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Preeti Khera & Neelesh Kumar

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RESEARCH ARTICLE

Role of machine learning in gait analysis: a review

Preeti Khera[a,b] and Neelesh Kumar[a,b]

[a]Academy of Scientific and Innovative Research, Ghaziabad, India; [b]Biomedical Instrumentation Unit, CSIR-CSIO, Chandigarh, India

ABSTRACT

Human biomechanics and gait form an integral part of life. The gait analysis involves a large number of interdependent parameters that were difficult to interpret due to a vast amount of data and their inter-relations. To simplify evaluation, the integration of machine learning (ML) with biomechanics is a promising solution. The purpose of this review is to familiarise the readers with key directions of implementation of ML techniques for gait analysis and gait rehabilitation. An extensive literature survey was based on research articles from nine databases published from 1980 to 2019. With over 943 studies identified, finally, 43 studies met the inclusion criteria. The outcome reported illustrates that supervised ML techniques showed accuracies above 90% in the identified gait analysis domain. The statistical results revealed support vector machine (SVM) as the best classifier (mean-score $= 0.87 \pm 0.07$) with remarkable generalisation capability even on small to medium datasets. It has also been analysed that the control strategies for gait rehabilitation are benefitted from reinforcement learning and (deep) neural-networks due to their ability to capture participants' variability. This review paper shows the success of ML techniques in detecting disorders, predicting rehabilitation length, and control of rehabilitation devices which make them suitable for clinical diagnosis.

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Artificial intelligence (AI); machine learning (ML); gait analysis; gait rehabilitation; pathology detection

1. Introduction

Human mobility is significant to perceive quality life and degradation to it can lead to abnormalities. The study of human biomechanics termed as gait analysis aimed at quantifying factors governing the functionality of lower limbs. This is crucial for the detection of gait abnormalities, recognition of postural instabilities, and assessment of clinical interventions and rehabilitation programs. The clinicians anticipate gait analysis for diagnosis and treatment selection but have been challenged by underlined complexities such as volume and non-unique correlations between an individual's gait. Therefore, it is evident that gait analysis would be benefitted from artificial intelligence (AI) techniques. These techniques are capable enough in handling high dimensional, temporal and complex data [1,2]. They build models that learn automatically from available databases, make accurate predictions, and behave intelligently [3,4]. The machine learning (ML) is being extensively used in multiple fields such as medical diagnosis [5–7], pattern recognition [8,9], image processing [10,11], classification [12–14], prediction analysis [15–17], monitoring [12,18], therefore, making them suitable for gait studies. Although, ML techniques have been used for numerous gait applications, viz. to diagnose gait disorders [14,19,20], to predict early intervention for fall-related risks due to a disability or aging [3,6,21], to determine motor recovery tasks [22,23], or in planning a rehabilitation or therapeutic interventions [24–26].

AI techniques are used to analyse the data, images, and recognise patterns by creating algorithms that help physicians to diagnose a specific disease/disorder timely and accurately. Moreover, such algorithms learn continuously, thus improving the diagnostic results. However, sometimes physicians need to simultaneously consider symptoms of the patient, treatment plans, potential side effects, another disease with similar signs, previous medical history, and many other aspects. The AI-technology, in turn, provides a solution to assist physicians by analysing a vast amount of data and ensure a holistic understanding of patient health records. Even AI techniques can predict the onset of disease by processing the large volume of data gathered longitudinally by monitoring the health status of an individual. The surgical robots to handle many complex operations are the advent of AI techniques for disease management. Thus, the ML models built using complex relationships can reduce diagnosis

CONTACT Preeti Khera kherapreeti33@gmail.com Academy of Scientific and Innovative Research, Ghaziabad, India
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time, enhance patient monitoring, and aids the clinicians in the selection of treatment but requires computing facilities at the implementation site. Nevertheless, early diagnosis can prevent loss of mobility [1] and can reduce healthcare costs which are the rising concern of developing countries [27].

However, the success rate of deployment of such techniques in its initial phase of evolvement was less due to a lack of technological advent in data processing. The data collection and storage capabilities were unmet. The gait analysis was limited to laboratories using video-based systems. Thereafter, with the technological advent vision and sensor capture methods for gait analysis were developed which led to the accumulation of a large number of interdependent parameters. Thus, a need to process such temporal and highly complex data comes in. Although statistical tools are used widely in gait analysis, they lack predictive power to generalise on unseen data. Hence, the integration of ML and biomedical gait analysis can help in providing the solution.

A challenge is to determine how well a machine performs the tasks on the unknown dataset. The variety of supervised and unsupervised learning techniques are explored for classification and prediction tasks using approaches like vision-based [21,24] and sensor-based [20,28,29]. The dynamic learning, i.e., reinforcement learning (RL) can be used to achieve better tracking control performance for rehabilitation strategies [30]. Another aspect of ML that cannot be left intact is an algorithm devised for feature extraction and selection phase [14,23,31] that can be used to enhance computational efficiency and reduces the burden of classification or learning by reducing computing intervals.

The main objectives of this review are highlighted below:

1. To identify the studies that have used AI or ML techniques in gait analysis and rehabilitation, and conduct a selection criterion for their inclusion.
2. To classify the gait studies based on recent applications areas in this domain which are categorised as gait activity detection (GAD), gait event detection (GED), gait disorder detection (a) due to pathology (GDDP) (b) due to aging (GDDA), gait asymmetry detection (GAsD) and neurological effects on gait (GNE), to assess the performance capabilities and their limitations. Future directions for the researchers are also highlighted.
3. To study the qualitative analysis of ML techniques in gait rehabilitation for the intent detection to generate the triggering and feedback for trajectory control.
4. To determine which AI or ML techniques are most widely used in gait analysis and rehabilitation based on performance measures.

The review structure is as follows: Section 2 describes the basic definition of ML models, types and applicability in gait-related studies, which are used in this review. Section 3 presents the steps of data collection. Section 4 describes a summary of studied literature, highlighting the outcomes, limitations and active areas of research in the gait domain using ML techniques. Section 5 mentions the advantages of the usage of ML in gait and future expectations. This review is expected to provide a significant impact in the field of human biomechanics to promote the clinical application of ML techniques to aid the diagnosis and assessment of lower limb pathologies.

2. Machine learning in gait studies

The growth of ML in gait analysis is modelling a biomechanical system $T(x)$ by determination of the relationship between input data $f(x)$ and outputs $y(x)$, although the input data are corrupted by noise $n(t)$ which demands the need for preprocessing of the input data. The input data are raw multidimensional array $\{u_i, v_i\}$, where, u_i corresponds to a number of subjects or their trails, and v_i depicts the data features such as kinematics, kinetics or neuromuscular signals. The model output is representative of the classification of gait events, activities or disorders. Evaluation of biomechanical system $T(x)$ using ML techniques uses an iterative process where the input dataset is divided into a training set, testing set and validation set. After the selection of a particular ML technique, the model is trained using a training set and validated to determine the level of the fitting. Finally, the performance is evaluated on an unseen test dataset. When suitable accuracy is reached the process is terminated otherwise the model parameters need retuning and retraining until the desired accuracy is achieved. Too many parameters lead to system complexity; therefore, feature selection can be done. The most commonly used techniques include supervised, unsupervised and RL.

2.1. Supervised learning

In this type of learning, a feature vector comprises of labelled data with the aim to determine a function that best maps the relation between input feature vectors and the corresponding label. Various algorithms that were explored in gait studies consist of support vector machine (SVM), neural networks (NNs), random forest (RF), hidden Markov model (HMM), ensemble learning, k-nearest neighbour (kNN) and decision trees (DTs). The popularity of using SVM for gait analysis was that it has good generalisation capability even for datasets that are not too large. It has kernels to deal with linear and nonlinear problems. The classification performance was not only limited to binary class but can be extended to multiclass [27,28] which is quite beneficial in gait studies.

The prolific technique in gait analysis is the use of NNs consisting of a single or multi-layer perceptron. The NN uses feed-forward and backward propagation algorithms and is free from the need for hand-crafted features but many times acts as a black box. NN was used widely in gait studies to deal with the problems related to prediction and pattern recognition. DT, a sub-class of RF were used for the highly nonlinear and complex relationships between variables. Besides being interpretable, lacks to provide the optimal solution. Though, being an ensemble of randomised DTs, RF chooses the prediction with the maximum number of votes. The kNN classifier is based on distance metric and was widely used in real-time applications [8,22] as it is free from underlying assumptions about the distribution of the dataset. Gait asymmetry studies correspond to the use of varying membership grades to account for linguistic information which cannot be expressed numerically uses fuzzy techniques [12,32]. Such techniques are less explored in gait studies due to problems in defining a number of linguistic variables and optimal selection of membership functions.

2.2. Unsupervised learning

In unsupervised learning, no labels were given to the learning algorithm. The algorithm itself devises the relationship between various inputs to determine an output. Most clustering techniques, determine clusters based on the distance between all feature vectors. These techniques were less explored in gait studies because accurately defining the learning objectives and to deal with a large number of feature vectors was a tedious task. However, such techniques can be used when the relationship between different observations is unknown. To deal with the large datasets, it is desirable to combine the classifier with some dimensionality reduction approaches. These unsupervised techniques are capable of learning distinct patterns for particular disorders. An explanatory study can ensure the appropriate selection of distance metrics for the given problem. Apart from the distance metric, the latent profile analysis of clustering can also be used for subgroup classification.

2.3. Reinforcement learning

In rehabilitation devices such as exoskeletons and walking assistive devices, RL is required for the systems to interact with a dynamic environment. The various control strategies were developed for gait rehabilitation. The RL and (deep) neural networks (DNNs) were widely used with rehabilitation devices due to their ability to better capture the participants' variability and thus, resulting in automation according to subject-specific needs. The summary of presently deployed techniques in gait studies with their merits, demerits, complexity and interpretability is presented in Table 1.

2.4. Feature extraction and selection in machine learning

To improve the processing capabilities and to reduce the complexities, dimensionality reduction techniques [23,31] were employed. These techniques were categorised as feature selection that selects a subset of features from the original feature set without changing their originality, and feature extraction leading to the mathematical transformation of original features to derive new features. Some classifiers like artificial neural network (ANN), DNN and convolutional neural network (CNN) automate the feature extraction and selection process. Techniques most frequently explored in gait analysis were principal component analysis (PCA) [20,27] which possibly constructs principal components by converting correlated variables into a set of linearly uncorrelated variables through orthogonal transformation. The Hill climbing approach [33] being a heuristic search tries to reduce the feature vector by the selection of the best possible attributes. In forward selection, initially, one feature vector is selected to determine the accuracy, and then the features are added until the optimal solution is generated. In the backward selection, the initialisation is done by using all features and then removing one feature at a time to search for an optimal solution. The linear classifiers such as linear discriminate analysis (LDA) [22,34] can be used to project the features from higher dimension space to lower dimensions. If the dataset cannot be separated linearly than non-discriminate classifiers can be used such as quadratic

Table 1. Summary of learning model, their merits and demerits of presently deployed ML techniques.

Learning model	Gait applications	Complexity	Interpretability	Merits	Demerits
				SVM	
Supervised	Activity detection Event detection Disorder detection Asymmetry detection Neurological studies	Moderate	Moderate	Good generalisation capability Stability	Feature scaling Selection of kernel function
				NN	
				Removes the need for handcrafting features complex relationship detection	Network function lacks explainability
				DT	
				Probabilistic approach	Lacks predictability of continuous attributes Instability
				RF	
				Combination of multiple decision trees with probabilistic approach Fast training	For large datasets, the memory requirement is high Tuning of hyper-parameters
				kNN	
				Instance-based learning	Feature scaling Sensitive to outliers
				Fuzzy	
				Rule-based with less complexity	Selection of membership function A large number of linguistic features
Unsupervised	Clustering of disorder Asymmetry detection Determination of gait activities	Moderate	Difficult	Ease of implementation	Time complexity
Reinforcement	Assistive devices Rehabilitation Automation	Moderate	Moderate	Continuous learning No model training	Limited learning

discriminate analysis (QDA), flexible discriminate analysis (FDA) and regularized discriminate analysis (RDA). They had to be tested first to avoid over-fitting of the model and were implemented offline to reduce the computational burden. A challenge is to devise the relationship between optimal attributes for observed gait patterns and to use some nonlinear dimensionality reduction techniques for gait studies. The technique explored for gait disorder detection is kernel PCA [14]. These methods usually suffer from slow convergence, local minima and high computational complexities. Gait related studies can also be benefitted in near future by incorporating advanced feature selection methods based on removing highly correlated features, ranking features based on imparting high accuracies, and wrapper approach for selection and elimination of feature vectors.

3. Methods

This section describes the search approach used for the selection of studies. The inclusion and exclusion criteria are discussed together with the information extraction to carry out the review.

3.1. Search approach

The review was accomplished according to the preferred reporting items for systematic reviews and meta-analyses (PRISMA) checklist as illustrated by Moher et al. [35]. It includes four phases viz. identification, screening, eligibility and finally inclusion of the searched articles. The consideration was focussed on search terms viz. artificial intelligence, gait rehabilitation, lower limb and machine learning for searched articles (i.e., journal and magazine articles, proceedings of international and national conferences, and extended articles published from January 1980 to May 2019) in the recommended databases including PubMed, IEEE Explore, Science Direct, Wiley online library, Mendeley, Springer Link, Web of Science, Elsevier (Gait & Posture, Artificial intelligence in Medicine, Engineering Applications of AI, Journal of Biomechanics, Knowledge-based Systems and Neurocomputing), and Cochrane.

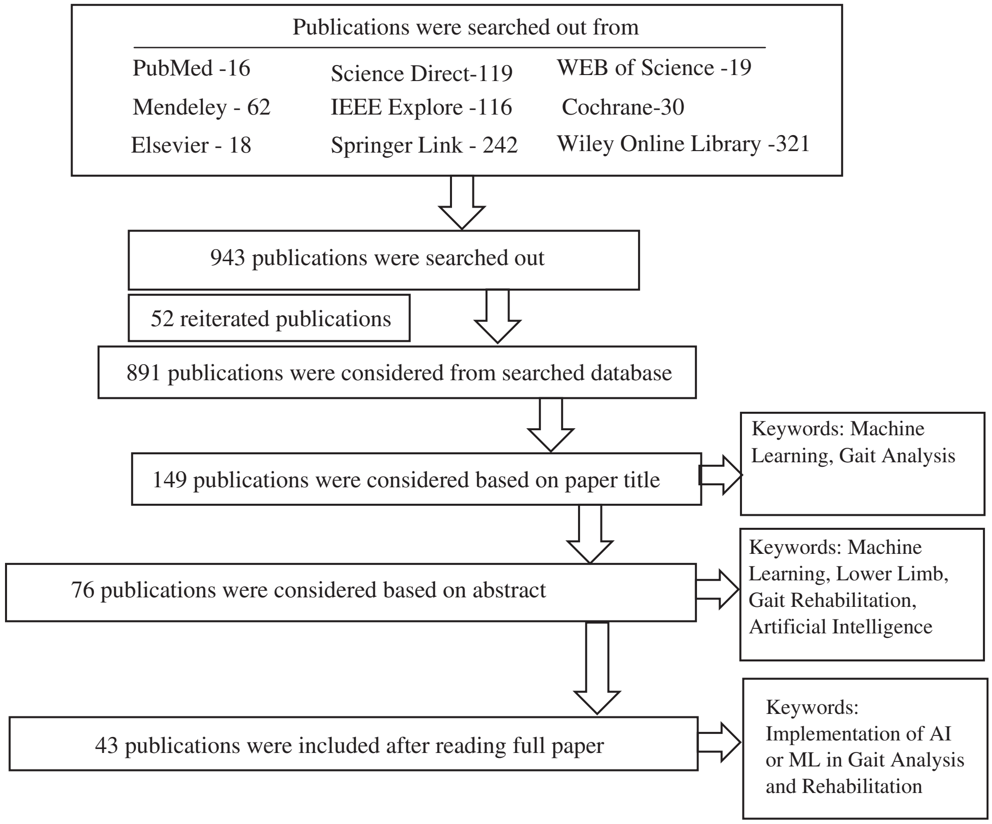

Figure 1. PRISMA flowchart of the selection process for review flow.

3.2. Selection criteria

The title and abstract screening were carried out by the authors (PK and NK) and independent reviewer(s) (VI) independently. The articles were screened based on the following questionnaires. (1) Has the article targeted the lower limb? (2) The gait analysis and gait rehabilitation be the focussed area? (3) Implementation of AI or ML for gait analysis and rehabilitation.

Based on the screening process, outcomes were reported. Throughout the study, the basic criterion was to traverse whether it is related to the lower limb or not, the inclusion of gait analysis or rehabilitation discussed in the articles or not. Whether or not the ML or AI approaches were used for gait analysis and rehabilitation. By considering all these factors, the selection of the papers was established based on keywords and outlined in Figure 1.

3.3. Inclusion and exclusion criteria

Machine learning and AI were the only keywords for the search. However, other possibilities may also exist and can be used with different names. This review includes only the lower limb whereas the upper limb is not targeted. The study focussing on sports biomechanics, gait for biometric, and security were not part of the inclusion criteria although they used ML. The review articles, book chapters and short communications were excluded. Related studies published in the English language were considered.

3.4. Data extraction

The authors (PK and NK) studied the full-length articles and information extracted is the objective of the study, measurement techniques, number of participants, pathology, parameters, methods, outcomes of the study, limitations, and its future scope (Table 2). The information about the dataset, as presented in Table 2 showing the size of data used for research which varies from small to large population size.

4. Results and discussion

Unlike, previous studies or methods which mainly focussed on gait analysis through observation by naked eyes lacks scientific and objective measures for its determination. The results were entirely based on the experience of the clinical expert or therapist. Now-a-days, with the advent of technological advances in

Table 2. Literature review of various studies ($n = 43$).

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
Gait activity detection										
1.	Lau et al., 2007 [7]	Development of accelerometer and gyroscope based sensor unit. Classification of five walking conditions.	Sensor unit at shank and foot (accelerometer and gyroscope)	3H (3M)	–	Stair ascending (SA) Stair descending (SD) Level ground (LG) Upslope (SU) Downslope (SD)	SVM RBF-ANN Bayesian Belief Network	Using SVM maximum accuracy for all classification tasks was achieved. 100% accuracy to classify SA from other activities, SD from other activities, and SA, SD, and other walking conditions. 85% for all 5 class classification. Accuracy increases from 78.82% to 84.71% by the addition of foot features together with the shank features.	–	To determine the effect of adding more input features from other sensors on accuracy. To perform real-time applications to aid in the decision making process a classifier is required.
2.	Pham et al., 2015 [36]	Use of muscle activities for recognition of human walking movement.	Motion capture system (kinematic data – joints (hip, knee and ankle) heel, toe) EMG data (iliopsoas, gluteus maximus, biceps femoris, rectus femoris, vastus lateralis, vastus medialis, tibialis anterior, gastrocnemius)	3H (3M)	–	Two principal components from EMG data in maximum voluntary contraction state in relation with stance and swing phase for Walking Running	Segmentation Feature extraction using LLE Classification using HMM	In walking, stance phase occurs for 60% of gait cycle at 4 km/h and 5 km/h, accuracy of 92%, and 93% in stance phase and 80% and 82% in swing phase, respectively. In running, stance phase is 40% of gait cycle at 7 km/h and 9 km/h, with accuracy 85% and 96% in stance phase and 89% and 85% in swing phase. Motion classification by HMM using extracted components from LLE results in accuracy 80% or more depending on different speeds for walking and running movements.	Reliability of analysis needs to be explored using more subject data.	Enhancement of framework for more speed changes. Controlling of wearable TTI-exo for supporting gait movements.
3.	Lonini et al., 2016 [37]	To differentiate between personal (patients group) model, global – patient models, global – healthy models for activity	Triaxial accelerometer	11H (6M, 5F), 10P (6M, 4F)	Knee-ankle-foot-orthosis (KAFO) for walking	131 time and frequency domain features for activity classification Sitting Standing Walking Stair down Stair up	Classification of five activities using RF 100 trees for personal models 50 trees for global models	Classifier used for global healthy model has low accuracy, i.e., 54.53%. Global patient and personal models have accuracies, i.e., 84.2% and 81%,	Need to improve generalisation of models. Accuracy is restricted for stair climbing due to tri-axial accelerometer on waist.	Use of different feature selection methods needs to be included for patient population. To explore Transfer learning methods.

(*continued*)

Table 2. Continued.

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
		recognition in individuals with lower limb injuries.						respectively. Personal shuffled model increases the accuracy from 84.2% to 96.7%. Sitting is easy to classify while stair climbing has lowest classification accuracy. For patients population condition-specific activity recognition algorithms are sufficient.		
4.	Devanne and Berretti, 2016 [20]	Abnormal gait detection. Re-identification through gait recognition.	3D data using depth sensor Kinect	12P (SPHERE dataset) DAI dataset 5H (frontal gait dataset)	Knee injury (knee cannot be bent) Foot dragged (using crutch) Left leg lead (LL) Right leg lead (RL) Freeze of gait (FoG)	Walking Stair climbing	Hierarchical Clustering algorithm PCA	LL and RL have better detection results compared to FoG.	Static abnormality detection is not possible like FoG.	Use of statistical methods to handle noisy or missing data. Inclusion of different other kinds of movements for sport gesture optimisation and rehabilitation.
5.	Leightley et al., 2017 [11]	Recognition of motions. Evaluation of human mobility impairments.	Microsoft Kinect (MoCap skeleton) Joint angles Both arms Both legs Torso	10H	–	Balance (eyes open) Chair rising Semi tandem Tandem balance Walking (4 m)	SVM RF ANN GRBM AdaBoost LPBoost RUSBoost Total Boost Bagging	To differentiate good mobility and poor mobility RF produced a maximum average recognition rate of 87.10%. GRBM producing lowermost average result of 73.08%. Determination of rehabilitation through the recognition of frames based on experimentally selected threshold.	Able to detect subtle differences between semi tandem and tandem using proposed feature set.	Using power analysis to clinically validate the proposed framework with more subjects.
6.	Recher et al., 2018 [38]	Four activity recognition chain (ARC). Reducing energy consumption. Identification of position at body to locate the sensor.	Kinematics data using wireless IMMU system at thorax, pelvis, right/left upper leg, right/left lower leg, right/ left foot	11P	Stroke	Sit Stand Transitions (sit to stand and stand to sit) Side steps Stairs and motion	Hierarchical weighted classifier	The position of sensor selection on body is dependent on ARC from being 5 to 3 sensors. User dependent model allows more reduction in number of sensors as compared to user-independent models.	Limited generalisation capability	To study the nature of knee stiffness and drop foot. To explore the possibilities of hierarchical-weighted classifier.

(*continued*)

Table 2. Continued.

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
								Preferable location for sensors being upper legs due to less variability and positioning the sensor on non-affected leg for user-independent model. Decision Fusion ARCs are more robust in performance than FARCs even during sensor failure.		
7.	Sok et al., 2018 [39]	Recognition of activities using waist worn accelerometer for ISCI subjects.	Accelerometer data	13P (9M, 4F)	Incomplete spinal cord injury	Parameters Mean *X*, *Y* and *Z* Absolute value of mean Moments: SD, skew, kurtosis RMS Extremes: min, max, abs min, abs max Cross product mean: *xy*, *xz*, *yz* Absolute mean of cross products Overall mean acceleration Activities Lying Sit Stand Walk Wheeling Stair climb	Static classification: SVM, NB, regularised LR, k-NN, DT, RF HMM with probability distributions (state transition and emission probabilities)	Classification of six activities, i.e., lying, sit, stand, walk, wheeling and stair climb. Intra subject 20-fold cross-validation using hybrid RF static HMM classification accuracy of 88.9%, i.e., 2.6% higher compared to static RF classifier with high precision and recall values. Subject wise cross-validation using 12 subjects' data as training and remaining one as testing provides an accuracy of 64.3% using SVM-HMM higher by 1.2% using only SVM.	More misclassifications between sit and wheeling or between walk and stair climbing, due to difficulty to distinguish the clips as accelerometer produces the same result. Challenging to interpret the criteria for decision making.	To embed a wearable metric with clip-based activity recognition. To test the model for variety of patient populations.
Gait event detection										
8.	Lau and Tong, 2008 [40]	Identification of gait events and evaluate the reliability of system based on accelerometer and gyroscope data.	Sensor units at thigh, shank, foot (accelerometer and gyroscope) FSR at 2nd middle phalanx, 1st metatarsal head, 5th metatarsal head, heel	3H (3M), 10P (2F, 8M)	Hemi paretic patients with dropped foot (DF)	Classification of turning points in stance and swing phase	Threshold detection method (based on turning points (TPs))	DF differs from normal gait as it has more peaks and troughs of high amplitude in stance and swing phase. Significant changes appear in gait patterns for different walking conditions. High performance in TPs appears at the time of phase transitions between stance and	–	To evaluate sensor systems at different terrains such as slope walking and stair climbing. Monitoring of gait patterns during daily activities.

(*continued*)

Table 2. Continued.

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
								swing phase. A single foot sensor data provides good performance in detection of TPs but in combination with other sensors, it can combine two directions for reliable operation.		
9.	Jung et al., 2012 [41]	Intent detection method consisting of a gait phase recogniser (to determine the intent to start moving unsound leg to swing) and gait pattern generator by estimating the unsound leg stance pattern using sound leg movement and echo control (echoing the swing pattern of previous gait).	Ground reaction force sensor Joint angles	–	Stroke	Two joint (hip and knee) angles Foot status value of one leg	NN	Classification of one stride into seven sub-phases using binary representation. Effectiveness of gait pattern generator is evaluated by comparing similarities between output and actual values in shape and time to evaluate unsound leg active joints.	–	Implementation of the developed hybrid method to real exoskeleton robot on walking rehabilitation.
10.	Yoo et al., 2013 [16]	To predict movement related to pain and radiographic severity associated with ascending stairs. Determination of knee OA initial stage.	Kinematics data using 3D motion analysis system	20H, 18P	Knee osteoarthritis (OA)	Time of stair ascent Maximal anterior pelvis tilting Knee flexion at initial foot contact Ankle dorsiflexion at initial foot contact	SVM	Detection of knee OA with accuracy of 97.4%. Prediction of pain determination with accuracy of 83.3% and radiographic severity 83.3%.	No optimal method to determine penalty parameter and scaling factor of Gaussian kernel function in SVM. Sample size too small.	To develop prediction model for progressive knee OA. Use of other machine learning methods for replication.
11.	Jiang et al., 2018 [42]	Wearable shoe pressure sensor graphene porous network system for human gait detection.	Plantar pressure of walking	10H	–	Normal pattern Toe-in Toe out Lame feet Heel feet	Ensemble learning algorithm – SVM + RF + LR	Normal pattern – 94.3% Toe-in – 83.1% Toe out – 94.2% Lame feet – 93.6% Heel feet – 96.8%	–	–
12.	Nazmi et al., 2018 [43]	Detection of gait events, i.e., stance and swing phase using sEMG.	sEmg signal from lower leg muscles – tibialis anterior (TA) and medial gastrocnemius (mGAS) Two FSR's at hallux and	8H (8M)	–	Time domain features RMS, SD, MAV, WL and IEMG	ANN using Levenberg Marquardt (LM) and scaled conjugate gradient (SCG)	During stance and swing phase TA and mGAS muscle activate, respectively. ANN accuracy statistics 87.5% and 77% using learned and	High difference in detection of phases using foot switch signal and ANN model being 29% and 10%	Incorporation of other TD features. Variations in hidden layer neurons.

(*continued*)

Table 2. Continued.

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
			heel under the sole of foot					unlearned data, respectively.	from unlearned data.	
13.	Souza and Stemmer, 2018 [8]	Extraction of patterns of gait analysis. Human identification using various pattern recognition methods.	Kinetic (GRF) Kinematics of lower body through Microsoft Kinect Sensor	10H	–	Oblique angle of pelvis Pelvis angle of rotation Left/right hip flexion/ adduction angles Left/right knee flexion angles Left/right ankle flexion angles	PNN LVQ DNN kNN Naïve Bayes Random forest SVM MLP	99% correct classification rate using PNN, DNN and kNN. DNN has reported highest response time of 99.51 s while kNN has least response time of 0.63 s. Lowest accuracy was reported by LVQ. SVM, MLP, NB, RF resulted in performance in the range of 97%.	–	To use the Kinect ability of tracking whole body and addition of more features for advanced application. Development of security software to detect the persons through their walking style.
14.	Huang et al., 2018 [30]	Modelling of LF-MAS of lower exoskeleton such that unaffected leg is leader and affected leg is follower. To achieve better tracking control performance.	Kinematics of hip and knee joint	3H	Hemiplegia patients (healthy subjects simulating hemiplegic condition)	Hip joint Knee joint Smart shoes with plantar sensors	Reinforcement learning framework Policy iteration adaptive dynamic programming	LF-MAS depicted good performance of unaffected leg. The subjects affected leg together with exoskeleton leg will lead to half gait cycle delay. Higher tracking error for unaffected leg during gait transitions. High knee joint error in comparison to hip joint due to large motion variation of knee as compared to hip during normal walking reported as nMSE.	Requirement to determine phase change in affected leg with each half gait cycle.	To validate the modelling of exoskeleton with hemiplegic patients together with a complex system model of LF-MAS.
15.	Thongsook et al., 2019 [26]	Gait phase recognition – stand, swing, push.	IMU FSR	–	–	Knee IMU Hip IMU Toe FSR Heel FSR	C4.5 decision tree MLP NARX	For larger training set C4.5 outperforms MLP and NARX with 100% accuracy as compared to 94.79% for MLP and 98.76% for NARX in gait phase recognition.	–	To control exoskeleton development of hydraulic power system for gait phase recognition by the use of C4.5.
16.	Farah et al., 2019 [5]	To identify gait phases at different walking surfaces at varied speeds.	IMU at knee and thigh	30H	–	Gait phases Loading response Push off Swing Terminal swing Walking surfaces Level Down-slope	Logistic model decision tree (LMT) Transition sequence verification and correction (TSVC)	GPR model provided an accuracy of 90.60% using LMT and it increases to 98.61% using TSVC.	The error rate of 10% not suitable for assistive control devices using GPR so TSVC is applied to improve the	–

(*continued*)

Table 2. Continued.

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
						Up-slope Right cross-slope Left cross-slope			overall performance.	
17.	Paulo et al., 2019 [3]	To automatically detect shifts in gait pattern.	Lower limb parameters such as thigh, knee, shin using IMU	5H (4M, 1F)	–	Spatiotemporal features Similarity rate Walking patterns – natural walk, left and right knee joint bending restrictions, respectively	One class SVM	The more distinct input and output results in low value of similarity rates. Can be used as an automatic progress detection tool for healthcare professionals.	Less variability of gait pattern acquired.	Improvement based on medically selected gait parameter shift. To determine a quantifiable shift in gait patterns.
Gait disorder detection										
18.	Muniz et al., 2006 [31]	To determine the usefulness of PCA in GRF in differentiating gait patterns of normal and impaired subjects.	GRF using force platforms with an instrumented treadmill gaitway	25H (13M, 12F), 6P (5M, 1F)	Lower limb fracture	Vertical component of GRF	LR	In PCA, the principal components determine the variance of GRF curve useful for analysis. Scatter diagram of PCC (first two coefficients) allows objective assessment of each patient and also able to determine the treatment effects.	Lacks the ability to access the non-linearity of PCA in classifying groups.	Use of more PCC with nonlinear separators.
19.	Lai et al., 2007 [33]	Classification of PFPS patients from healthy group with reduced features using hill-climbing feature selection algorithm.	Rear-foot kinematics Foot GRF	14H, 13P (14F, 13F)	Patellofemoral pain syndrome (PFPS) on the right knee	14 features from GRF 16 kinematics features	SVM	14 GRF feature set results in 85.19% accuracy using polynomial kernel. 16 kinematics features resulted in an accuracy of 74.07%. Using optimal feature set from both GRF and kinematic data achieved accuracy of 88.88%. The optimal set of features are time to max rear foot abduction and adduction, time to max peak eversion and dorsiflexion, first and second vertical peak GRFs.	–	To investigate the direct relationship between rear-foot kinematics and GRFs.
20.	Nair et al., 2010 [34]	To identify muscles required to distinguish arthritis and healthy group. To develop an	EMG patterns of each leg	7H, 18P (8 RA, 10 OA)	Rheumatoid arthritis (RA) and osteoarthritis (OA)	RA + OA groups: Soleus Gastrocnemius medialis Tibialis anterior Vastus lateralis Biceps femoris	LSK (developed algo) SOM LVQ MLP LDA	Classification accuracy of 91.48 ± 7.57% for RA patients and 96.67 ± 3.77% for OA patients using CGF LSK kernel algorithm.	Current rehabilitative measures are needed to understand muscular	To compare neural nets, kernel methods and regression analysis to map nonlinearity in

(*continued*)

Table 2. Continued.

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
		algorithm for the treatment of biological data.				Peroneus brevis (RA only) Gluteus medialis (OA only)		The most dominant muscle for OA is gluteus medialis and for RA are soleus and biceps femoris.	differences during gait.	EMG and kinematics approach.
21.	Mu et al., 2010 [14]	Classification of patients with different foot lesions.	Foot kinematics	27P	Pathological plantar hyperkeratosis (PPH)	Leg Heel Midfoot First metatarsal Hallux	KPCA FLDA	Reduced feature space of $d = 46$ and accuracy 94.1% using KPCA, DCT and FLDA. Foot kinematics contains information relevant for pathology classification and KPCA produces lower dimensionality.	In consideration of foot kinematics, the motion of proximal segments affecting plantar surfaces needs to be taken into account.	Inclusion of kinematics dataset using proximal segments, i.e., thigh and trunk.
22.	Alaqtash et al., 2011 [19]	Classification of gaits of healthy, CP and multiple sclerosis participants using 3D GRFs components.	Three GRF components	12H, 4CP and 4MS	Cerebral palsy (CP) Multiple sclerosis (MS)	F_z, F_y, F_x, F_xF_y, F_yF_z, F_xF_z, $F_xF_yF_z$ (computed using maximum and minimum amplitudes and interval of occurrences' a set of 19 features)	Nearest neighbour classifier (NNC) Artificial neural network (ANN)	GRF parameters using NNC has higher accuracy rate than DWT. The healthy and impaired gait patterns can be distinguished using one feature, i.e., M-shaped value of F_z. Optimal feature set, i.e., F_z, F_{x1}, T_{x3}, F_{x3}, T_{y3} and T_{y2}. 85% accuracy without feature selection and 95% for selected set of six features.	–	–
23.	Gestel et al., 2011 [13]	A classification approach that characterises CP gait by membership degrees.	3D gait analysis of ankle and knee	139P (58 hemiplegia, 80 diplegic and 1 triplegic)	Cerebral palsy (CP)	Ankle and knee joint movement patterns	Bayesian network	A Bayesian network is standard tool for 3DGA with probabilistic, non-linearity handling approach and enhanced clinical interpretation. Able to identify mixed joint movement patterns of CP. Accuracy is high, i.e., 82–91% for distinct movements.	Reliability of outcome depends upon expert input.	Strengthening of clinical relevance by inclusion of other joints and plane.
24.	Lee et al., 2015 [44]	A wearable platform to measure knee kinematics. To develop detection algorithm to detect	Electro goniometer angular sensor to measure knee angles 3-axis accelerometer on thigh	17H (scripted data), 4H (unscripted data)	–	Mean and SD of time series Cross covariance Signal entropy Range of amplitude	One class SVM (LibSVM) Binary classifier RF with 100 trees Multi-class RF with 100 trees Hybrid classifier with	LibSVM separates walking data from other movements of daily activities. Same feature set for stairs up climbing	More precise decision boundaries are required to recognise fast walking from	Extension to other activities using wearable technologies in human context

(*continued*)

Table 2. Continued.

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
		occurrences of walking using accelerometer.				Dominant frequency Correlation coefficients	one class SVM and RF	and walking at slow speed as well as for stairs down climbing and walking at fast speed. Hybrid classifier used to distinguish occurrence of walking from stairs using one class classifier and to distinguish different walking speeds from stairs up and down climbing using multi-class classifiers. Precision and recall vary inversely with decision boundaries. Multi-class classifier (RF) showed the best performance, 90% precision and 75% recall.	stairs down climbing, slow walking from stairs up climbing, and slow walking from transitional activities.	for patients with knee OA.
25.	Williams et al., 2015 [28]	To develop prediction system for TBI gait disorders.	Joint angles (pelvis, hip, knee and ankle)	102P	TBI related gait disorders	Kinematic signals from pelvis and lower limb (hip, knee and ankle)	Multiclass SVM	Classification into 6 classes, i.e., spastic hemiparesis, nonspastic hemiparesis, unilateral ataxia/ dyspraxia, spastic bilateral paresis, nonspastic bilateral paresis, bilateral ataxia/dyspraxia. Unaffected limb classification accuracy results in 82.35%. Affected limb classification accuracy results in 76.47%.	Applicable only to participants that walk without physical assistance.	To refine classification by adding modelling with GRF, joint moments and powers as well as EMG.
26.	Adil et al., 2016 [45]	Classification of foot drop (crouch gait) patients from healthy subjects using sEMG signal and to explore the effect of GRF on minor, moderate and serious spastic	sEMG signal from both the legs using muscles Gastrocnemius, tibialis anterior GRF	5H, 5P	Foot drop	Time domain features RMS, MAV, WL, ZC,VAR	Classification using ELM, SVM and NN	96.8% classification accuracy achieved using ELM with minimum processing time. 93%, 82.2% accuracy using SVM and NN, respectively. Mild patients have smaller GRF than moderate but severe	–	–

(*continued*)

Table 2. Continued.

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
		diplegic cerebral palsy patients.						spastic patients have maximum GRF.		
27.	Cho et al., 2018 [46]	Automatic recognition of scoliosis and control group. Classification of mild, moderate scoliosis and normal group.	IMU-based system (seven sensors on both lower limbs)	24P, 18H	Scoliosis (right tilting of trunk)	72 features (kinematic aspects)	ReliefF for feature selection SVM	20 features showed maximum accuracy of 95.2% (ReliefF + SVM) and 85.7% using only SVM. 90.5% accuracy for distinguishing healthy and scoliosis group and 81% between mild, moderate and normal group.	Limited space size. According to location of apex gait patterns are not analysed.	Inclusion of more factors related to study for patients group classification.
28.	Guo et al., 2017 [27]	Classification of normal and pathological gait using foot pressure data in young children.	Foot-pressure data (GAITRite)	95H, 6P	Equinus gait pattern (common gait pattern for cerebral palsy)	Spatiotemporal foot pressure data	PCA Discriminative mapping SVM RF	94.36% and 97.50% accuracy achieved using SVM and RF, respectively, based on age information together with other spatiotemporal features. Possibility to detect minimal variations of gait development during early stages.	Less sample size for pathological group	Development of classifier to determine multiple degrees of abnormality in children with spastic gait.
29.	Cui et al., 2018 [47]	Development of an automatic gait analysis system for recognition and assessment of the gait abnormality.	Fusion of GRF, MT and EMG	21P, 21H (16M, 5F)	Post stroke hemi paretic patients	28 markers 2 force plates 8 pair of electrodes	Five classification methods – NB, SVM, NN, KNN, RF Two rule-based fusion methods – AR and MR	Recognition performance Single modal – RF, accuracy 92.26% based on GRF data. Two modal – SVM fusion, accuracy 95.83% based on MT and GRF data. Three modal – SVM fusion, accuracy 98.21% based on MT, GRF and EMG. Assessment WAMS has potential in clinical application for given pathology class and subjects walking ability is expressed as a real number between 0 and 1.	Time normalisation weakens subject velocities Lack of standard evaluation metrics Architecture limited to only abnormal gait after stroke Lacks assessment about therapeutic treatment	Different modal gait data can increase both recognition and performance.
30.	Zeng et al, 2019 [18]	Classification of gait patterns between ACL-D and contralateral ACL-I knee in impaired individuals.	Kinematic signals	43P	Anterior cruciate ligament (ACL) (full tear)	Flexion/extension of knee, hip, ankle Ankle internal/ external rotation	PSR (phase space reconstruction) ED (Euclidean distance) NN	The classification accuracy of 95.4%, 93.3% and 94.8% to distinguish ACL-D and ACL-I under normal, fast and both	Detection deficient due to the presence of other injuries like posterior cruciate ligament having	To assist in diagnosis by inclusion of other dataset having same gait patterns that result in knee injury.

(*continued*)

Table 2. Continued.

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
								speeds walking speeds.	same gait patterns.	Detection of optimal PSR parameters by exploring relation between classification performance and PSR parameters.
31.	Zhang and Ma, 2019 [48]	Classification of sagittal gait patterns in children with cerebral palsy.	Sagittal kinematic signals from ankle, knee, hip and pelvic joints	102P	Cerebral palsy (spastic diplegia)	Classification groups True equinus Jump gait Apparent equinus Crouch gait	ANN Discriminant analysis Naïve Bayes Decision tree (DT) KNN SVM Random forest	ANN has high prediction accuracy (93.5%). DT (84.3%), SVM (85%), RF (83.6%), NB (82.1%), kNN (77.9%) and DA (84.3%) produces good accuracies. DT being transparent has good accuracy and can be used for clinical applications. Ankle DF and PF and knee IC good performance features for classification.	The closeness between different gait patterns affects accuracy. Less sample size of training data, i.e., 200 gait trails.	Development of intelligent systems for motor impairment assessment in combination with motion captures technology.
Gait due to aging										
32.	Begg et al., 2005 [21]	Automated gait classification of young old gait types using minimum foot clearance data.	Foot clearance data at self-paced walking on treadmill using PEAK-2D motion analysis system Two reflective markers at left shoe on fifth metatarsal head (MH) and great toe (TM)	58H (30 young, 28 elderly)	–	24 features were extracted from minimum foot clearance (MFC) during walking occurring at mid-swing phase of gait cycle	SVM (linear, polynomial, RBF)	A hill-climbing algorithm selected 3–5 features for classification and improved classifier performance with some selected features. The best feature for young/old binary classification is CV. The CV contains information about variability and central tendency (aspects of MFC distribution for separation between age groups). With RBF kernel maximum performance achieved using $g = 1$ and $C = 10$.	–	To include force platforms and EMG data to improve classification power. SVM can be used to discriminate normal and impaired gait patterns.
33.	Begg et al., 2006 [6]	Automated recognition in gait variations related to aging.	GRF Kinematics	12Y, 12O (6M, 6F)	–	Temporal-spatial Foot GRF Lower limb joint angular data	Three NN (standard backpropagation, scaled conjugate gradient, backpropagation with Bayesian	83.3% classification accuracy in recognition of young and elderly using BR NN. With 3 selected features	–	To apply NN for the recognition of gait changes due to pathology or falling behaviour. Incorporation of

(*continued*)

Table 2. Continued.

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
							regularisation) LDA	(i.e., knee range of motion during swing phase, maximum horizontal (anterior–posterior) push-off force, step length) 100% generalisation accuracy is achieved. Thus feature selection improves accuracy. Performance of BR remains unaltered over threshold range (−0.4 to 0.4).		other feature selection methods like backward elimination techniques and genetic algorithms.
Gait asymmetry detection										
34.	Arosha Senanayake et al., 2014 [12]	To monitor and classify the recovery status of ACL reconstructed subject.	Kinematics (IMU at shank and thigh) EMG data (vastus medialis, vastus lateralis, semitendinosus, biceps femoris, gastrocnemius)	6H, 13P	ACL reconstructed (3 months to 1 year) after injury	Walking at 4 km/h, 5 km/h, 6 km/h Single leg balance test	Fuzzy clustering techniques (ANFIS, FURIA) SVM Hybrid CBR	ANFIS showed better performance for walking ambulation 4 and 5 km/h. FURIA and linear SVM have highest classification accuracies for 6 km/h and balance test. Overall best performance by FURIA for all activities.	Semi-automated process based on expert knowledge and intelligent framework.	Inclusion of more data from other activities based on rehabilitation protocol. To consider anthropometric data for evaluation of recovery.
35.	Semwal et al., 2014 [32]	To employ push recovery in humanoid robots. To simplify its complex non-linear behaviour to linear using ML techniques.	Joint angles (hip, knee, ankle)	5H (5 left handed dataset, 5 right handed dataset)	–	Force applied Direction of motion (DoM)	Fuzzy logic based learning approach	Determination of hip, knee, ankle and fall (unable to recover) strategy depending upon applied force and DoM. Hierarchical fuzzy techniques can streamline complex behaviour. Fuzzy inference system being less computationally intensive can handle forces from all directions.	Complex applications depending upon many factors lead to an exponential increase in rule-set.	–
36.	Liu et al., 2016 [25]	To determine the gait trajectories of wearer for modelling knee joints of lower limb exoskeleton using LSTM and DRGL for	SIAT exoskeleton	20H	–	Knee joint trajectories	LSTM DRGL (deep rehabilitation gait learning)	LSTM learns the gait features with reduced mean square error and gradually decreasing cost and reaching a stable convergence. DRGL can be used to	Less gait dataset results in instabilities in new recovery trajectory.	Need to obtain complete gait features.

(*continued*)

Table 2. Continued.

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
		modelling knee joints of lower limb exoskeleton.						predict and correct abnormal knee joint trajectories depending on wearers other joints.		
37.	Paulo et al., 2017 [24]	Development of ISR-AIWALKER for lower limb rehabilitation in HMI and gait analysis system.	Vision-based approach – leap motion controller-kinematic model of lower limb using RGB and depth map	HMI safety system – 10H (8M, 2F) HMI operation – 5H Gait analysis system-10 (9M,1F)	–	Robotic walker HMI – leap motion controller Gait analysis system	SVM (cubic kernel)	Gait asymmetry pattern detection 88.3%. 94.76% classification accuracy of user's stability safety system, i.e., incorrect gripping trajectories are discovered and the system stops walker operation.	Leap motion sensor is based on IR reflection Undetectable gait pattern with no leg separation Gait analysis in linear motion	Gait analysis system to perceive the shifting gait patterns over time. To develop a tool for clinicians to identify gait changes and for therapeutic interventions.
38.	Sobral et al., 2018 [49]	To develop gait indices – NGI and AGI (Normal and Abnormal Gait Index) to access the recovery status after ACL reconstruction.	Vertical ground reaction force	28H (28M), 5P (5M)	Anterior cruciate ligament (ACL) reconstruction	8 force sensors in instrumented shoes for walking conditions – very slow, slow, normal, fast and very fast	ELM	New gait indices discriminated healthy and impaired gait patterns based on symmetry (SI) and difference between 16 different parameters from VGRF for gait error (GE). A normal gait has GE and |SI| lower than 1 and ideally equal to zero.	Lacks GE calculation variables from centre of pressure and fore-aft and medial-lateral GRF.	To determine GE implementation of PCA to compute variance of all variables to reduce the number of variables is needed.
39.	Qiu et al., 2019 [29]	Gait quality assessment for clinical decision support using multi-sensor fusion and decision making algorithms.	Kinematics data from both ankles Spatio-temporal Parameters Nonlinear parameters	20H, 20P (13M, 7F)	Neurological diseases	Spatio-temporal gait parameters Walking Speed Step length Stride Time Foot elevation Gait phase detection Heel strike Foot flat Heel off Foot swing Non-linear parameters Gait asymmetry Gait regularity Gait complexity	HMM	Based on gait abnormality, a decision support tool using BSN. Ankle rigidity can lead to abnormality. Higher gait symmetry score leads to abnormality. Gait regularity of spatio-temporal parameters leads to determine degree of motion abnormality.	Implementation is offline and needs to be tested for clinical settings	To ensure low power consumption by BSN hardware and real-time monitoring.
Neurological effects on gait										
40.	Hortal et al., 2015 [50]	To identify the voluntary initiation and gait cycle stop.	32 channel EEG signal, IMUs and Wireless motion analysis system	3H (3M)	–	32 electrodes EEG cap IMUs – lumbar, right thigh, leg and foot, left thigh, leg and foot	SVM (RBF kernel)	Good detection accuracy for rest and walking state, i.e., 70.5% and 75%. Low accuracy for start	High false positive rate limits its real-time application.	To reduce false positives, other features and classifiers are to be tested.

(*continued*)

Table 2. Continued.

S. no.	Source of study	Objective of the study	Measurement techniques	Participants	Pathology	Parameters/ activity performed	Method	Outcomes	Limitations	Future scope
								and stop state, i.e., 30.6% and 17%.		
41.	Costa et al., 2016 [22]	To study the cognitive mechanisms depending on user's gait attention.	Treadmill walk and EEG	12H (4F, 8M), 3P (3M)	Incomplete SCI	32 channel EEG recording	Classification based on attentional tasks using LDA, SVM, KNN, NB, DTL	γ (gamma) band provides attention mechanisms. Attention to visual tasks causes a decrease in gait consideration. Patients' attention level to gait increases during non-attentional tasks. 67% success rate for healthy using SVM and 59% for patients using LDA and KNN achieved.	To interpret the low-frequency band cortical information.	To determine attention level during lower limb rehabilitation in real-time.
42.	Goh et al., 2018 [23]	Decoding cortical processes under varied walking conditions using EEG signal for gait determination. A SSRL topology of deep neural network to learn spatial spectral representation of multi-channel EEG signal at the time of walk.	EEG at walking (free walking, exoskeleton assisted walking)	27H	–	Normal walk without exoskeleton support Walking with exoskeleton At zero force At low assistive force At high assistive force	RF-FS SVM-PCA SVM-FS SSRL (raw)	SSRL includes feature extraction, dimensionality reduction thus achieving accuracy of 77.8%. The contralateral brain activation in sensorimotor on left hemisphere corresponds to right lower limb with the exoskeleton, i.e., discovering gait related brain regions.	Increase in computational cost with the increase in no. of parameters.	Improvement in topology of SSRL for cross-subject gait pattern classification. To enhance abnormal gait diagnosis.
43.	Park et al., 2019 [51]	To reduce delay time at the time of controlling exoskeletons with EEG decoders by considering short segment EEG data (0.2 s) based on gait/stand intention that is 0.5 s prior to actual gait/ stand movements.	32 channel wireless EEG system in walking condition based on cue signs	3H, 8P (5 subacute, 3 chronic stroke patients)	Stroke	19 channels for healthy and subacute stroke patients, 32 channels for chronic stroke patients	CNN	A spatio-spectral CNN model with accuracies 85.2% for chronic, 85.9% for subacute, and 77.4% for healthy on gait recognition. Gait and stand intention recognition average accuracy of 77.3% and 77.7%, respectively.	19 EEG channels data not enough to reflect spatial features.	Stroke patient's gait intention would lead to reactive exoskeleton.

abs: absolute; ANFIS: adaptive neuro-fuzzy inference system; AR: average rule fusion algorithm; BSN: body sensor network; CART: classification and regression tree; CBR: case based reasoning; DCT: discrete cosine transform; DF: dorsi flexion; DTL: decision tree learning; DWT: discrete wavelet transform; ELM: extreme learning machine; FLDA: Fisher's linear discriminant analysis; FoG: freezing of gait; FURIA: fuzzy unordered rule induction algorithm; GRBM: Gaussian restricted Boltzmann machines; GRF: ground reaction force; IC: initial contact; IEMG: integrated electromyography; LF-MAS: leader follower multi-agent system; LLE: locally linear embedding; LR: logistic regression; LLE: locally linear embedding; LSK: least-squares kernel; LVQ: learning vector quantization; MAV: mean absolute value; MR: max rule fusion algorithm; MT: marker trajectory; NARX: non-linear auto regression with exogenous variables; NB: Naïve Bayes; nMSE: normalized mean square error; PF: plantar flexion; PNN: probabilistic neural networks; RBF: radial basis function; RMS: root mean square; SD: standard deviation; sEMG: surface electromyography; SOM: Kohonen self organizing map; SSRL: spatio-spectral representation learning; TBI: traumatic brain injury; TD: time domain; VAR: variance; WAMS: walking ability mean score; WL: waveform length; ZC: zero crossing.

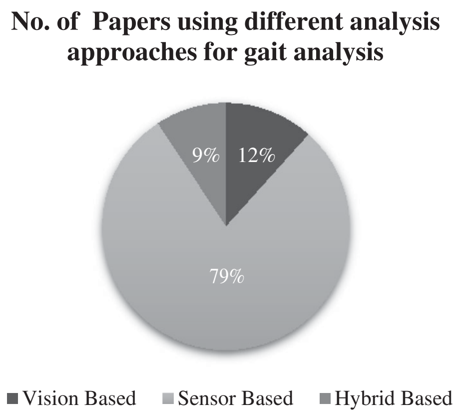

Figure 2. Literature classification of studies based on the human gait analysis approach.

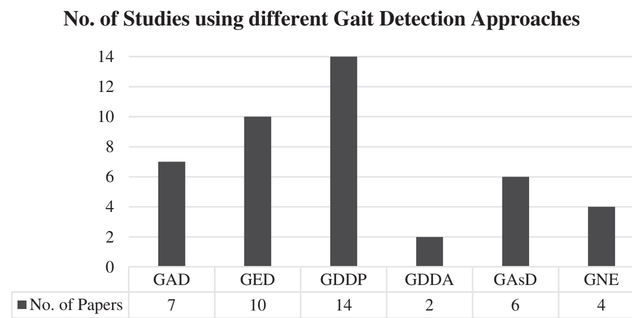

Figure 3. Classification of studies as per the literature review.

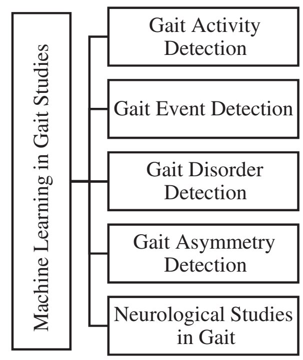

Figure 4. Taxonomy of Machine Learning Application.

the field of computer processing, the integration of learning frameworks with computing had led the researchers to find new directions to propose smart systems capable of inferring and handling bulks of data. This automated diagnosis will pave the way to plan rehabilitation interventions using robotic-assisted therapies, motor rehabilitation, etc. The following section discusses ML in gait detection under five categories that report the major findings in each domain and the use of ML techniques for gait rehabilitation.

4.1. Assessed outcomes

The most commonly used human gait analysis approaches are shown in Figure 2. The popularity of using sensor-based approaches is portability, reliability and unrestricted environmental conditions.

4.1.1. Machine learning in human gait analysis

The selected studies were separated on the basis of recent application areas in the human gait domain. Figure 3 shows the number of studies used for GAD, GED, gait disorder detection (a) due to pathology (GDDP) (b) due to aging (GDDA), GAsD and GNE.

4.1.1.1. Gait activity detection. The basic study that explored the ML in gait was to demonstrate recognition of normal gait for performing various activities. This led to the detection of motion from motion capture systems and inertial sensors to identify various activities ranging from levelled surfaces (level ground walk), transition phase (sit to stand, stand to sit) to unlevelled surfaces (stair ascending/descending, up/down slope). The worth noting point from Table 2 is that GAD carried out using supervised ML techniques shows good classification accuracies using a sensor-based approach Figure 4.

These studies were reported on both pathological as well as healthy groups, activity tracking being valuable to determine patient outcomes [39]. Further, the research carried out by Lau et al. [7] demonstrated SVM as the best predictor for activity classification. Thus, a single sensor placed either at the shank or foot can accurately classify the activities. Together with kinematics, muscle movement was useful for robotics, exoskeleton control and rehabilitation applications. The study [36,38] discussed that reduction in the dimensionality of data helps to achieve high recognition performance. In [37], researchers discussed the need for a global patient model containing particular deformity in the training phase to evaluate the efficacy of models on test datasets. The model trained on healthy subjects was not considered capable enough to draw inferences on the patient group, although personal model training was not required. Considerable work was reported by Devanne and Berretti [20] to detect walking and stair climbing using depth sensors for abnormity detection along with person re-identification by considering shape variations of motion trajectories. The study by Leightley et al. [11] proposed a need for the models free from the human interpretation and also, representative at the same time to assist clinicians in the decision-making process. The development of technological advances and computationally efficient techniques has aided the professionals to refine the physical and drug therapies for patient's improvement. Sok et al. [39] classified the activities of incomplete spinal cord injury (SCI) patients using dynamic classifiers which proved better than static ones. The studies related to the biomechanics of gait were useful to detect the impairments in gait and articulation of the treatment plans but the interaction between numerous inputs of a locomotor system was rather difficult to characterise. Thus, ML models are used for analysing implicit interactions between the locomotor system inputs for healthy and impaired subjects with accuracy levels of more than 80% for depicting multiple activities. The developed models for optimisation have reduced the analysis time and can assist the clinicians in selecting the key parameter for the intended pathological group.

The analysis showed that activity detection was a crucial design parameter for gait assistive walking systems and control of wearable orthotic device like exoskeleton. Moreover, different classifiers were tested by researchers but clear evidence is not available to test a particular classifier for levelled and unlevelled terrains. To conclude, a technique of ML that is supervised learning worked efficiently in this domain, and further research is required on the patient's gait. This type of model, once trained can do much better on a similar group of patients and can assist the physiotherapists. The precision, objectivity and reliability in outcome evaluation will definitely help the clinician's plan or refine the rehabilitation to improve the patient's mobility. From the above discussion, the limitations reported are less generalisation capability of the ML model, reliability needs to be strengthened by the inclusion of more data samples and evaluation of ML models for unlevelled terrains or real-life scenarios which is an area of scope for further research.

4.1.1.2. Gait event detection. The fundamental study to detect gait phases and sub-phases refer to as GED. The gait phase detection mainly needs to determine two characteristic time points, i.e., when the foot is in contact with the ground (heel strike) and when it is off the ground (toe-off). However, the sub-phases of gait, i.e., loading, push off, swing and terminal swing provides insight into individual variations and dynamic assessment of one's gait [5]. Accurate GED decides about control strategy to use for rehabilitation robots to avoid harm to patients. Also, in functional electrical stimulation (FES), real-time orthotics control, and gait rehabilitation, gait phase detection is crucial [5]. Electromyography (EMG) signals can also be useful in gait phase recognition as they provide activation of electrical indicators of nerves and muscles during relaxation and contraction states [43] together with force-sensitive resistors (FSRs). Some studies (Table 2) have used joint angles and ground reaction force for event detection by using multi or hybrid supervised classifiers. The authors Jung et al. [41] studied gait phase recognition for robotic exoskeletons using NN and the intent detection method for rehabilitation of stroke patients. Further, Yoo et al. [16] demonstrated the association between changes in movement and prognosis of knee osteoarthritis (OA). Another study by Jiang et al. [42] was successful in designing of gait recognition system using an ensemble learning framework for the classification of patterns in therapeutic interventions. Using the NN classifier, human recognition with 99% accuracy rates was reported [8]. Another researcher Farah et al. [5] identified four gait phases across different walking conditions using local sensor signals from thigh and knee through a logistic model DT. As in conventional rehabilitation, the monitoring and follow up process is slow, continuous and entirely dependent on the professional's experience; therefore, Paulo et al. [3] used one-class SVM to automatically detect shifts in gait pattern. Reinforcement and adaptive learning were utilised for adaptive controllers with hemiplegia patients [30].

Thus, it can be interpreted that ML provides the basis for automatic gait phases detection required for rehabilitation, FES to uniquely recognise human gait to plan diagnosis and therapy that considers individual needs. The supervised and RL techniques proved to be beneficial in this domain because RL helps to track one's capability particularly suited for the rehabilitation phase. For, real-time implementation, more rigorous trials are required to attain 100% accuracy before deployment. It will be beneficial for automatic clinical analysis tool development and therapeutic interventions. The shortcomings can be articulated as small sample size, monitoring of gait during activities of daily living and to detect the quantifiable shift in gait pattern.

4.1.1.3. Gait disorder detection. Gait is a person's pattern of walking. Walking involves balance and coordination of muscles so that the body is propelled forward in a rhythm. The deviation from normal walking leads to gait abnormalities. The causes of gait disorders include neurological conditions (e.g., sensory or motor impairments), orthopaedic problems (e.g., OA and skeletal deformities) and medical conditions (illness or injuries). To diagnose these disorders is referred to as gait disorder detection. Earlier, the normalcy index [52] criterion was used to quantify deterioration in one's gait. Till now the wide ranges of studies include disorder detection that is embarked upon by ML approaches to determine abnormality in gait with high prediction accuracies. Research in healthy gait is essential to determine the deviation for disorder detection. In recent years [47], integration of the joint angle approach, ground reaction forces and electrophysiological phenomena for data collection during walking had significantly aided the automatic gait study with high performance (98.1%). The concurrent recognition of multimodal data is desirable for qualitative and quantitative gait abnormality assessment in clinical practices and such methods performed better than single models [2].

Gait disorders are sub-divided as antalgic gait patterns arising from pathologies in lower extremities such as knee OA [16], rheumatoid OA [34] and patellofemoral pain syndrome [33]. These patterns were characterised by pain in weight-bearing structure and resemble limping movements. The variability in gait disorders due to stroke [38,41,47], Parkinson's disease [11], cerebral palsy (CP) [19] and multiple sclerosis [19] leads to apraxic gait resulting in loss of ability to initiate and coordinate movement. Another type being ataxic gait in which a person suffers a loss of proprioception. Elderly related gait disorders are senile gait due to aging and sensory ataxic when the brain does not receive sensory inputs and myopathic due to muscle atrophy. These disorders cause fall-related injuries [6,21] that lead to high medical expenses.

To detect disorders, ML is an emerging paradigm in biomedical for pathology determination. It has been observed through the extensive survey; the choice of a classifier largely depends on features and their correlation with outcomes. However, some studies have reported gait disorders are due to traumatic brain injuries, and then their rehabilitation required sub-classification to predict functional implications [28]. Apart from depicting abnormality only, the level-based approach is essential. It has also been validated by another study [46] conducted for scoliosis. The ML techniques provided a solution to the problem with the inclusion of multi-class support. Another study by Sok et al. [39] determined that accuracy increases with hybrid classification.

Early work by Lai et al. [33] applied SVM to classify deviation in gait patterns due to patellofemoral pain syndrome on the right knee. Studies in knee pathologies mainly focussed on the detection and quantification of biomechanical factors. The study marked an initial attempt to explain biomechanical relationships of optimal selected features. The study by Zeng et al. [18] used NN to detect anterior cruciate ligament (ACL) in impaired individuals using kinematic signals. It was demonstrated by Nair et al. [34] that EMG inputs also play a crucial role in arthritis detection. Another study [45] used the EMG signal to distinguish a foot drop from healthy subjects. Many neurological conditions as studied in [13,19,27,28,46–48] are used to detect toe walking, a disorder indicative of more serious pathologies with unknown aetiology such as CP, neuropathy and myopathy making it difficult to identify. In CP, the challenge is to detect the type and severity of gait [13] such as type's I-IV, hemiplegia, diplegia and triplegia so timely measures can be applied (Table 2).

To conclude, earlier efforts to carry out gait diagnosis were performed through observations for measuring gait deterioration. The reassurances of patient revival and rehabilitation remained complicated without quantifications after surgical interventions. Recently, research is investigating the possibility of ML models to identify and evaluate the treatment measures. Monitoring and screening of at-risk gait are significant as detection of initial signs would enable protective actions such as physical movements and dietary regimes. Also, the development of disorders like knee OA, and balance impairments in the elderly occurs slowly over time to measure improvements. However, this progression needs to be tracked with the application of ML techniques towards prediction, interpolation and extrapolation investigations. Moreover, clinicians' effective diagnostic tools may consist of multimodal data for better predictions to assist physicians. These results reported are encouraging for decision making, rehabilitation planning and therapeutic interventions. As seen through analysis that SVM is a frequently used classifier among various classifiers used in the studies for pathology determination. The primary reason for using SVM in maximum studies is due to its better generalisation ability for the newer dataset by reducing empirical risks and can be used to detect movement disorders and their severity levels. Table 3 describes the accuracy statistics of using SVM classifier for gait disorder detection. Using descriptive statistics, parameters obtained are mean 87.55, standard error 1.98 and deviation of 7.42. Despite an aggregation of different studies, results reported were obtained using different sensors for varying conditions and involving various gait pathologies, SVM has shown remarkable capabilities for pathology determination. The future perspective is to devise a tool that entails different gait pathologies rather than a single one.

Table 3. Statistical analysis.

Gait disorder detection using SVM classifier

Study	Subjects		Parameters	Accuracy (%)
	Healthy	Pathology		
Lai et al., 2007 [33]	14	13	GRF	85.19
			Kinematics	74.07
			GRF and kinematics	88.88
Williams et al., 2015 [28]		102	Kinematics (unaffected limbs)	82.35
			Kinematics (affected limbs)	76.47
Adil et al., 2016 [45]	5	5	sEMG signal	93
Cho et al., 2018 [46]	24	18	Kinematics (using feature selection algorithm)	95.2
			Kinematics	85.7
			Kinematics (without feature selection algorithm)	90.5
			Kinematics (with severity levels)	81
Guo et al., 2017 [27]	95	6	Foot pressure data	94.36
Cui et al., 2018 [47]	21	21	MT and GRF	95.83
			MT, GRF and EMG	98.21
Zhang and Ma, 2019 [48]		102	Kinematics	85

4.1.1.4. Gait asymmetry detection. The detection of small differences between the step motions of two lower limbs, results in asymmetric gait. The geriatric studies mainly emphasised on balance or postural controls to determine fall-risk. The higher asymmetries in lower limb dysfunction are indicative of fall-risk. Such type of evaluation finds applications particularly in rehabilitation [24], identification and determination of diseases that relates to reduced balance stability [25,53]. People with balance difficulties were analysed using inertial sensors (IMUs) or force plates. But the inclusion of EMG signals aids in fall prediction [53] as standing balance involves significant muscle usage. Even to access the recovery of the patients, gait indexes were developed to access the symmetry between dominant and non-dominant limb [50]. The results presented were encouraging and promising as highlighted in Table 2.

Arosha Senanayake et al. [12] combined fuzzy techniques with other classifiers for the development of the learning models to determine the recovery stages of ACL reconstructed subjects. This ML model consisting of kinematics and neuromuscular signals can be used by physiatrists, physiotherapists and clinicians for monitoring patient progress and recovery. To handle the more complex dataset, simple fuzzy rules were not enough. Thus, Semwal et al. [32] proposed hierarchical fuzzy systems for complex behaviour that leads to an exponential increase in a number of rules. Further, research was carried by Paulo et al. [24] to test the gait asymmetry using SVM and human machine interface (HMI) and overall pattern accuracy was about 88.3%. Another study by Liu et al. [25] used long short term memory (LSTM) to learn the correlations between gait features using gait trajectories from healthy subjects imitating knee injuries. The research by Qiu et al. [29] proposed health care monitoring using multi-sensor data fusion through ML and wearable devices.

The analysis shows that ML coupled with wearable sensors can be used to diagnose postural instabilities. Age, injury or illness can be the potential causes of balance difficulties resulting in fall-related injuries. The ML models developed using kinematics, kinetics and neuromuscular signals can aid physicians, physiotherapists in diagnosis, and monitoring recovery status. However, the analysis reported through these studies is offline. The ongoing research is using LSTM and DNNs to work on captured signals to draw inferences for clinical perspectives.

4.1.1.5. Neurological studies in gait. To determine participant's gait by studying the cognitive mechanisms [22], decoding cortical processes under different walking conditions [23], gait intention recognition [39] referred to as neurological gait studies. Gait is no longer considered related to motor functions only but also an activity that requires attention and executive functions. The decline in cognitive functions leads to gait dysfunction. Thus, cognitive analysis plays an important role in gait intervention studies. A study by Goh et al. [23] discussed that electroencephalogram (EEG) has unfolded the concept of event-related synchronisation/desynchronisation (ERS/ERD) at times of motor imagery of gait, ankle movements or lower limb movements. Further work by, Costa et al. [22] determined that the severity level and duration of a patient's recovery, by the cognitive mechanism through ML techniques were helpful in the determination of rehabilitation strategy. Another implementation by Hortal et al. [50] described the gait initiation and stopping using EEG signals that could prove to be beneficial in designing assistive devices for patients with motor disabilities.

The results of combining ML, gait, and the cognitive mechanism will be beneficial in the development of real-time systems at the time of rehabilitation processes, exoskeleton designs and clinical diagnosis. However, the accuracies achieved were around 70–80% using different supervised learning classifiers. This was due to difficulty in studying the cognitive mechanism using EEG and modelling it with gait. More precision is needed during data collection and in feature engineering to make robust systems.

4.1.2. Machine learning for gait rehabilitation

Rehabilitation helps to improve the patient's lost functions due to neurological disease, injury or illness. Gait rehabilitation can lead to mobility of bedbound, restoration in gait [54] and gait improvement [55,56]. The basic understanding of the biomechanical system has resulted in the simulation of prosthetic controls and robotic rehabilitation. Now, together with the advent of the applications of ML, the shift can be made from just modelling of partial differential equations to intelligent control. The various control strategies for gait rehabilitation were developed [57,58]. The study by Dallali et al. [57] applied ANN for control of ankle-foot-prostheses and able to predict the impedance with good prediction accuracy (∼90%). Using the EMG signal of lower extremity, the method was able to control ankle impedance in dorsi-plantar and inversion-eversion directions. The intent to start and stop the gait based on EEG signal using SVM classifier had been tested on both healthy and patient groups with minimum latencies in real-time. To avoid the latencies, Park et al. [51] predicted the gait intention prior to the actual event using CNN. Thus, such systems can be used for the development of lower limb exoskeletons for SCI and stroke patients [50,51]. Even, the trained general regression neural network (GRNN) based model utilised in [59] for robotic gait rehabilitation depicts that the trained model showed better results in comparison to gait parameter equations methods. The purpose of robotic rehabilitation is to generate repetitive and progressive movements according to motor disabilities [59] for gait improvement. The performance of ML lies in its learning capability from a great amount of variability hidden in human characteristics. Further research by Huang et al. [30] had defined the trajectory approach in which movement of the healthy side is followed by the abnormal side and which helps in increasing the motivation level of an individual to generate active movements. Therefore, achieving better tracking performance required for paraplegic and hemiplegic patients. The RL framework was used for optimal policy control for the adaptation of patients to different walking conditions. By the use of LSTM and deep rehabilitation gait learning (DRGL) study carried out by Liu et al. [25] predicted and corrected abnormal joint trajectories of the knee based on normal joints of the wearers. The rehabilitation outcome will depend entirely on patients' ability to adapt to the speed and load variations determined by the device. Another study where ML has been successful is in predicting rehabilitation length and discharge schedule of the patient after an injury or illness using a sensor-based approach and on-going research is to plan more precise predictions. A study by Pla et al. [15] predicted the rehabilitation schedule for lower limb fractured subjects using SVM with accuracy statistics as $87.69 \pm 4.07\%$. This will enable improvement in patient's quality of life and reduction in cost after surgery.

Thus, if control strategies are successfully applied in dynamic walking conditions, they will assist the amputee population when interacting with the prostheses allowing for more natural gait based on their intent to walk. Recently, another on-going area in this field is in the use of brain–machine interfaces for gait prostheses using ML techniques that may lead to benefits in deriving the relationship between diverse signals and movement. Moreover, the robotic rehabilitation used for intervention is complex in nature involving multiple degrees-of-freedom (DOFs) causing it to be very expensive. Since this process involves continuous monitoring in a duration of a few months or years. A need of the hour is to develop affordable and portable devices to train individuals in home environments [58,60]. The home-based therapy is a promising solution. The robots when used in combination with rehabilitation approaches such as proprioceptive and haptic simulation will have the potential to recover cognitive ability together with motor functions.

4.2. Future perspectives

The joint efforts of ML and biomedical engineering have shown greater potential in gait detection such as activity detection, event detection, disorder detection, asymmetry detection and control of rehabilitation devices. They used data, algorithms, patterns and learning theory to arrive at the model. The greatest asset is saving time by circumventing multiple visits to medical professionals and avoiding long treatment duration. The review by Devanne and Berretti [20] proposed a need for the inclusion of statistical methods to handle noisy and missing data to ensure reliability. Strengthening of the tool can be achieved by the inclusion of all joint angles and planes required for gait diagnosis [13]. Another major concern is to make its applicability worldwide by overcoming its black box nature and to derive means to visualise the relationship between gait disorders and ML models.

Undoubtedly, further research in this area is not to doubt on the classifiers' accuracy. But the need is to handle feature engineering using domain knowledge. The gait analysis is diverse due to its non-stationary, temporal and complex nature. The contemporary state of the art is pathology detection at different levels because it needs a high degree of robustness to participants' variability. Therefore, much of the research lies in feature analysis methods and how to quantify the underlying biomechanics in learning models. However, the complex and tedious process of feature engineering is overcome by deep learning (a complex form of NN) and ongoing research is in the determination of the basis of decision making. Another burning area is in depicting the optimal classifier for a given dataset. Progress made during the last few decades in gait research has been established and for expansion, the future directions are highlighted in Table 2 with their current limitations.

A great need is to make the journey from offline analysis, i.e., laboratory-based experiments to real-time scenarios, i.e., clinician's efficient intelligent tools. A much needful is required to deal with patients' gait rather than normal gait though a basic understanding will pave way for abnormality detection. The generalisation of the model with different conditions, more population size, and transfer learning approach is needed, as this model once trained can be used on patients with similar impairments [37]. The ambitious application areas for gait analysis such as prediction of onset of diseases, the progression of the disease, rehabilitation rates and planning trajectories identical to human natural gait for controlling rehabilitation devices will get benefitted using AI in near future. However, technology development has proven useful by providing portability, continuous monitoring and cost-effective solution to gait study domains by the development of sensor-based approaches. The development of these approaches requires long-term data collection, monitoring of patient state, determining rehabilitation modules, and systematic data storage for training and validation of learning techniques. However, these techniques may possibly be applicable as assisting devices for physicians in clinical diagnosis and control of gait rehabilitation devices that can help physiotherapists in therapeutic interventions being adaptive to different conditions and entails different gait pathologies.

5. Conclusions

In this review, the progress made in gait studies with AI applications during the past few decades has been reported. The popularity of ML techniques in the gait domain is due to the fact that it can provide accurate, robust and fast classification by extracting simple features using highly temporal and nonlinear biomechanical data. The variability, instinctive, flexibility and adaptability of such dynamic approaches give them uptake over conventional ones based on thresholding, static detection and observational methods. Moreover, it simplifies the walking evaluation. The observational gait assessment is subjective in nature and lacks validity, reliability, sensitivity and specificity.

After literature screening, it has been depicted that the current studies are mainly focussing on sensor-based approach (86%); around 76.7% when using sensor approach alone and an additional 9.3% when used with other approaches thus, determining a shift from a laboratory-based environment to real walking environment.

The accuracy rates found for gait detection are: activity detection (∼85–100%), event detection (∼95%), abnormality detection (∼90–98%), asymmetry detection (∼85–95%) and GNE (∼67–86%). Though, these studies were carried out with different methods in varying conditions and for distinct domains. For activity detection, an accelerometer is the most used sensor for physical activity recognition (∼85–95%) but for activities such as stair ascent and descent, performance improves with the addition of gyroscopic data for binary classification tasks. The combination of sensors at foot, shank and thigh is considered to be the best position to determine all types of activities. The GED has been successfully computed using ML, the best accuracies are reported using IMUs and FSRs; for three event detection (nearly 100%), four events (∼98%), five events (∼83–97%) and seven events a further decrease in accuracy was reported. The success rate of IMUs in abnormality detection is around 95% and KPCA is the best dimensionality reduction technique for non-linear data. The IMUs have predicted gait abnormality with an asymmetry score close to 1 for neurological disorders. Further, from the analysis, it can be concluded that these predictive models can support healthcare professionals with this cost-effective solution but until now little has been done for its practical implementation as a diagnostics tool.

The coming years are looking forward to continuous monitoring, routine diagnostics and generating feedback for controlling techniques in gait analysis in real-time. Thereby, it can assist the rehabilitation by providing information to medical professionals and even to the patients. Hence, more exhaustive research needs to be done before using inertial sensors and ML techniques as a standardised clinical diagnostic tool. As a step towards standardisation of the method, it has to be tested more rigorously on the patient group as well. In consequence, the future intellectual systems for gait analysis will be based on sensor technology consisting of automated monitoring with biofeedback for walking detection in indoor and outdoor environments. Thus, it will enable benefits for a healthy quality of life.

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Disclosure statement

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