.*

Keywords - *CNN, DL techniques, Gait analysis, RNN.*

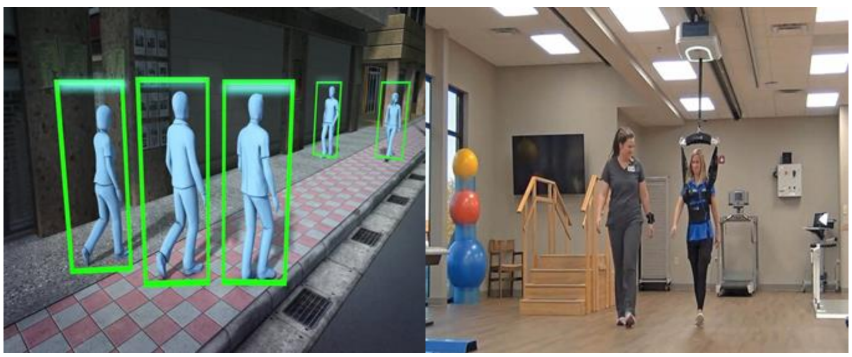
1. Introduction

Human gait is bipedal, with forward propulsion as the body's center of gravity, characterized by alternate sinuous movements of distinct body parts that need little energy [1]. Gait analysis is the systematic study of human walking with the primary goal of identifying and categorizing the uniqueness of each individual's walking style for various important applications. Gait analysis is essential in fields like healthcare, sports, robotics, and security. Providing objective data on how a person moves allows for better diagnosis, treatment, performance optimization, and even personal identification based on movement patterns. Understanding and analysing gait can improve outcomes in diverse areas, whether for clinical rehabilitation, athletic performance enhancement, or security applications.

Gait pattern variability refers to the natural fluctuations or differences observed in a person's walking or running patterns over time. Gait pattern variability necessitates biological data for clinical investigation, enabling the exact identification of compromised body components [2]. Early detection can help to avoid significant health problems in skeletal illnesses, vascular concerns, and mental issues [3]. The human gait refers to locomotion achieved through the movement of human limbs. Human gaits are the various ways in which a human can move. In the field of orthopaedics, identifying and treating patients with fractures requires a precise grasp of gait patterns. The human walking pattern known as gait analysis offers important new understandings of the biomechanics and functional restrictions related to musculoskeletal injuries.

The applications of gait analysis are shown in Figure 1. The gold standard gait analysis technique involves extracting gait patterns from the human body using opto-photogrammetric equipment outfitted with retroreflective markers [4]. However, this technique is expensive and involves extensive testing. Alternative techniques, such as wrist and shoe sensors, have been developed [5] to overcome these limitations. Technological advancements have led to the creation of marker-free gait monitoring devices that are both affordable and non-invasive [6, 7]. These systems can estimate skeletal joints by utilizing RGB cameras with 2D and 3D inputs. The model-free technique uses pre-defined human anatomy, whereas model-based approaches use posture estimation algorithms to predict skeleton joints [8-10].

(a) (b) (c)



(d) (e)

Fig. 1 Gait analysis applications (a) Sports, (b) Smart prosthetic leg, (c) Robotics, (d) Surveillance, and (e) Rehabilitation.

DL has recently revolutionized gait analysis, creating new prospects for more accurate, efficient, and scalable examinations. DL is a type of machine learning that involves training artificial neural networks with multiple layers to learn and extract complex patterns from large datasets. This feature makes DL particularly well-suited for analysing the high-dimensional, time-series data collected during gait analysis [11].

The application of DL to gait analysis involves several key components:

- Data Acquisition: Modern gait analysis employs various data sources, including wearable sensors, video recordings, and motion capture systems. Wearable sensors provide continuous monitoring of gait dynamics in natural environments, while video recordings and motion capture systems offer detailed spatial and temporal data of gait movements.
- Feature Extraction: DL algorithms, such as CNNs and RNNs, properly extract meaningful gait features from raw data. CNNs are particularly effective for analyzing spatial patterns in video and motion capture data, whereas RNNs excel in handling temporal sequences, making them ideal for time-series gait data.
- Pattern Recognition: DL algorithms may detect complicated patterns and anomalies in gait data, which may indicate specific conditions or stages of recovery. For example, minor variations in stride length, cadence, or joint angles can indicate the course of efficacy in fracture patients.
- Predictive Modelling: DL algorithms can predict future gait patterns and outcomes using massive datasets, allowing for the construction of personalized rehabilitation regimens. These projections can assist physicians in adjusting interventions to patients' individual needs, increasing the success of rehabilitation.
- Real-Time Analysis and Feedback: DL provides real-time gait data processing, allowing patients and clinicians to receive instant feedback. This functionality is critical for tracking progress and making necessary changes to rehabilitation methods.

DL into gait analysis shows great promise for expanding the science of rehabilitation. It enhances the precision and depth of gait assessments, allows for continuous and non-intrusive monitoring, and supports the development of individualized treatment strategies. By overcoming the limitations of traditional methods, DL is poised to transform the way gait analysis is conducted, ultimately improving outcomes for patients with fractures and Parkinson's disease [12]. Using deep learning methods for gait analysis has become a viable path for improving the effectiveness of fracture diagnosis and treatment planning as medical research adopts new technologies.

2. Background of the Study

Many research studies have devised, implemented, and endorsed numerous approaches and procedures for identifying a specific person based on their gait characteristics. Gait recognition [13] is a significant approach for following people while they walk. Gait data can be gathered in two ways: Wearable Sensors and Non-wearable Sensors. Wearable sensors, including pressure sensors, accelerometers, and gyroscopes, are commonly used to capture human motion data for gait analysis [14]. In contrast, non-wearable gait recognition relies on visual input from image sensors, often referred to as "vision-based gait recognition" [15]. Biometrics involves identifying individuals based on physical characteristics (fingerprints, face, iris, voice, hand geometry, or retina) or behavioral traits (typing patterns, stride, or walking behavior).

Gait analysis is a biometric technique that allows for the identification of individuals based on their walking patterns, as shown in Figure 2. Human motion capture is applied in various fields to assess, interpret, and replicate diverse movement behaviors (P P Min, 2019). Gait disorder analysis often involves measuring joint kinematics and kinetics in all three dimensions. Key features that make human gait distinctive include:

- The ability to identify individuals from a distance.
- Functionality in challenging environments, such as low light or poor resolution.
- The ease of capturing gait data in public spaces without specialized equipment.

Gait recognition has been widely employed to solve various difficulties over the last 30 years. The recent trend has shifted from non-deep to DL techniques based on the gait recognition solution [17].

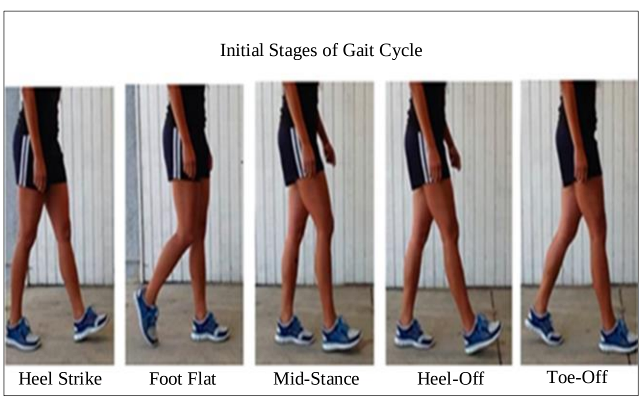


Fig. 2 Initial stages of the gait cycle

2.1. Gait Phases

The gait cycle is defined as the time between consecutive strikes of the same foot during human locomotion. The entire gait cycle is divided into two separate phases, such.

- Stance
- Swing.

2.1.1. Stance Phase

This phase of gait accounts for almost 60% of the gait cycle. It starts when the foot touches the ground and ends when the foot is taken off the ground [18].

2.1.2. Swing Phase

It includes a ratio for the final 40% of the gait cycle. It starts when the foot is raised off the ground and finishes when the same foot touches the ground again [19]. Figure 3 depicts quantifying the gait cycle impression in terms of the stance and swing phases seen during the subject's locomotion.

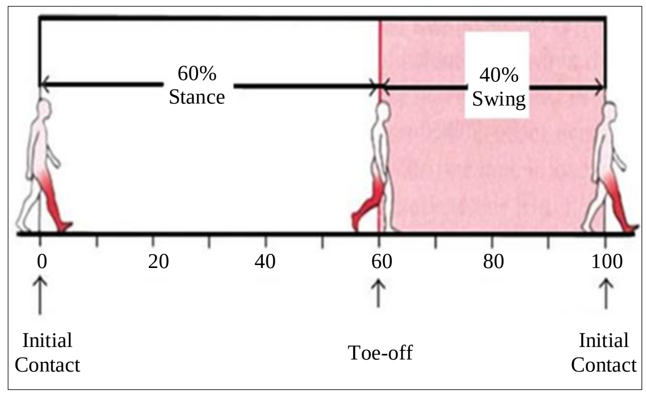


Fig. 3 Stance and swing of gait phase

3. Literature Survey

A comprehensive search of the current literature is conducted to acquire relevant data from reputable publications such as IEEE, Sensors, Elsevier, and conferences. Initially, simple keywords were used to obtain relevant gait analysis articles considering reputed journals and conferences within the search box. They were electronically searched, such as Gait evaluation with DL (DL), Gait evaluation for rehabilitation, etc., yielding an approximation of (1000-1500) articles for DL and a total of (5000-7000) articles on rehabilitation. Then, imposing the criteria on the search string by other keywords such as Knee fracture, Hip fracture, and Ankle fracture and illuminating duplicate and unrelated articles provided about 400 articles focusing on Knee fracture and (1300-1600) on rehabilitation. Finally, after removing the articles that were not in full text and following the screening and acceptability criteria, a total of 282 and 102 articles were selected for GAIT analysis for rehabilitation based on sensor-based, vision-based, and hybrid techniques, respectively, to be further studied. Gait acquisition methodologies are broadly classified into two types: vision-based and sensor-based.

3.1. Vision-Based (VB)

Vision-based gait analysis employs optoelectronic Motion Capture (Mocap) technology to evaluate a person's stride in a manner comparable to how the human eye functions

[20]. This camera-based method accurately measures gait with various cameras, including analog, digital, and depth cameras. This method has two subcategories: marker-based and marker-less (or appearance-based), yielding accurate gait assessments [21].

3.1.1. Model-Based

This modality uses human body modelling to generate clinically significant gains. Initially, retroreflective markers are attached to the human body, indicating the location of indicator points for measuring joint angles. The recommended body landmarks are then recognised with a video-based optoelectronic device like VICON or Polaris [22]. Retroreflective marks may be passive or active [23]. Passive markers are usually coated with reflective material layers, allowing them to reflect light emitted by an LED-equipped camera and pinpoint the body's landmarks.

Alternatively, active markers are LEDs directly affixed to the subject's body, with the camera recording joint positions via infrared radiation. Ishikawa et al. (2024) the angle of elevation when walking was investigated in both patients and Healthy Controls (HC) [24]. They used eight metal plug-in gait markers and a nine-camera motion capture system. The study indicated that the planar law was advantageous for patients, with an AUC of 0.69 ± 0.767, precision of 0.84 ± 0.23, recall of 0.57 ± 0.26, F-measure of 0.66 ± 0.15, and a threshold of 8.56 ± 1.80.

Roiz et al. [25] used a 3D human motion analysis system with six infrared cameras and eighteen active markers to examine gait metrics in 12 people with idiopathic Parkinson's Disease (PD) and 15 healthy controls. The findings revealed significant differences between PD patients and healthy persons, with gait factors corresponding to clinical parameters. Zhang et al. (2026) [26] created a system for analyzing, extracting, and comparing the gait parameters of six Parkinson's disease patients walking under three conditions: without help, pushing a roller walker, and holding a powered walker at varying speeds.

This study tracked body landmarks with nine Vicon Mocap system cameras and reflective markers. The results indicated a significant decrease in the asymmetry index from 6.7% to 0.56% under the first condition, with even lower values under the third condition, confirming the motorized walker's ability to enhance gait symmetry in PD patients. Pachoulakis et al. [27] used a stereoscopic vision recording setup consisting of two Panasonic NV-GS500 camcorders (25 frames per second) with a resolution of 720x576 and reflective markers to represent the kinesiological condition of a PD subject. The results showed that this approach has a significant potential for measuring PD. Although model-based methods are highly accurate at locating body landmarks, they require controlled and complicated laboratory environments to meet gait acquisition goals.

3.1.2. Model-Free

One of the distinguishing features of the Marker-Less (ML) modality, also known by its name. Specifically, appearance-based modality eliminates the need to manually develop a model of the human body to collect gait data. The model-free modality captures defective gait using a single video camera, such as the Kinect V2, with no markings on the patient's body. It focuses on shape, camera angle, and appearance, gathering films using a camera and then using background subtraction to extract a silhouette image with shape and motion parameters [22].

Verlekar et al. [21] designed a system that uses a single 2D video camera to diagnose and classify gait disorders automatically. This system examines both foot-related features and body-related features. Using an SVM, the system obtained an impressive 98.8% accuracy, beating existing markerless video-based systems and demonstrating reliability for diagnosing various diseases, including knee problems. However, the system had certain limitations, including the inability to analyze arm movements in silhouette photographs and the need for a camera.

Cui et al. [28] A system for accurate gait analysis of fracture patients has been presented, which uses a single Kinect sensor and a depth-sensing RGB-D camera to record joint depth information. The researchers computed kinematic, kinetic, and spatiotemporal data and used DTW to calculate knee joint angles. Using SVM for classification, the Kinect sensor displayed excellent efficiency in fracture detection with a 97% accuracy rate.

Video-based cameras, such as 2D/3D and CCD, have proved critical in VBML gait collecting for PD diagnosis. Shaw et al. [29] used markerless gait capture technology to analyze the gait characteristics of 16 patients with Parkinson's disease and 16 healthy controls. Silhouette images captured with a high-quality video camera enabled the Hidden Markov Model (HMM) to achieve 99.7% PD detection accuracy. Furthermore, numerous academics have investigated the wide range of applications for Kinect sensors provided by Microsoft.

Prochazka et al. [30] used the MS Kinect sensor to classify healthy and PD persons, reaching a 94.1% accuracy through Bayesian classification with spatiotemporal characteristics. Dranca et al. [31] created a Kinect-based system to differentiate severity levels among 30 PD patients. Using two Kinect sensors and a 30fps sampling rate, scientists detected roughly 115 linked variables and used a Bayesian network to predict PD phases with an accuracy of approximately 93.4%.

Aside from video cameras and Kinect systems, smartphone technology has shown new insights into this subject [32]. For example, a study examined the stride length parameter of Parkinson's disease patients using a mobile phone camera with a 30fps sample rate, demonstrating the system's capability with an absolute inaccuracy of 0.62 cm.

3.2. Sensor-Based (SB)

Another major gait acquisition technique uses sensors attached to the human body. These are divided into two subcategories based on their ability to be worn on the subject's body: non-wearable sensors and wearable sensors.

3.2.1. NWS

FLS are used in NWS to measure gait characteristics. Force plates, electronic pressure mats, and instrumented treadmills are examples of sensors integrated into the floor platform that can directly measure the force vector.

3.2.2. Wearable Sensors

Wearable sensors are an emerging technology for gait collection that requires individuals to wear them on their bodies. These sensors can be classified into several sorts based on their purpose. Kotti et al. [33] developed a rule-based technique to compare fractured subjects to healthy individuals and achieved a 5-fold Cross-Validation accuracy of 72.61% ± 4.24%. Mezghani et al. [34] developed a system that used two Kistler force platforms and a treadmill to identify between broken and healthy patients, attaining an overall accuracy of 91% with GRF settings and the Nearest Neighbour Classifier.

3.2.3. Inertial Sensors (IS)

These electrical devices work based on inertial measurement. They use three major sensors to measure the subject's bodily movements: accelerometers, gyroscopes and magnetometers. These sensors are frequently coupled in Inertial Measurement Units (IMUs), efficiently collecting linear and angular readings. Mezghani et al. [35] created an IMU-based system with an accelerometer range of ±8 g and a gyroscope range of ±2000 degrees per second. The study, which included 20 patients with idiopathic illnesses, found that this novel strategy was successful for population monitoring.

3.2.4. Electromyography

In rehabilitation, these sensors detect muscle electrical impulses that reflect patients' muscle activity and patterns, which might vary greatly. These patterns show muscular strength and aid in calculating various gait metrics. EMG sensors can be introduced into muscles with cables or needles or put on the skin with integrated electrodes.

Kozey et al. [36] tracked 38 knee patients throughout time using surface EMG electrodes to measure lower limb movements, ground response forces, and kinetic moments. They discovered changes in gait speed and muscle activation among groups due to aging and other factors. Putri et al. [37] employed pattern recognition to analyze EMG signals and distinguish between 15 patients with gait issues and 8 healthy controls. They reached 88.4% accuracy with an Artificial Neural Network, emphasizing the necessity of EMG in gait diagnosis.

3.2.5. Insole Shoe Sensors (INS)

Pressure shoe technology monitors pressure distributions during walking activity via force-sensitive resistors, allowing for comparison of gait variances [38]. Zeng et al. [39] suggested a method for distinguishing between fractured and healthy humans based on phase space reconstruction, empirical mode decomposition, and neural networks. The study employed data from the PhysioNet dataset using empirical decomposition with a neural network to achieve 81.1% accuracy.

3.2.6. Clothing Sensors (CLS)

Clothing sensors, also known as smart fabric, have greatly enhanced clinical gait assessment by detecting body movement and joint angles. Bergmann et al. [40] suggested a new clothing sensor system that incorporates sensors inside clothing and compared it to a gold standard system. The proposed system's reliability was verified by a coefficient of determination greater than 0.99. Okuma et al. [41] conducted a full-body garment study to identify fall events in people with Parkinson's disease, resulting in reliable identification of fall occurrences in both groups.

3.3. Gait Recognition Techniques

There are two broad techniques in existence for gait analysis:

- Model-free method
- Model-based method.

The first broad approach focuses on extracting statistical features from the appearance of gait sequences, whereas the model-based method targets the extractionof the gait features from the model of human motion explicitly based on its prior knowledge [42].

The model-free technique has lower computing overheads than the model-based approach. Like the approach, the model-based approach is insensitive to the subject's clothing and appearance. This system implemented a model-free approach of a simple averaged silhouette technique for appearance-based gait recognition using eigenvectors and Euclidean distance in the video sequences. The complete process is separated into various stages such as:

- Subject Detection
- Tracking
- Feature Extraction
- Training
- Recognition

The improved recognition rate is achieved by experimenting with each subject in different recording settings, such as walking with arms in pockets, wearing a backpack, static occlusion, and dynamic occlusion [43].

3.3.1. Silhouette-Based Gait Recognition

Silhouette uses shadows of people walking for optimal performance based on the human shape, even for low-resolution input imagescaptured from a distance. This type of gait recognition has found its major role in security-based applications and forensics. GEI is considered the baseline and one of the most effective patterns for evaluating the performance of silhouette-based gaitrecognition. The major challenges that exist in silhouette-based gait recognition are Pedestrian detection, monitoring, and classifications concerning their walking speed, clothing, items of baggage, occlusion, and other similar parameters that reflect along with the subject silhouette. In such instances, it is essential to find the bestway of mounting multiple 3D/moving cameras to get better viewpoints and directionalcharacteristics for enhanced gait recognition results [44].

The existence of several object obstacles, such as buildings, construction beams, bridge columns/pillars, vehicles, trees, etc., helps the occlusion of various parts of the individual's body. Thus, occlusion handling is a difficult yet critical issue in gait recognition. Formulation of occlusion management in gait recognition can be doneon its relative position, such as relative static-based occlusion (tree, building, bridge, etc.) and relative dynamic-based occlusion (moving vehicles, people). To handle these occlusions, an efficient CNN and GAN (Generative Adversarial Networks) have been proposed through spatiotemporal silhouette sequence reconstruction and image/video inpainting techniques [45].

Spatiotemporal silhouette analysis is offered for a series of images using the background removal method and simple segmentation technique for tracking the moving shadows of walking subjects. Then, appropriate PCA for dimensionality reduction and Eigen transformation over time-varied input signals were performed for this silhouette imagesequence. Finally, SVM classification techniques are used to recognise patterns in the lower-dimensional eigenspace [46]. Implicit captureof the structural and transitional features of gait is done by this method very efficientlyfor the outdoor image series.

This study presents a novel approach for combining appearance-based and model-based gait identification approaches [47]. It uses a CNN trained on silhouettes and a GCN trained on skeletal data. Two new modules were added to the GCN to improve the representation of skeletal data. The system processes spatiotemporal data using a dual-branch model and a multidimensional attention module. When tested on the CASIA B dataset, this method produced promising results.

3.3.2. Machine Learning-Based Gait Analysis

Kececi et al. [48] used three distinct SML models to detect human activity.

- RF
- Naive Bayes
- Instant Based Learning classifiers.

The hugaDB collection contains data on standing, sitting, running, and walking, which were acquired using accelerometers and gyros. Among the machine learning models tested, random forest performed better in terms of classification accuracy and needed less setup time. Moon, Le, Minaya, and Choi [49] presented a multi-model gait detection classifier that combines convolutional and recurrent neural networks with an SVFE. Wang et al. [50] used CNN and LSTM to create a classifier that automatically extracts numerous features from sound data for gesture identification. Shao et al. [51] also contributed to this research area.

Hnatiuc et al. [52] created a system that uses gait as a biometric to identify people from a distance. They employed IMU sensors in smartphones and an Arduino resistive flex sensor to capture walking patterns. Individuals were identified using a variety of classifiers, including tree, rule-based, SVM, K-nearest neighbors, and NB, which were trained on data from various subjects.

The study employs Artificial Neural Networks and SVMs to detect muscular Parkinson's disease in patients by analyzing their stride [53]. During training, the researchers consider kinetic, kinematic, and spatiotemporal aspects while employing intra- and inter-group normalization procedures. The findings indicate that intra-group normalized spatiotemporal parameter combination increases performance for both neural networks and SVMs.

Saboor et al. [54] investigate WS and ML techniques in human gait analysis. Their research focuses on two major advancements: using wearable devices for efficient and cost-effective data collecting and applying MLMs for gait evaluation. They discuss current advances in step analysis employing wearables and MLMs, concentrating on step boundaries and material elements of stride measurement. The study discovered that employing PCA to remove redundant stride data improves SVM classification accuracy to 87%, beating a 101-layer step design without PCA.

Table 1 summarizes a detailed assessment of various models, data sets, gaitfeatures, and gait recognition accuracy during the literature review. The study focusedon utilizing DL algorithms with different metrics such as performance, characteristics, advantages, and limits. Table 2 summarizes the details of the gait analysis of fracture patients and rehabilitation of patients.

Table 1. Summary of gait analysis in various models

Reference	Model	Data set	Gait feature	Accuracy
Wang et al. [55]	CNN	CASIA A	GEI	95%
Wang et al. [56]	CNN	CASIA A/B	GEI	98.30%
Wazzeh et al. [57]	CNN	OU-ISIR	GEI	97%
Rohan et al. [58]	CNN	Skeletal Images	GEI	97.30%
Zou et al. [59]	CNN	Data Collected Using Sensors	GEI	97%
Shao et al. [60]	CNN LeNet5	CASIA B	GEI	98%
Sung et al. [61]	DCNN	CASIA B	Gait Type (Walking, Running, Climbing and Descending)	90%
Chakravorty et al. [62]	DCNN	Market Dataset-Tsinghua Univ	GEI	93.60%
Turner et al. [63]	LSTM	Data Collected Using a Pressure Sensor	Axial Acceleration	83.20%
Peinado-Contreras et al. [13]	LSTM	Sensor Collected Data	Vertical Acceleration-Gravity Force	97%

Table 2. Summary of gait analysis of fracture patients and rehabilitation

Reference	Model	Dataset	Skeletal joint	Description	Performance
Jung et al. [68]	CNN	EMG data of multiple individuals	Ankle	Uses a hybrid system comprised of a Powered Ankle Foot Orthosis (PAFO), and FES presents the coordination control.	Consideration of volitional muscle activity lowers the energy consumption by PAFO and FES.
Ettefagh et al. [70]	3D CNN	Online dataset of 30 healthy people	Lower limb like knee, hip.	Analyzed people completing seven lower limb rehabilitation activities.	Identifies the exercises with an accuracy of 95.71%, Precision of 95.83%, recall of 95.71% and F1 score of 95.74%.
Alazeb et al. [71]	PCA and a Reweighted Genetic Algorithm	mRI and MHEALTH	Parkinson's sufferer	The system employs RGB, inertial, and depth sensor data, with features computed using a notch filter.	An average accuracy of 97% is achieved.
Yu Jing et al. [73]	BiLSTM SVM	Provided by the Institute of Software, Chinese Academy of Sciences	NDD Patients	Extracted stride speed, step, cadence, left and right swing to diagnose NDD. Used Kinect technology and machine learning for diagnosis.	For BiLSTM: Accuracy-93.2% For SVM: Accuracy-77.5%
Mennella et al. [76]	LSTM, GRU, MLP	Data collected from the SensFloor and IMU sensors	Patients suffering from physical impairments or disabilities	Speed, average number of steps, and other information are analyzed to recognize asymmetric and unstable gait patterns. The system incorporates a range of motion categorization and compensating pattern recognition.	Achieved mean accuracies of 89% for ROM-class assessment and 98% for compensatory pattern categorization.
Michael Tschuggnall et al. [78]	RF regressor and classifier, Extra trees Algorithms	Anonymized real-world dataset of the Vamed Rehabilitation Center Kitzbühel	Knee, Hip, Foot injuries	Predict the success of patients' rehab based on their health status at the start of the treatment.	Weighted F1 scores from 40% to over 65% are achieved.

3.3.3. DL and Wearables in Gait Analysis

The study by Khan et al. aims to improve DL models for human gait analysis. It highlights feature selection to enhance CNN model performance. Using the KELM, the study achieved the highest recognition accuracy for the CASIA Gait Database, ensuring a significant improvement over previous systems with 96.50% and 96.90% accuracy. Innovative gait classifiers now classify data from various sensors, further advancing the field.

This study presents a DL-based gait classification method that employs multiple sensor arrays and a smart insole [64]. The device measures gait data using pressure and acceleration sensor arrays and a gyro sensor integrated into the insole. A deep convolutional neural network extracts features with more than 90% classification accuracy.

Two promising technologies, namely non-invasive wearable sensors and DL algorithms, were chosen from a wide range of technologies for inclusion in this study due to their crucial importance in modern gait analysis [60]. This technique assesses gait issues based on individual symptoms, regardless of additional neuromuscular movement disorders that the patients may have. Here, the researcher monitored the in-shoe pressure of twelve healthy volunteers while subjected to eight artificially generated gait modifications with underside shoe alterations.

Using the LSTM network, this approach achieves 82% precision with test dataof 96,000 samples in classifying the person’s gait. While reviewing the study, it was discovered that the data set used here was of small volume and had limited computational power and poor power efficiency.

This study collects gait data using smartphone inertial sensors, which is practical and cost-effective [61]. Features are retrieved using CNN and RNN, followed by modelling with a hybrid Deep Neural Network. Smartphone sensor data revealed user identification and authentication accuracy.

Traditional therapy encounters problems that rehabilitation robots help resolve. Machine learning is revolutionizing therapy and result prediction, yet it faces challenges such as model interpretability, costs, and restrictions. Zhang et al. [65] investigate the relationship between ML using various models, datasets, and applications. They emphasize prospective applications, such as virtual reality and DL, in rehabilitation training.

Yoo et al. [66] created a deep-learning model to predict gait recovery following severe concussion (SCI) after release from acute rehab. They analyzed data from 405 patients at Korea University Anam Hospital from 2008 to 2022. Using 71 independent variables from the literature, including patient demographics, SCI scores, and neurological characteristics, they discovered that the RNN outperformed the linear regression, Ridge, and Lasso algorithms. Lower-extremity motor strength and the severity of neurological impairment were also significant predictors.

From 2019 to 2023, Mizuguchi et al. [67] investigated 417 older people with CHF at seven different sites. They discovered that a higher predicted CFS, estimated using smartphone camera body-tracking data and Light-GBM models, was independently associated with an elevated all-cause mortality risk. The Light-GBM models demonstrated significant accuracy in predicting CFS levels, underlining its potential in clinical prognosis.

Jung et al. [68] provide a unique gait rehabilitation strategy that employs a hybrid system of PAFO and foot-elbow splints with coordinated control. PAFO alters joint angles and impedance profiles using biomechanical models, whereas FES patterns are derived from electromyograms of healthy persons. A CNN-based prediction algorithm calculates voluntary joint torque using patient electromyograms. Healthy subjects walking on a treadmill revealed lower energy expenditure and adjustable ankle motion by including voluntary muscular action. This system offers assist-as-needed therapy, which improves gait rehabilitation outcomes with active patient participation.

Ramli et al. [69] utilized an iPhone accelerometer to measure gait in 15 normally developing (TD) and 15 DMD children aged 3 to 16. Participants undertook various walking and running exercises, and temporospectral gait characteristics were recorded. These measures revealed variations such as shorter steps and greater mediolateral power, indicating a Trendelenberg-like gait in DMD. The study found that machine learning applied to smartphone accelerometer data may accurately detect gait features linked with DMD throughout a wide age range, from toddlers to teenagers.

Ettefagh et al. [70] examined depth videos and body pressure data from an online dataset of 30 healthy individuals participating in seven lower limb rehabilitation activities. Three DL models were built to identify the data: depth movies, pressure data frames, and a combination of the two. The models' performance was assessed using cross-validation procedures that removed one or more subjects. The model trained on depth and pressure data fusion achieved the highest accuracy and stability, rating 95.74% on the F1 scale. This emphasizes data fusion's need to identify lower limb rehabilitation exercises appropriately.

Alazeb et al. [71] created an AI-powered system to guide Parkinson's disease treatment based on RGB, inertial, and depth sensor data. They used a notch filter to extract features from the sensors, focusing on silhouette analysis and four important movement characteristics: principal component analysis and a reweighted genetic algorithm combined and classified features. Cross-validation on the MRI and MHEALTH datasets produced high recognition accuracies of 97.29% and 97.94%, respectively. The work emphasizes the necessity of extending datasets to better rehabilitation using multi-modal sensor-based human activity detection.

Lan et al. [72] studied the application of DL and 3D gait analysis data to evaluate gait abnormalities in children. They analyzed data from 371 children and 6400 gait cycles to determine the accuracy of DL models. The study discovered that these models had high diagnostic accuracy when discriminating between healthy and pathological gait, recognizing specific gait problems, and calculating the time of gait anomalies. Overall, their LSTM model performed well, demonstrating the possibility of 3D gait analysis to provide deep pathological insights for diagnostic purposes.

Jing et al. [73] used motion data from 41 people aged 25 to 85 to characterize gait styles using SVMs and Bi-LSTM classifiers. They trained these classifiers on spatiotemporal characteristics and used 10-fold cross-validation to achieve the best generalization performance. The Bi-LSTM classifier outperformed a heuristic technique, with average accuracy, recall, and F1-score of 90.54%, 90.41%, and 90.38%, respectively, whereas SVM achieved 86.99%, 86.62%, and 86.67%. The Bi-LSTM technique also performed well in gait segmentation evaluation, with 93.2% accuracy versus 77.5% for SVM.

Monge et al. [74] proposed a non-intrusive smart sensing system for improving health monitoring in hospitals and rehabilitation facilities. Their system combines a SensFloor smart carpet with an IMU wearable sensor on the user's back. Machine learning algorithms analyze real-time data stored in the cloud, available to physical therapists and patients. This strategy allows for more personalized training regimens and better rehabilitation outcomes by leveraging modern sensing technologies.

Maskeliūnas et al. [75] created Biomac VR, a virtual reality rehabilitation system that combines physical training monitoring with upper-limb rehabilitation technology. The system uses the CPM, a DL motion detection model, to properly track important body parts in conjunction with depth sensors. It assesses the efficacy of physical exercise in various circumstances, offering real-time analysis with an average reaction time of 23ms. The system's algorithmic skeletal traits identify healthy persons and those suffering from lower back pain, allowing for the study of physiotherapy activities, tracking rehabilitation progress, and rating treatment success.

Mennella et al. [76] describe a novel approach to real-time monitoring and assessment of rehabilitation activities that employ machine learning and motion capture technology. The system accurately assesses workout performance by identifying deviations and categorizing ROM and compensatory tendencies. It performed quite well, with mean accuracies of 89% for ROM classification and 98% for compensatory pattern recognition. This sophisticated method improves standard rehabilitation assessments and outcomes in home-based rehabilitation programs.

Galasso et al. [77] use kinematic gait data from 37 healthy persons to estimate physical activity levels using the IPAQ. They use ML techniques to process complex time series data efficiently. Using NCA on the statistical feature space improved accuracy by up to 20% for models such as K-Nearest Neighbours, RF, and Rough-Set-Exploration-System Library.

Michael Tschuggnall [78] used an anonymized real-world dataset of the Vamed Rehabilitation Center Kitzbühel. Using Random Forest regressor and classifier, Extra trees Algorithms Predicted the success of the rehab of knee, hip and ankle injured patients based on their health status at the start of the treatment and achieved the weighted F1 score from 40 % to 65%.

Chandrasen Pandey [82] used ground reaction force patterns to classify healthy control and Gait disorders. A deep learning-based architecture, GaitRec-Net, is proposed for this classification.

4. Deep Learning - Based Methods

The machine learning uses two different categories of algorithms: Supervised and unsupervised. The supervised algorithm uses labelled data in classification techniques such as Logistic Regression, Random Forest, Neural Networks, Support Vector Machines (SVM), CatBoost, K-Nearest Neighbors (KNN) and Decision Trees. The unlabeled data is used in unsupervised algorithms such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). Conventional machine learning methods cannot effectively retrieve the hierarchical or higher-level features. However, deep learning is a category of ML technique that creates numerous layers that can recognize specific properties of the dataset using ordered layers of neural networks.

The various present deep learning methods are CNN, 3D CNN, LSTM, Bi-LSTM, and Multilayer Perceptron (MLP). This part defines the architecture of CNN and LSTM deep learning methods for gait analysis, gait classification and rehabilitation. The architecture of Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (Bi-LSTM) is quite similar, with only one difference: Bi-LSTM processes data in forward and backward direction, while a standard LSTM processes data in only forward direction. The CNN architecture with 1D CNNs is used for sequential or time-series data. 2D CNNs are used for image data. 3D CNNs are used for volumetric or temporal-spatial data.

4.1. Convolutional Neural Networks (CNN)

The CNN network consisted of several convolutional layers placed alternately between pooling and normalization layers. Each convolutional layer calculates the convolution between the inputs and sets of filters. The training was performed in a supervised manner. The structure of CNN consists of a Convolutional Layer, Batch Normalization Layer, Rectifier Linear Units (ReLU), Pooling Layer and Fully Connected Layer. The NN architecture model is shown in Figure 4.

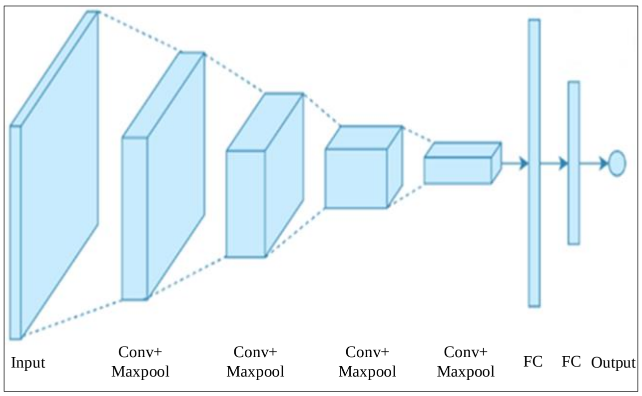


Fig. 4 CNN architecture model

The CNN architecture used in this study was designed with five convolutional layers and three fully connected layers. However, the final implementation consisted of only four convolutional layers and a single fully connected layer.

Batch normalization, ReLU activation, and pooling layers were strategically placed between the convolutional layers to enhance the model's performance. The CNN structure alternates convolutional layers with pooling and normalization layers. Each convolutional layer computes the convolution between the input data and a set of filters. The model was trained in a supervised fashion.

For gait analysis, each walking sequence was mapped to its corresponding subject and reshaped into a 60x26 three-dimensional array, with columns representing joint points at a specific time frame and rows representing joint data over time. After reshaping, the gait data was randomly split into training and testing datasets, with a 50:50 ratio to promote better generalization.

4.2. Recurrent Neural Network (RNN)

A Recurrent Neural Network (RNN) [79] is a specialized type of Artificial Neural Network (ANN) designed to handle sequential data or time-series data. Unlike conventional feed-forward neural networks, which assume data points are independent, RNNs are built to process sequences where each data point depends on its predecessors. This is achieved by incorporating a form of "memory" that allows the network to store and use information from previous inputs to influence the current output in the sequence. In an RNN, this is facilitated by a feedback loop that allows information to persist across time steps. When an RNN is processed over multiple time steps, it can be "unrolled" for a specific number of steps (e.g., kkk steps) to compute the output at each step. This unrolled structure mirrors a feed-forward neural network, where each time step is treated as a separate layer. The RNN architecture model is shown in Figure 5.

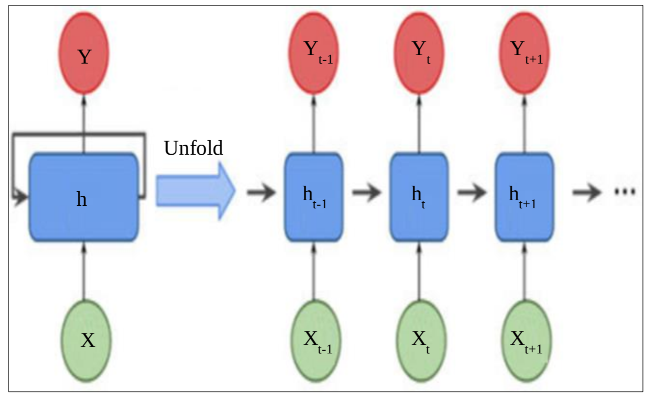


Fig. 5 RNN architecture model [80]

4.3. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a specialized type of Recurrent Neural Network (RNN) designed to handle sequential data, such as time series, speech, and text. LSTM was introduced to address the limitations of traditional RNNs, particularly the vanishing gradient problem, which makes it difficult for RNNs to capture long-range dependencies in sequences.

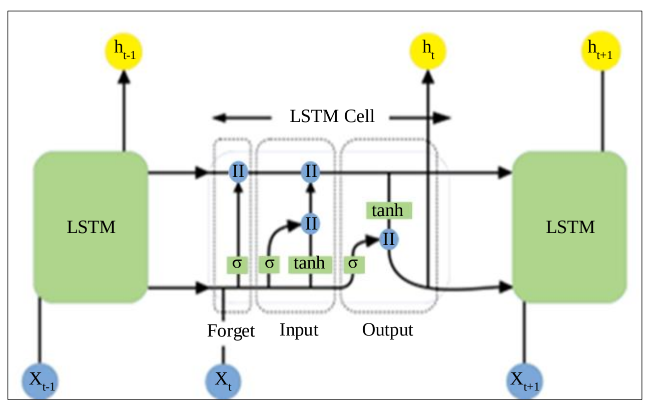


Fig. 6 LSTM architecture model [81]

The LSTM architecture consists of a cell state and three primary gates: the input gate**,** forget gate, and output gate, as shown in Figure 6.

1. Cell State**:** The cell state is the "memory" of the LSTM unit, carrying information across time steps. It enables the network to maintain context from previous steps and helps learn long-term dependencies.

2. Forget Gate: This gate decides what information from the cell state should be discarded or "forgotten." It takes the previous hidden state and the current input to output values between 0 and 1, representing the degree to which each value in the cell state should be forgotten.
3. Input Gate: The input gate controls what new information should be added to the cell state. It uses a tanh activation function to generate candidate values and a sigmoid activation to decide which of them should be updated.
4. Output Gate: The output gate determines the next hidden state based on the cell state and the input, providing the final output of the LSTM for the current time step.

LSTMs are widely used in applications like speech recognition, language modelling, and time-series forecasting, where long-range dependencies are important.

4.4. Methodological Framework for Gait Analysis Using Deep Learning

A comprehensive methodological framework for gait analysis using deep learning techniques, focusing on their applications in rehabilitation settings. A comparison of different deep learning approaches—such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and others are discussed in Table 3.

Table 3. Comparison of different deep learning approaches

Algorithm	Advantages	Limitations	Best Use Case
CNN	Excellent at spatial feature extraction from images and videos.	Struggles with sequential data (time dependencies).	Video-based gait classification (e.g., detecting falls).
RNN	Model's temporal dependencies in sequential data.	Cannot capture long-range dependencies effectively.	Time-series analysis for gait cycle prediction.
LSTM	Captures long-range dependencies and is good with sequential data.	Computationally expensive, especially with long sequences.	Personalized rehabilitation, phase detection.
3D-CNN	Captures both spatial and temporal patterns in video or motion data.	Requires large datasets and high computational power.	Video or 3D motion capture data for gait analysis.
1D-CNN	CNNs can automatically learn spatial or temporal features from raw input data, reducing the need for manual feature extraction.	Cannot model long-range dependencies well with a single convolution layer.	Time series classification, speech/audio recognition, text classification.
Bi-LSTM	Bi-LSTMs are designed to capture both short-term and long-term dependencies, essential for sequential data where context from both the past and future is needed.	Due to the sequential nature and memory handling, training Bi-LSTMs typically takes longer training time, especially with large datasets.	Medical time series, where future context can significantly influence prediction.

5. Datasets

The different datasets used for gait analysis and rehabilitation are CASIA gait Database, GaitRec, GaitRecNet, mHealth, and TUM Gait Dataset.

5.1. CASIA Gait Database

The dataset is one of the most commonly used resources for gait recognition research, featuring walking sequences from 124 subjects across various conditions. These conditions include normal walking, walking with bags, and walking in different types of clothing, as well as gait sequences captured from multiple viewpoints. It is primarily used for gait recognition and person identification tasks but also has applications in gait classification, particularly in rehabilitation settings. The dataset includes a range of data types such as video recordings, 2D/3D gait data, silhouette images, and motion capture data, making it versatile for various gait analysis applications [55, 56].

5.2. mHealth Dataset

The MHealth Dataset contains two sets of data: one with healthy subjects and another with elderly subjects. It consists of time-series data recorded from smartphones equipped with accelerometers and gyroscopes. The dataset includes data from 10 subjects (5 male, 5 female), each performing 12 distinct activities, such as walking, running, sitting, standing, and cycling. The data is sampled at 50 Hz (50 samples per second), yielding high-resolution measurements of 3D accelerometer and gyroscope readings for each axis (X, Y, Z). Each subject performs the activities under controlled conditions, either holding the smartphone in their hand or placing it in their pocket. In terms of size, the dataset includes around 5 hours of data, with each activity's duration varying, totalling approximately 2.9 million data points. The data is provided in CSV format for easy access and use in machine learning, making it ideal for tasks like activity recognition, gait classification, and fall detection [71].

5.3. GaitRec Dataset

The GaitRec dataset is a comprehensive, open-source resource widely used in gait research, particularly for analyzing Ground Reaction Forces (GRF). It includes walking trials from 2084 patients with various musculoskeletal impairments and data from 211 healthy controls. The dataset captures information from patients undergoing treatment for conditions such as joint replacements, fractures, ligament ruptures, and other disorders affecting the hip, knee, ankle, or calcaneus during their rehabilitation at the Austrian Workers Compensation Board's (AUVA) rehabilitation centre.

The primary value of this dataset lies in its ability to differentiate between healthy and pathological gait patterns. It is divided into five major classes: (1) Healthy Controls (HC), (2) GD-Hip, (3) GD-Knee, (4) GD-Ankle, and (5) GD-Calcaneus, with each gait disorder further categorized into a dual-level hierarchy. For example, disorders in the Hip, Knee, and Ankle classes include primary disorders and more complex combinations of impairments, such as Pelvis (P) and Coxa (C) issues in the Hip category. This detailed classification enables a nuanced understanding of gait disorders, focusing on precisely identifying the 27 derived classes for improved gait diagnosis. The GaitRec dataset is instrumental in distinguishing between healthy and pathological gait, evaluating therapy progress, and predicting individualized treatment outcomes [83].

5.4. GaitRecNet Database

The GaitRecNet dataset is a comprehensive resource for analyzing human gait, focusing on classifying gait disorders through the use of Ground Reaction Force (GRF) data [82]. This dataset is extensively used in research related to gait analysis, rehabilitation, and clinical applications. Also, this dataset is widely used in research focused on improving gait analysis methodologies, developing predictive models for rehabilitation, and enhancing clinical decision-making in musculoskeletal therapy. It includes bilateral GRF walking trials from a large group of patients with various musculoskeletal impairments, such as hip, knee, ankle, and calcaneus disorders, alongside data from healthy controls for comparative analysis. By leveraging GRF data, the GaitRecNet dataset supports a deeper understanding of how musculoskeletal impairments affect gait and aids in developing more accurate, individualized treatment plans for patients.

5.5. TUM Gait Dataset

The TUM Gait Dataset, created by the Technical University of Munich (TUM), is a widely used resource for gait analysis and recognition. It contains data from 10 subjects (8 males and 2 females). It features gait recordings under four walking conditions: normal walking, walking with a bag, walking in casual clothing, and walking in formal attire. These conditions help explore how external factors influence gait patterns.

The data was collected using a camera-based system with controlled lighting, capturing 3D motion data from multiple viewpoints to accurately represent each subject's gait. Additionally, the dataset includes silhouette images to support gait analysis and identification. With multiple walking sequences for each subject, the dataset enables detailed analysis of gait features such as stride length, speed, and joint movement. It is valuable for applications in gait recognition, biomechanical analysis, human identification, and rehabilitation, particularly for monitoring progress and diagnosing movement disorders. The comparison of characteristics, sources and limitations of different gait datasets is shown in Table 4.

Table 4. Comparison of characteristics, sources and limitations of different gait datasets

Dataset	Characteristics	Sources	Limitations
TUM Gait Dataset	3D motion capture, silhouette images, different walking conditions (normal, walking with a bag, casual/formal clothing)	Technical University of Munich, camera-based system, 10 subjects (8 male, 2 female)	Small sample size (10 subjects), controlled lab environment, limited real-world applicability
CASIA Gait Dataset	Video recordings of walking styles under various conditions (normal, obstacles, different clothes)	Chinese Academy of Sciences, multi-view video setup, 74 subjects	Limited diversity (mainly male, Asian subjects), lab-based, lacks environmental variability
mHealth Dataset	IMU sensor data (accelerometer, gyroscope), real-world walking tasks with mobile sensors	University of California, Irvine (UCI), smartphone sensors, 10 subjects (healthy)	Small sample size, limited variety of gait conditions, less suitable for biomechanical analysis
GaitRecNet	GRF data, 3D motion capture, data from patients with musculoskeletal impairments and healthy controls	Austrian Workers Compensation Board (AUVA), clinical data, 2084 patients, 211 healthy controls	Limited generalization to broader populations, clinical setting, not publicly available

6. Applications of Gait Rehabilitation

Gait rehabilitation is a multidisciplinary field crucial in improving mobility, preventing falls, and enhancing the quality of life for patients with various conditions. The applications of gait rehabilitation span neurological, musculoskeletal, and orthopaedic domains and often involve a combination of physical therapy, assistive technologies, prosthetics, and cognitive techniques. The ultimate goal is to help individuals regain or maintain the ability to walk safely and efficiently, regardless of the underlying cause of their gait disturbance.

Gait rehabilitation aims to restore or improve walking ability, enhance mobility, reduce fall risk, and increase independence in daily activities. Real-world applications in rehabilitation are crucial for helping individuals recover from injury, illness, or surgery, and they span various settings like hospitals, outpatient clinics, and even home-based care. Here are some practical examples:

6.1. Stroke Rehabilitation

Telehealth and virtual therapy have become vital tools in stroke rehabilitation, enabling patients to continue their recovery from home through video sessions. These platforms facilitate motor exercises, cognitive training, and speech therapy, providing patients with the flexibility and convenience of remote care. Additionally, wearable devices that track movement, muscle activity, and overall rehabilitation progress are being integrated into treatment plans. These devices offer real-time feedback, allowing both patients and clinicians to monitor improvements in motor skills and adjust therapies as needed, enhancing the effectiveness of rehabilitation and promoting better outcomes.

Stroke remains a major global health challenge, requiring comprehensive rehabilitation strategies to improve recovery outcomes. The various rehabilitation approaches, including physical, occupational, speech, and cognitive therapies, highlight the importance of early identification of rehabilitation needs [85]. It emphasizes the role of technological innovations, such as neurostimulation and assistive technologies, in enhancing stroke recovery. The manuscript also examines future directions, including personalized rehabilitation, neuroplasticity, and emerging assistive devices, potentially transforming stroke rehabilitation. By addressing these critical aspects, the paper aims to offer valuable insights for optimizing stroke recovery and improving survivors' quality of life.

6.2. Orthopedic Rehabilitation

After joint replacement or fracture surgery, patients typically follow a rehabilitation program focused on restoring strength, mobility, and flexibility. Physical therapy is key in rebuilding muscle strength and improving joint function, particularly after hip or knee replacements. In addition to traditional exercises, aquatic therapy offers significant benefits, as the buoyancy of water reduces stress on the joints while providing resistance to help strengthen muscles. This water-based approach is especially effective for individuals recovering from major surgeries, as it allows for safe, low-impact movement that accelerates recovery while minimizing the risk of further injury.

6.3. Neurological Disorder Rehabilitation

Rehabilitation for Parkinson's disease [71] emphasizes exercise routines designed to enhance gait, flexibility, and posture, which are crucial for maintaining mobility and coordination. In recent years, alternative therapies like dance and boxing have gained popularity, offering dynamic ways to support movement and improve balance.

For individuals with Multiple Sclerosis (MS), therapy typically includes physical exercises to address symptoms such as fatigue and muscle weakness. At the same time, speech therapy and cognitive training are integral components of a holistic care plan. Together, these therapeutic approaches help manage MS symptoms and improve overall function and quality of life.

7. Challenges in the Clinical Settings

Gait analysis in clinical settings encounters multiple challenges, including patient variability, technology limitations, and difficulties integrating new systems into existing workflows. Patients at various stages of recovery, such as those recovering from stroke or surgery, may display inconsistent gait patterns, making data interpretation more complex. For instance, patients using assistive devices may exhibit altered movement dynamics that traditional systems struggle to capture accurately.

Moreover, advanced technologies like motion capture systems and wearable sensors can be expensive and require specialized expertise, limiting their widespread adoption. More affordable, portable options, such as smartphone applications and wearable sensors, could be developed to overcome these challenges. Simplifying data collection and implementing automated systems can also facilitate smoother integration into clinical routines, reducing the burden on healthcare providers. Additionally, training clinicians and standardizing gait analysis procedures can improve the reliability of assessments, ultimately enhancing patient care and outcomes.

The PCG-based adaptive approach helps therapists by providing a wide range of gait exercises suitable for diverse patient groups and allowing for dynamic adjustments to the difficulty levels of various gait tasks to meet individual needs. The PCG-based adaptive gamified gait rehabilitation can effectively assist physiotherapists in delivering personalized treatment outcomes tailored to individual needs [86].

8. Performance Metrics Used by the Classification Approaches in Gait Classification

In gait classification tasks, various performance metrics are used to evaluate the effectiveness of classification models. These metrics help assess how well the model differentiates between various gait patterns or classes (e.g., walking, running, or abnormal gait). Here's a list of key performance metrics commonly used in gait classification.

8.1. Accuracy

Accuracy is the ratio of correctly predicted instances (both true positives and true negatives) to the total number of instances. It gives an overall measure of how well the model is performing.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \tag{1}$$

Where,

TP - True Positives (correctly predicted positive instances)

TN - True Negatives (correctly predicted negative instances)

FP - False Positives (incorrectly predicted positive instances)

FN - False Negatives (incorrectly predicted negative instances)

8.2. Precision

Precision is the ratio of correctly predicted positive instances to the total predicted positive instances. It indicates how many of the predicted positive instances are positive.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

8.3. Recall

Recall is the ratio of correctly predicted positive instances to all instances that are actually positive. It shows how many actual positive instances were captured by the model.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

8.4. F1 Score

The F1 Score is the harmonic mean of Precision and Recall. It balances the two metrics and is especially useful when you need a balance between Precision and Recall or an uneven class distribution.

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

The performance metrics for gait classification and rehabilitation of different datasets and classifiers are compared in Table 5.

Table 5. Comparison of different classifiers with performance metrics of different datasets

Research article	Dataset	Classifier	F1 Score	Recall	Precision	Accuracy
Darshan Jani et. al [83]	GaitRec	CATBOOST	0.948	0.947	0.948	0.947
Darshan Jani et. al [83]	GaitRec	Optimized CATBOOST	0.950	-	-	0.960
Chandrasen Pandey et al. [82]	GaitRecNet	1D CNN	0.92	0.99	0.96	0.916
Nazia Ejaz et al. [84]	Force values from left and right force sensors on the smart walker's handlebar are collected	Random Forest	0.95	0.95	0.95	0.954
Ettefagh et al. [70]	Multi model dataset	3D CNN	0.957	0.957	0.958	0.957
Yu Jing et al. [73]	Provided by the Institute of Software, Chinese Academy of Sciences	SVM	0.866	0.866	0.869	0.775

9. Conclusion

This survey explores the transformative impact of digitalization on gait analysis, particularly the integration of image and video data with human activity monitoring. Advances in machine learning and deep learning have greatly enhanced the accuracy and efficiency of gait analysis, enabling detailed and precise assessments that were once challenging to achieve with traditional methods. Various approaches to gait recognition were examined, highlighting their unique advantages and applications. These advancements have revolutionized the field, providing more sophisticated tools for analyzing and understanding human movement.

1. Model-Free Methods: These techniques rely on direct analysis of gait patterns without constructing detailed

human body models. They offer simplicity and computational efficiency, making them suitable for real-time applications.

2. Model-Based Methods: By creating detailed models of the human body, these methods provide more precise and robust gait analysis. They can account for individual anatomical differences and are less susceptible to external variations. The trade-off is increased computational complexity and the need for more sophisticated data acquisition systems.
3. Wearable/Non-Wearable Based Gait Recognition: WS, such as accelerometers and gyroscopes, provide continuous and unobtrusive gait monitoring in natural environments. Non-wearable methods, including video and motion capture systems, offer high-fidelity data and detailed spatial-temporal analysis but require controlled settings and may be more intrusive.
4. Silhouette-Based Gait Recognition: This approach uses the contour or outline of a person's body to analyze gait. It is particularly effective in recognizing individuals based on their walking patterns and can be applied in various security and surveillance applications. Silhouette-based methods balance between model-free simplicity and the detailed analysis of model-based techniques.

The convergence of digitalization, machine learning, and DL in gait analysis offers significant promise for rehabilitating fracture patients and entities with PD. Detailed insights into gait dynamics, these advanced techniques enable the development of personalized rehabilitation protocols, monitor recovery progress, and assess the effectiveness of interventions with unprecedented precision. Finally, combining DL and digitalization in gait analysis constitutes a significant step forward in both clinical and research settings. A survey has highlighted a current state-of-the-art method and its application, underscoring potential continued innovation and improved patient outcomes. As the field progresses, it is crucial to address challenges such as data standardization, computational requirements, and interdisciplinary collaboration to fully realize the benefits of these advanced techniques in gait analysis.

Future research in Deep Learning (DL)-enhanced gait analysis will focus on improving recognition, real-time monitoring, and disease diagnosis through better sensor integration and adaptive models. Key areas include personalized rehabilitation systems, cross-population model generalization, and gait as a biometric for secure authentication. Interdisciplinary collaboration with biomechanics, neuroscience, healthcare, AI ethics, and cybersecurity is essential to address challenges such as data bias, privacy, and model interpretability, ensuring the technology's reliability and fairness across diverse applications.

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