We performed an electronic database search of published works from 2012 to mid-2021 that focus on human gait studies and apply machine learning techniques. We identified six key applications of machine learning using gait data: 1) Gait analysis where analyzing techniques and certain biomechanical analysis factors are improved by utilizing artificial intelligence algorithms, 2) Health and Wellness, with applications in gait monitoring for abnormal gait detection, recognition of human activities, fall detection and sports performance, 3) Human Pose Tracking using one-person or multi-person tracking and localization systems such as OpenPose, Simultaneous Localization and Mapping (SLAM), etc., 4) Gait-based biometrics with applications in person identification, authentication, and re-identification as well as gender and age recognition 5) “Smart gait” applications ranging from smart socks, shoes, and other wearables to smart homes and smart retail stores that incorporate continuous monitoring and control systems and 6) Animation that reconstructs human motion utilizing gait data, simulation and machine learning techniques. Our goal is to provide a single broad-based survey of the applications of machine learning technology in gait analysis and identify future areas of potential study and growth. We discuss the machine learning techniques that have been used with a focus on the tasks they perform, the problems they attempt to solve, and the trade-offs they navigate.

Keywords: review, human gait analysis, biometrics, machine learning, artificial intelligence

1 INTRODUCTION

Smart Gait (SG) is a term for any integrated human gait data analysis system utilizing Artificial Intelligence (AI). It is a growing research field capitalizing on the advancements in modern sensing technologies, automation, cloud computing, data analytics, parallel processing, and Internet of Things (IoT).

Some of the most prominent tasks SG performs are gait phase detection, gait event prediction, human activity recognition, fall detection, recognition of a person’s age and gender, abnormal gait detection such as fatigued state, stroke and neurological disease (ND), Parkinson’s Disease (PD), estimation of joint angles and moments, the walking person’s intent recognition and trajectory prediction, human pose estimation, localization and mapping, person identification, re-identification and authentication, step counting, assessment of physical skill and mobility, balance assessment, fall risk assessment, gait modeling, and simulation. Often SG performs a combination of two or more tasks simultaneously.

SG systems can analyze single or multiple gaits simultaneously. The multi-gait SG performs tasks such as crowd and occupancy sensing, crowd behavior prediction, multi-gait recognition as in
identifying a person walking with one or more others, generating multi-gait for animation and virtual environments, and detecting abnormal gait in crowds or indoors for security applications. SG is thus a smart tool in the toolbox of experts in many fields such as health and wellness, security, user privacy, forensics, enhanced user experience, animation, energy, wearable and related fields like insurance, longevity, geriatrics, workplace safety, and productivity. SG can also easily be integrated with other smart systems that utilize heart rate, audio, haptic, speech, etc., for an even wider reach across many applications and industries. As such, SG is a component of many smart devices, smart homes, stores, cities, and energy grids.

This work reviews most of the research in the field of smart gait in recent years. It provides a broad-based survey of the current state of the field and identifies future areas of potential study and growth. First, we performed an electronic database search on six well-known electronic libraries: IEEE Xplore, Science Direct, PubMed Central, Google Scholar, ACM, and Web of Science. We searched for “artificial intelligence” AND “human” AND “gait” in the full text (when available), title, keywords, and abstract. Due to the sheer volume of the work and based on the assumption that most of the more recent works build and improve upon previous work, we limited our search to 2012 to mid-year 2021. We started our work in early 2020 by reviewing papers published in 2012-2019, and updated our review with papers from 2020 and the first half of 2021 as we continued our work through the end of July 2021. All references were downloaded into EndNote. Figure 1 offers an overview of the number of references located by this original search and the number of references located by this original search and the number of citations on Google Scholar and the journal's impact factor.

Additionally, 393 review papers were originally excluded from this study. None of the works in our database search presents a comprehensive overview. The above-mentioned papers were not used in our study; the reader is encouraged to read them if they wish to go deeper into any of the discussed topics.

We identified six main applications of SG: 1) Gait analysis where analyzing techniques are improved through AI algorithms, 2) Health and Wellness, with applications in research on animal and robotic gait, and 3) no AI - such as human gait studies that do not incorporate machine learning methods. After the exclusions by title, our database was reduced to about 3500 papers, which were then reviewed by title and abstract. The final selection criteria included at least one paper for each application, even smaller niche examples such as depression detection by gait (Fang et al., 2019). In areas where many papers existed for the same application, such as neurological disease gait detection, the most impactful papers were selected by looking at the overall influence of the paper by the number of citations on Google Scholar and the journal’s impact factor.

1) studies in related fields but not exactly within the inclusion criteria of this work. For instance, Najafi and Mishra (2021) compiled a narrative review on digital health technologies for diabetic foot syndrome. While ML algorithms are probably embedded in some of the technologies they discuss, the study does not mention or discuss artificial intelligence.

2) studies that partially overlap with our studies, such as the literature review on PD diagnosis by Mei et al. (2021), that in addition to PD diagnosis by gait, also discuss other modalities such as voice, handwriting, magnetic resonance imaging (MRI), etc.

3) studies that are in the scope of this review but only cover a specific topic such as human motion trajectory prediction (Rudenko et al., 2020), wearable sensing technologies for sports biomechanics (Taborri et al., 2020), self-powered sensors and systems (Wu et al., 2020), person re-identification (Wang et al., 2016), (Nambiar et al., 2019), (Karanam et al., 2019), machine learning in soft robotics (Kim et al., 2021), ambient assisted living technologies (mostly AI-enabled and gait-related) (Cicirelli et al., 2021), human action recognition (Gurbuz and Amin, 2019), biomechanics (Halilaj et al., 2018), gait recognition (Kusakunniran, 2020), (Singh et al., 2018), (Wan C. et al., 2018), gait event detection and gait phase recognition (Prasanth et al., 2021), clinical gait diagnostics of knee osteoarthritis (Paris et al., 2020), knee pathology assessment (Abid et al., 2019), data preprocessing in gait classification (Burdack et al., 2019), age estimation (Aderinola et al., 2021), and benchmark datasets (Nunes et al., 2019). A survey paper by Alzubaidi et al. (2021) provides an overview of deep learning, with helpful definitions and a discussion of strengths, limitations, and future trends of various deep learning techniques. Similarly, Abiodun et al. (2019) review Artificial Neural Network (ANN) applications in pattern recognition. Our paper’s goal is to review applications of SG technology, in a wider, all-encompassing overview. The above-mentioned papers were not used in our study; the reader is encouraged to read them if they wish to go deeper into any of the discussed topics.

Figure 1: Number of papers by year of publication.
TABLE 1 | Smart gait vocabulary.

| SG Vocabulary                      | Definition/Context in our papers |
|------------------------------------|----------------------------------|
| Artificial Intelligence            | Artificial Intelligence is a technology that enables computers and devices to act intelligently and make decisions like humans (Amisha et al., 2019) |
| Machine Learning (ML)              | Machine Learning is a subfield of AI that enables computers and devices to learn from data without being explicitly programmed (Mahesh, 2020). It includes supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. DL is a subfield of ML that extracts useful information directly from raw data to learn representations for pattern recognition (Esteve et al., 2019), (Pouyanfar et al., 2018). It is often referred to as the “black box” approach to reflect the abstract layers of human brain-like neural networks it consists of |
| Abnormal Gait Detection            | The task of distinguishing a healthy gait from a pathological gait. Some of the pathologies that affect the walking pattern as discussed in this paper include dementia, Huntington’s disease (HD), PD, Autism Spectrum Disorder (ASD), Amyotrophic Lateral Sclerosis (ALS), Post-Stroke Hemiparetic (PSH), Acquired Brain Injury (ABI), depression, neuromuscular disease, lower extremity muscle fatigue, spastic diplegia, Cerebral Palsy (CP), etc. |
| Human Identification               | Presented gait data is compared to a set of gait data with known identities (labeled training data) to determine whom the unknown gait belongs to |
| Human Re-identification            | The task of identifying images of the same person from non-overlapping camera views at different times and locations. Gait is a behavioral biometric feature that is unobtrusive, hard to fake or conceal, and can be perceived from a distance without requiring the subject’s active collaboration (Nambari et al., 2019) |
| Fall Detection                     | A binary classification task, usually concurrent with activity recognition that classifies an activity as fall or no fall |
| Activity Recognition               | A classification task that maps features extracted from various sensor raw data to classes corresponding to activities such as sitting, lying, running, walking, stair climbing |
| Gender Recognition                 | Gender Recognition is a binary classification that maps features to qualitative outputs: male and female |
| Smart Home                         | A smart home utilizes context-aware and location-aware technologies to create intelligent automation and ubiquitous computing home environment for comfort, energy management, safety, and security (Hsu et al., 2017) |
| Gait Event Detection               | Detection of a sequence of events that specifies the transition from one gait phase to another during each gait cycle (Mannini et al., 2014) |
| Kinetic and Kinematic analysis     | Kinematics studies the motion of body segments without considering masses or causal forces. Kinetics studies the relation between motion and its causes |
| Biometric Authentication           | An automated method of verifying a person’s identity based on their biometric (gait) characteristics |
| Crowd Density                      | The density level of people in a crowded scene |
| Anomaly detection                  | It labels a behavior pattern that is “far away” from a trained model as anomalous, where “far away” is measured by a time-varying threshold (Sun et al., 2017) |
| Gait estimation from Pose          | Parameters such as step length, stride length, stride time, cadence, etc., are estimated from the human pose |
| Human Gait Motion Modelling        | A probabilistic manifold-based motion modeling framework able to model with a variety of walking styles from different individuals and with different strides (Ding and Fan, 2019) |
| Occupant Activity Sensing          | Actively knowing the identity of the people within a monitored area and what they are doing (Yang et al., 2018) |
| Multi-Gait Recognition             | Multi-gait is a term used by authors (Chen et al., 2018) to refer to the changed gait of a person walking with other people. Multi-gait recognition is the task of identifying a person when he is walking with different people |
| Brain-Computer Interface (BCI)     | A technology that translates signals from human brain activity such as walking intention to a command sent to an external assistive, adaptive, or rehabilitative device, such as a prosthetic leg (Bekkaem et al., 2020), (Khan et al., 2018) |
| Hybrid BCI (hBCI)                  | A system that fuses two bio-signals, where at least one is intentionally controlled. The different signals, such as data from electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS), are processed in real-time to establish and maintain communication between the brain and the computer. The output is evaluated through a feedback control loop. Compared with systems that use one modality alone, hBCI improves classification accuracy and the number of control commands by integrating the complementary properties of different modalities and removing artifacts (Khan et al., 2021). |
| Kinetic Energy Harvesting (KEH)    | Technology that converts kinetic motion into energy. The individuality of the gait pattern can be captured in the output voltage signals of KEH systems, with the added benefit of energy savings, compared to accelerometers. Thus KEH systems are used as sensors and energy sources simultaneously (Lan et al., 2020) (Xu et al., 2021) |
| The Digital Human                  | Digital replicate of a human in the virtual space. Automatic, continuous gait monitoring will be an integral part of such systems (Zhang et al., 2020g) |
| IoT                                | IoT is a ubiquitous system of objects that are connected to the network, uniquely identifiable, capable of collecting, communicating, and processing data and AI-enabled to make autonomous decisions, individually or collectively (Chettri and Bera, 2019). Gait is an important biometric feature for continuous behavioral authentication in IoT systems (Liang et al., 2020) |

The paper is organized in the following sections: Section 2) Smart Gait Vocabulary, sections 3–8 discuss the applications of gait monitoring for abnormal gait detection, recognition of human activities, fall detection, and sports performance, 3) Human Pose Tracking covering one-person or multi-person tracking and localization systems, 4) Gait-based biometrics with applications in person identification, authentication, and re-identification as well as gender and race recognition 5) Smart Gait devices and environments ranging from smart socks, shoes, and other wearables, to smart homes and smart retail stores that incorporate continuous monitoring and control systems and 6) Animation that reconstructs human motion through gait modeling, simulation, and machine learning techniques. The categories are sometimes not easy to separate and overlap. For instance, gait phase detection algorithms could belong to Health and Wellness, SG Devices, or Gait Recognition categories.
AI in 3) Gait Analysis 4) Health and wellness 5) Tracking Human Pose 6) Gait Based Biometrics 7) Smart Gait devices and 8) Animation. In sections 9 and 10, we conclude with 9) Discussion and Future Trends and (10) Conclusions.

2 THE SMART GAIT VOCABULARY

Here we introduce certain key definitions of essential terms commonly used in SG studies (See Table 1).

3 GAIT ANALYSIS

Machine learning techniques are successfully utilized to improve many aspects of gait analysis. In this collection of papers AI 1) helps with data aggregation and pre-processing, 2) works along with another AI to improve its performance, interpretability, or accuracy, and 3) classifies gait phases and predicts gait events.

3.1 Data Aggregation and Pre-processing Using ML Techniques

Deep learning models can automatically extract the optimal features directly from raw spatiotemporal gait data without requiring data preprocessing or engineering (end-to-end approach) (Costilla-Reyes et al., 2021), (Morbidoni et al., 2019), etc. In other cases, when conventional machine learning techniques are deployed, much work goes into feature extraction and selection to ensure that the input features explain most of the variance in the data and achieve good performance and high accuracy of the algorithm. Of the six commonly used data preprocessing techniques, Ground Reaction Force (GRF) filtering, time derivative, time normalization, data reduction, weight normalization, and data scaling, (Burdack et al., 2020) found that only GRF filtering and supervised data reduction techniques such as Principal Component Analysis (PCA) increased the performance of ML classifiers, with Random Forest (RF) being more robust in feature reduction than Support Vector Machines (SVM), Multi-Layer Perceptron (MLP) and Convolutional Neural Networks (CNN).

PCA is a dimension reduction technique that transforms the original feature space into a set of linearly uncorrelated variables called principal components (PCs). The first few PCs alone are usually enough to account for most of the variance in the data. For instance, the first 3–6 PCs alone accounted for 84–99% of the overall variance (Dolatabadi et al., 2017). Other variants of PCA have been suggested in the SG literature, such as kernel-based PCA (Semwal et al., 2015), multi-linear PCA that achieves sparse and discriminative tensor to vector projection (Zhang et al., 2015), or a combination of PCA, linear discriminant analysis (LDA) and other feature reduction techniques (Wu C. et al., 2019). Phinyomark et al., (2015) attempt to evaluate the importance of intermediate to higher-order PCs in running biomechanics, finding that low order PCs (that account for up to 90% of the cumulative variance in the data) can be successfully used for age and gender recognition. Still, the more subtle running behavior patterns such as between-group variations in improvements after a 6-weeks rehabilitation program of runners with patellofemoral pain (PFP) can be captured by intermediate and high order PC’s (that explain 90–99% and 99–100% of the variance of the data correspondingly). PCA, some variation of PCA, or a combination of PCA and other linear dimension reduction techniques were used in most papers we reviewed. t-Distributed Stochastic Neighbor Embedding (t-SNE) was used by Costilla-Reyes et al. (2021) to achieve a 2D representation and visualization of different age clusters of the trained data. Besides feature reduction, AI is employed for data augmentation (Bhattacharya et al., 2020) or data engineering (Johnson et al., 2021).

Other considerations in carefully selecting the input features are avoiding overfitting (Zhang et al., 2020a), improving interpretability, especially in medical applications (Dindorf et al., 2020b), (Horst et al., 2019), reducing the energy expenditure of wearable sensors (Ito et al., 2020), (Russell et al., 2021), improving patient comfort (Di Nardo et al., 2020), fairness to people with disabilities (Trewin et al., 2019) and user experience (Kim et al., 2020). To achieve the highest possible accuracy, usually, more complex sensing technology is required. The goal is to apply feature reduction and selection to avoid redundant features such that only the significant features are extracted from the minimum sensing hardware (Khademi et al., 2019). Information Gain (IG) and not PCA is used to improve interpretability by preserving and ranking the original features (Onodera et al., 2017).

3.2 AI2AI

We define AI2AI as an AI-based procedure whose purpose is to make another AI better. Better AI is defined based on the task. As indicated above, it includes better performance, higher accuracy, better interpretability, robustness, lower cost, lower energy expenditure, reduced overall system complexity, unobtrusive sensing technology, and automatic and real-time processing. For instance, Zhu et al. (2020) use an Improved Artificial Fish Swarm Algorithm (IASA) to optimize the parameters of the RF algorithm for knee contact force (KCF) prediction. Bhattacharya et al. (2020) use a novel Conditional Variational Autoencoder (CVAE) trained on an annotated dataset of 4,227 human gaits recorded on video to generate thousands of new realistic annotated gaits. Their data augmentation generative network improves the accuracy of their novel Spatial-Temporal Graph Convolutional Network (ST-GCN) algorithm to classify the four human emotions: happy, sad, angry, and neutral by 6%. Lu et al. (2021) apply transfer learning and domain adaptation to label the data for a cross-domain human activity recognition task.

Similarly, as a first phase to creating an activity recognition algorithm for construction workers (Kim and Cho, 2020), the authors first implemented five ML algorithms 32 times each, once for every possible combination of the number of Inertial Measurement Unit (IMU) sensors and their location in the body, and compared their performance by a cross-validation (CV) technique. This systematic approach of evaluating how many sensors are sufficient for activity recognition and where they should be placed in the construction workers’ body revealed...
3.3 Gait Phase Classification and Gait Event Prediction

Gait analysis evaluates a person’s walking pattern, which is seen as a sequence of gait cycles, where each gait cycle follows the movement of a single limb from heel-strike to heel-strike again (Gage et al., 1995). The two main gait phases are the stance phase and the swing phase. Depending on the reason for gait analysis, detecting just these two phases can be enough. That simplification permits less complex and cheaper gait analysis, which is desirable, especially in wearable systems (Di Nardo et al., 2020). A more common four-phase cycle includes initial contact, mid-stance, pre-swing, and swing (Jiang et al., 2018). The importance of AI in these studies is in facilitating real-time gait analysis, appreciated in many control devices like orthotics and prosthetics, rehabilitation monitoring, and fall detection systems for aging-in-place applications. (See Table 2).

4 HEALTH AND WELLNESS

Clinical gait analysis, though by itself not reliable for a definitive diagnosis of neurological disease or other impairment, often suggests a pathology if it detects a pattern different from a typical walking behavior considered the normal gait. Normal gait is a controlled, coordinated, and repetitive series of limb movements that advance the body in the desired direction with minimum energy expenditure (Gage et al., 1995). There are four reasons for performing a clinical gait analysis: diagnosis, assessment, monitoring, and prediction (Baker et al., 2016). In these applications, the AI can continuously monitor and learn data, look for patterns, classify human activities and detect the anomaly. If connected to a display, it is an excellent monitoring and assessment tool. AI also predicts a future gait event, in which case it can either alert a human operator such as a clinician, caretaker, or facility supervisor or, if integrated with a control device, activate an automatic response to prevent falls or injury. For instance, WeedGait passively monitors the gait of a person and then alerts them if they are at risk of Driving Under the Influence of Marijuana (DUIM) (Li et al., 2019), while an in-home rehabilitation system provides qualitative and quantitative feedback to post-stroke survivors (Lee et al., 2019).

We identified four major applications of ML gait analysis in health and wellness: 1) detecting abnormal gait due to a person’s condition or disease, 2) sports management, 3) fall detection, and 4) activity recognition.

4.1 Abnormal Gait

AI is well suited at learning patterns and detecting an anomaly in the data based on a pre-defined abnormal event (supervised learning) or a clustering algorithm (unsupervised learning), or a combination of the two. A very wide range of human diseases and conditions can affect the way a person walks such as Parkinson’s (Flagg et al., 2021), (Wahid et al., 2015), Huntington’s (Acosta-Escalante et al., 2018), ALS (Aich et al., 2018), idiopathic normal-pressure hydrocephalus (iNPH).
neuromuscular disease (Gotlin et al., 2018), pediatric hereditary spastic paraplegia (HSP) (Pulido-Valdeolivas et al., 2018), aging (Strath et al., 2015), (Costilla-Reyes et al., 2021), dementia (Kenney et al., 2018), (Arifoglu and Bouchachia, 2017), fatigue (Zhang J. et al., 2014), depression (Fang et al., 2019), anxiety (Zhao et al., 2019), emotional state (Bhattacharya et al., 2020), dual task, or walking while performing a cognitive task (Costilla-Reyes et al., 2021), knee osteoarthritis, (Kotti et al., 2017), stroke dual task, or walking while performing a cognitive task (Costilla-Reyes et al., 2021), or walking while performing a cognitive task (Costilla-Reyes et al., 2021).

There is a need to minimize the distance between the experimental setup and the real-life application of a system. For instance, the use of a home monitoring system for abnormal gait was studied (Guo et al., 2019), but the subjects used in the study were healthy subjects imitating abnormal gaits due to fatigue/non-fatigue states, subjective self-reported thresholds or the need for data preprocessing or engineering. (Costilla-Reyes et al., 2021).

Similarly, there is also the problem of a small sample size. Given the clinical nature of these studies and the impaired gait participants they require, the barriers to experimentally collecting sufficient data are understandable. For instance, 19 healthy participants had to consent to intravenous injection of lipopolysaccharide to induce inflammation in a fatigued gait study and were paid 3500SEK each.
In some scenarios, the number of input features is larger than the sample size (Zhang et al., 2015). In others, the sample size is too small to be representative enough to support any assertions fully and reduces the paper to the level of an exploratory effort (Baghdadi et al., 2021). In others, researchers generate synthetic data (Arifoglu and Bouchachia, 2017) that reflect features similar to the disease for an abnormal gait detection task; apply deep AI technique to reduce the number of required labels and consequently the time cost of manual labeling in a gait phase detection task. Finally, there is a developing trend to take measurements out of the lab (Russell et al., 2021) and into the subjects’ natural environments and implement deep learning techniques to do the labeling (Costilla-Reyes et al., 2021), (Cronin et al., 2019).

Many of these techniques in aggregating, pre-processing, and learning the data, often represent work-around strategies to cost, user privacy, and clinical constraints. They both simplify the systems and introduce some errors in them simultaneously.

2) Can’t see in the dark: The Black Box problem.

This refers to the low interpretability of complex AI systems which can pose a problem, especially in medical applications. Explainable AI (XAI) is a recent trend in AI research that attempts to address this concern and the related issues of transparency, trustworthiness, and clinical acceptance (Dindorf et al., 2020b), (Khodabandehloo et al., 2021). Interpretable deep gait is the first attempt to make deep learning gait analysis more interpretable using layer-wise relevance propagation (LPR) while still achieving high accuracy (Horst et al., 2019).

3) Can’t leave the parking lot: the research to commercialization gap and the need for government approval.

Medical devices that utilize data and ML techniques will need Food and Drug Administration (FDA) approval and general buy-in from medical professionals and their patients. Doctors, clinicians, therapists, carers, et al. will need to be willing and capable of embracing the newness of the technology. To date, the authors are not aware of any FDA-approved medical devices that utilize AI and gait data. Neurodegenerative diseases are not symptomatic until years after their onset, but clinical usefulness needs to be demonstrated for the approval of a medical device. The cost of developing, installing, and maintaining such systems also becomes a barrier to their commercialization and practical usefulness (König et al., 2015).

The most recent advancements seem to address some of these concerns, but those are only in the beginning phases, and the long-term implications on user safety and privacy, as well as their actual performance, remain to be proved.

4.1.1 Fatigued Gait

Fatigue is defined as “a lower level of strength, physical capacity, and performance” (Lu et al., 2017). Detecting the onset of fatigue and creating systems that manage the associated risks is an important part of production quality and human factors engineering in the workplace.

Measuring and analyzing gait for fatigue monitoring makes sense because 1) walking is a task that is possible to track via unintrusive technology suitable to workplace settings, such as video, wearable sensors, radar, and force plates on the floor or any combination of these. 2) Walking is a significant part of occupational tasks for workers in manufacturing, mining, construction, nursing, warehouse and distribution centers (Baghdadi et al., 2021). 3) In the context of advanced manufacturing (known as Industry 4.0) for example (but other modern occupational settings as well), in which a worker’s daily tasks involve interacting with automation, computing, and sensing technologies, the most relevant features extracted from readily available gait data can be pre-processed and analyzed through ML techniques, often real-time, which makes it possible to detect the onset of fatigue with accuracy and speed, at a relatively low cost. 4) Lastly, fatigue in the walking behavior is correlated to fatigue in other physical tasks, and while safety systems in the workplace should be custom-tailored to the relevant tasks, detecting fatigue in a worker’s gait could serve as an excellent general fatigue monitoring technique applicable to most industrial settings.

There are two main goals in fatigued gait studies: 1) intra-person recognition or continuous recognition of the person walking in different fatigue states 2) inter-person recognition or the recognition of fatigue in an individual. The first one answers the question: Can we still identify the person by their gait in a fatigued state? The second one answers the question: Can we recognize the onset of fatigue to avoid overtraining and injury in sports or improve worker safety in the workplace? Researchers conclude that a person’s gait pattern maintains its individuality even while manifesting situation-dependency, as is the case with fatigue (Janssen et al., 2011).

Only seven features extracted from one wearable sensor are needed for fatigue detection, with an average accuracy of greater than 0.85 (Sedighi Maman et al., 2020). Still, in the workplace, the individual fatigue detection accuracy of 0.85 may mean high misclassification rates across many subjects (Baghdadi et al., 2021), thus the authors suggest a multivariate hierarchical time series clustering algorithm using Dynamic Time Wrapping (DTW) as a dissimilarity measure. Detecting fatigue from smartphone sensors was suggested (Maghded et al., 2020) as part of a multi-modal sensing and machine learning framework to detect Covid-19 and predict its severity and outcome through an app on the user’s phone.

Overall, fatigue studies utilizing gait data and AI point to the importance of SG in managing fatigue in the workplace, sports performance management, rehabilitation exercises, reducing fall risk in the elderly, and finally, as part of an integrated system for overall health management, both at the individual level and in public health applications, as is the case with Covid-19 related studies. The fact that most studies we reviewed collected gait data from just one sensor or just the smartphone (Karvekar, 2019) shows that effort is already invested in making these systems unintrusive, cost-effective, and adaptable (see Table 3).

4.1.2 Neurological Disease

Gait-based detection and classification algorithms for disease diagnosis and monitoring are one of the major applications we saw, and Parkinsonian gait, with its many classifiable features,
such as freezing of gait (FoG), shuffling steps, slow gait, gait asymmetry, etc., is the most prevalent disease in the studies (See Table 4). Researchers propose an automated, accurate, and sensor-free gait detection deep learning algorithm that depends on video recordings from pervasive devices such as smartphones, web cameras, and surveillance cameras as cheaper and more accessible alternatives to Vicon camera systems (Ajay et al., 2018). Procházka et al. (2015) move away from expensive, complex camera systems and recommend using MS Kinect image and depth sensors for synchronized data acquisition and spatial modeling of a moving person. The recommended Bayesian Classification (BC) algorithm distinguishes PD gait from healthy gait based on decision boundaries of three features: gait speed, stride length, and age, with an achieved accuracy of 94.1%. Wahid et al. (2015) contribute to the gait-based PD detection by suggesting that the spatial-temporal gait data be normalized first using multiple regression to account for the patient’s age, height, body mass, gender, and walking speed. (Wan S. et al., 2018) employ a deep MLP to analyze both movement and speech data captured through a smartphone and estimate the severity of PD. Ye et al. (2018) go a step further and propose a Neural Network (NN) combined with Fuzzy Logic (FL) approach that recognizes the gait of patients with neurodegenerative disease (ND) from normal gait. Since the motor function impairment in various NDs such as ALS, HD, and PD is caused by different factors, the particle swarm optimization (PSO) algorithm was used along with an adaptive neuro-fuzzy inference system (ANFIS) to classify the non-linear gait dynamics. Bilgin (2017) also attempts to distinguish ALS from other ND diseases and healthy patients using Discrete Wavelet Transform (DWT), LDA, and Naïve Bayesian Classifier (NBC).

One of the most encouraging recent developments in ND gait research using AI is the DREAM PDDB Challenge launched by Sage Bionetworks that promotes an open and competitive research infrastructure with large-scale data for developing digital signatures of PD. Similar challenges in computer vision, such as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) (Russakovsky et al., 2015), have shown to be conducive to tremendous growth with classification accuracy improving year after year against the previously established benchmark. The DREAM PDDB challenge utilizes the self-reported and sensor data collected through the mPower app (Bot et al., 2016) from 15,000 PD and healthy control (HC) subjects. The best performing team as of July 2021 reported Area Under the Receiver-Operating Characteristic Curve (AUROC) of 0.86 with a deep CNN algorithm that employs three spatial and temporal data augmentation techniques to deal with overfitting.

Another initiative, still in the early phases but very promising, is the Early Detection of Neurodegenerative Diseases (EDoN) project. Launched in February 2020, it is a global research initiative that has secured generous funding, prominent cross-disciplinary expertise, and UK government support (Wakefield, 2020). It is already in the first phase of collecting smartwatch data (gait data along with heart rate, sleep, navigation data, etc.) from volunteers in the Greater Boston area through a partnership with Boston University Alzheimer’s Disease Research Centre (BUADRC). The data will be used to generate a digital “fingerprint” for dementia which, in the application phase, will detect dementia 10–15 years earlier than the current clinical methods.

4.2 Sports

The general trend we see in sports and fitness applications of ML-based gait analysis systems is to create low-cost, adaptable, fast, easy, and scalable systems that reach the right balance of accuracy and comfort for the given application (See Table 5). In sports management and sports injury prevention, gait data is lower limb movements signals acquired from various sensing technologies: video, IMUs, force plates, etc. SG monitors walking and running activities but also water sports, basketball, and football.

| Reference            | Algorithm/best accuracy reported | How is data collected                                      | Task                                                                 |
|----------------------|----------------------------------|------------------------------------------------------------|----------------------------------------------------------------------|
| Russell et al. (2021)| CNN 97.8%                        | accelerometer worn around the chest, GPS watch for location tracking, 1 person | HAR: Climb Gate/Lay/Sit/Walk/Run. Variations in terrain and fatigue fatigue development over time |
| Baghdadi et al. (2021)| MHTSCA with DTW as a dissimilarity measure | one sensor in the torso, 15 subjects | 4-phase fatigue management framework in the workplace (1) detection (2) Identification (3) diagnosis: whole-body vs. localized (4) recovery detection of fatigue due to Covid-19 |
| Sedighi Maman et al. (2020)| RF with BSS 85.5% | smartphone sensors, images and videos from the camera | detection of fatigue: baseline, low, medium, and strong fatigued states |
| Maghdid et al. (2020)| CNN/RNN | smartphone sensors, images and videos from the camera | detection of fatigue after MMH tasks |
| Karvekar, (2019)    | 2-class SVM 91%                   | 24 subjects, smartphone attached to the shank              | detection of fatigue: baseline, low, medium, and strong fatigued states |
| Baghdadi et al. (2018) | SVM 90%                         | one IMU in the ankle, 20 subjects | detection of fatigue after MMH tasks |
| Zhang et al. (2014a) | SVM 96%                          | 17 subjects, IMU at sternum level | recognition of localized fatigued/non-fatigued state |
| Janssen et al. (2011) | SVM and SOM with PCA 98.1% | 9 subjects GRFs | inter and intra-personal gait classification before, during, and after leg exhaustion |

Legend: Best Subset Selection (BSS), Manual Material Handling (MMH), Multivariate Hierarchical Time Series Clustering Algorithm (MHTSCA).
| Reference                         | Algorithm/Best Accuracy | Data Collection/Input                                      | Pathology/Task Output                                      |
|---------------------------------|-------------------------|------------------------------------------------------------|------------------------------------------------------------|
| Lu et al. (2020)                 | SVM with PCA 88.89%     | Kinect camera with image rectification                      | Automatic depression detection                             |
| Khodabandeeloo et al. (2021)     | HealthXAI CART          | Partial CASAS dataset, 192 subjects: 19 PwD, 54 MCI        | Numerical score and explanation of the decline of cognitive functions of the elderly |
| Iosa et al. (2021)               | ANN 93.9%               | IMU at the waist belt, N = 33, HC = 17, stroke = 16        | Stroke prognosis tool, unable-to-return to work             |
| Flagg et al. (2021)              | Bidirectional GRU       | GaithNDD, GaitPDB. Streaming of live and historical GRFs    | ND: PD, HD, ALS gait normally analysis                     |
| Costilla-Reyes et al. (2021)     | Novel DNN with t-SNE    | Own dataset: UOM-GAIT-69. Tomography floor sensor raw data. N = 69, healthy normal/fast/dual-task | Age-related differences in healthy adults undertaking dual tasks |
| Zhu et al. (2020)                | RF with IFASA RMSE = 0.073 | 3 patients with knee replacement. Public dataset/challenge² | Knee joint impairment KFC prediction                       |
| Zhou et al. (2020)               | Kernel PCA with SVM, RF, ANN: 90% | N = 239, young = 57, old healthy = 55, 127 = old-geriatric condition | Geriatric condition                                        |
| Zhang et al. (2020a)             | Deep CNN AUC = 0.87     | DTW F1-score                                              | PD vs healthy gait; Large scale screening                  |
| Zeng et al. (2020)               | RF neural network with DL | 95.61%                                                   | Chronic unilateral ACL deficiency. Classify ACL-/D/ACL-I knees |
| Pepa et al. (2020)               | Novel FL, Sp = 95.2%, Se = 84.9% | Smartphone data                                           | Real time, interpretable FoG detection                     |
| Lasselin et al. (2020)           | MLR                     | N = 19, lipo polysaccharide-induced inflammation. Kinect camera data | Effects of inflammation on human gait                      |
| Kaur et al. (2020)               | LR, SVM, RF              | 4 people with MS. GRFs from instrumented treadmill         | GML4MS framework, HC/MS mild and moderate classifier      |
| Bhattacharya et al. (2020)       | ST-GCN and CVAE 88%     | 4,277 human gaits in video and synthetic gaits by novel     | Emotion classification: happy, sad, angry, or neutral       |
| Li et al. (2019)                 | WeedGait, by LSTM and SVM 92.3% | STEP-Gen                                                  | assesses marijuana-induced gait impairment                  |
| Guo et al. (2019)                | SVM and BiLSTM          | N = 16, light-telepresence robot equipped with a single     | passively, warns against DUIM online                       |
| (Zhang et al., 2019b)            | ANN (a = 50) 93.5%      | RGB-D camera with no additional sensing feedback           | normal, in-toeing, out-toeing, and drop-foot gait           |
| Sato et al. (2019)               | ST-ACF DTW, KNN with OpenPose | CASIA-B dataset. Frontal videos of two PD patients         | Gait classification for CP patients with spastic diplegia   |
| Fang et al. (2019)               | RF 91.58%               | 95 graduate students. 52 score-depressed, 43 HC. Two MS    | Quantifying normal and Parkinsonian gait features from home movies |
| Acosta-Escalante et al. (2018)   | Logitboost & RF 94.5% on raw data | N = 14, HD = 7, HC = 7. Smart phones (IPhone 5S) affixed to both ankles | Depression analysis                                         |
| Ye et al. (2018)                 | ANFPS/PSO with LOOCV. 94.4% | 64 subjects, ALS = 13, PD = 15, HD = 20, HC = 16, ND          | HD gait classification                                       |
| Pulido-Valdeolivas et al. (2018) | RF with DTW             | 26 HSP and 33 healthy children. Optokinetic IGA system     | Classification of Gait Patterns in Patients with various ND |
| Wan et al. (2018b)               | DMLP, 97.9%             | N = 60, phone worn on the waist. Biomedical voice recordings (UCl dataset) and smartphone 3-axial acceleration | Monitoring HSP progression and personalizing therapies      |
| Hasan et al. (2018)              | ANN, SVM with SNPDA 93.3% | 3D/GRF data of 60 children: 30 ASD and 30 typically developing | Analyze speech and movement data captured by smartphone to estimate the severity of PD |
| Cui et al. (2018)                | SVM w/PCA 98.21%         | N = 42, 21 post-stroke, 21 HC MT, GFR and EMG              | Identifying ASD Gait                                        |
| Ajay et al. (2018)               | DT. 93.75%              | 49 YouTube videos of varying resolution. Video obtained through any pervasive devices | Recognition and Assessment of PSH Gait                     |
| Arlogu and Bouchachia, (2017)    | LSTHM HAR: 96.7% AAD: 91.43% | 48 subjects, ALS = 13, PD = 15, HD = 20, HC = 16, ND          | PD gait classification                                       |
| Bilgin, (2017)                   | LDA, NBC, 90.93%        | Kinect dataset collected in 3 households through            | HAR and AAD for elderly people with dementia               |
| Dolatabadi et al. (2017)         | GPLVM-thold and KNN- DTW F-score > 0.94 | 300 gradient sensors. 3 ALS, 15 PD, 20 HD, and 16 HC        | Classification of ALS among other ND diseases and healthy subjects |
| Shetty and Rao, (2016)           | SVM with Gaussian       | N = 40, HC = 20, mobility impaired = 20. Two Kinect sensors | Discernnt between healthy and pathological gait patterns because of stroke or ABI |
| Procházká et al. (2015)          | RBF 83.3%              | GaithNDD, GFR measurements. N = 64, 15 PD, 18 HD, 13 ALS, 16 HC | Distinguish PD gait from HD, ALS, and HC                     |
| Wahid et al. (2015)              | NBC 94.1%               | N = 51, 18 PD, 18 HC - age-matched, and 15 young HC. MS      | PD diagnosis                                                |
|                                 | RF with MR normalization | N = 49; PD = 23 HC = 26, 15 Reflected markers, 2 force platforms | PD diagnosis and management using normalized spatial-temporal gait |

Legend: Decision Tree (DT), K-Nearest Neighbors (KNN), Center for Advanced Studies in Adaptive Systems (CASAS) (Cook et al., 2013), Classification and Regression Trees (CART), Gated Recurrent Unit (GRU), Root Mean Square Error (RMSE), Receiver-Operating Characteristic (ROC), AIC Deficient (ACL-D), AIC-intact (ACL-I), Radial Basis Function (RBF), Deterministic Learning (DL), Multivariable Linear Regression (MLR), Multiple Sclerosis (MS), Gait data-based ML framework for MS prediction (GML4MS), Linear Regression (LR), Abnormal Activity Detection (AAD), Gaussian Process (GP) Latent Variable Models (GPLVM), OpenPose (Cao et al., 2017), Datasets: CASIA-B (Yu et al., 2006), Gait in Neurodegenerative Disease Database (GaithNDD) (Hausdorff et al., 2000), Gait in Parkinson’s Disease (GaitPDB) (Goldberger et al., 2000), CASAS (Cook et al., 2013), Note https://simtk.org/projects/kneeloads, ND Public Dataset (Hausdorff et al., 2000).
A deep learning algorithm trained with a relatively small number of labeled images was able to predict the locations of joint markers with the same accuracy as a human labeler, thus providing a low-cost system for kinematic analysis with sufficient accuracy for applications in sports biomechanics, training, coaching, and rehabilitation (Cronin et al., 2019). A kinematic and kinetic analysis aided by ML techniques was carried out to identify the effects of the shoes on the biomechanics of running. The conclusion: changes in the midsole resilience are more subject-dependent, but the changes in the upper shoe structure seem to be more subject-independent (Onodera et al., 2017). A smart exercise mat unobtrusively recognizes which exercise the subject is performing and counts the number of repetitions. It is soft, cheap, and smart, and it has an accuracy like pedometers when it comes to monitoring strength-related exercises performed on the ground. This is a great alternative to the exercise mats athletes commonly use in the gym (Sundholm et al., 2014).

SG systems in sports applications are diverse, performing data engineering (Johnson et al., 2021) and data labeling (Cronin et al., 2019), evaluating the role of the shoe structure on running biomechanics (Onodera et al., 2017), monitoring fatigue to prevent injury (Russell et al., 2021), (Zhang J. et al., 2014), counting steps (Kang et al., 2018), assessing physical autonomy and functional ability (Khan et al., 2015), articulating real-time control of an electrical muscle stimulation (EMS) device for sports training (Hassan et al., 2017), predicting and preventing injury (Taborri et al., 2021), achieving multi-player tracking, identification, and re-identification (Zhang R. et al., 2020), classifying and counting different sports activities (Sundholm et al., 2014), and recognizing and analyzing sports behavior (Guo and Wang, 2021).

Researchers voice concern over the validity of the laboratory setting-based AI models versus real-world scenario-based models in sports. CNN and LSTM perform better than SVM (previously suggested in the literature) in the football shot and pass detection task in three scenarios closer to the real-world setting. The integrity of the collected data, selected features, and evaluation method must be reconsidered once AI systems are deployed in the real world (Stoeve et al., 2021). Estimating kinematic data (that would usually be collected in a lab, using force plates) from kinetic data that is easily measured in the field using IMU sensors is the focus of the study by (Johnson et al., 2021). Further studies will be needed to translate the research done in the lab to systems that can reliably and accurately deploy in their practical, real-world setting, especially for time-sensitive applications such as preventing sports injury in near real-time after detecting a potentially harmful event. Additionally, an area of potential growth in the future will be the application of sports monitoring, injury prevention, and training optimization for people with disabilities (Rum et al., 2021).

4.3 Fall Detection and Human Activity Recognition

Gait analysis is beneficial in monitoring the activities of daily living (ADL) in the elderly to improve the quality of their lives and health care in their homes and outside hospitals. HAR using wearables poses four main concerns, and often there are tradeoffs to navigate: 1) Energy considerations 2) Activity recognition accuracy 3) robustness over different users and different activities 4) user experience. These SG systems recognize several ADLs such as bending, squatting, walking, lying down, rolling out of bed, and the transitions between them to detect falls, minimize the false alarms on lying down versus falling events while trying to keep these systems low cost, automatic, adaptable, and unobtrusive. To the effect of the low-cost fall detection systems, (Ma et al., 2014b) propose to extract curvature scale space (CSS) features of human silhouette from video clips recorded with an inexpensive Kinect depth camera. They find that their Extreme Learning Machine (ELM) algorithm, combined with a variable-length PSO algorithm, performs no worse than state-of-the-art systems that depend on expensive, complex multi-camera systems. The performance of the algorithm is enhanced by using calibration techniques to address issues of misplaced or misaligned sensors (Yu et al., 2018). The detection time is essential for fall prevention systems, such that a control device has enough time to respond and prevent the fall (Mori et al., 2020). Researchers have been concerned with the false alarms in automatic fall detection systems, especially in activities such as lying in bed and falling. Chelli and Pätzold (2019) report 100% fall detection accuracy without any false alarms when implementing quadratic SVM and ensemble bagged tree (EBT) algorithms on acceleration and angular velocity data from two public datasets. In an earlier paper, Hakim et al. (2017) also reported near-flawless accuracies on their SVM classifier using smartphone data.

Gait data for these studies were collected from force sensors and three-axis accelerometers concealed under intelligent tiles (Daher et al., 2017), built-in smartphone IMU sensors (Hakim et al., 2017), wearable sEMG sensors (Xi et al., 2017), wearable motion sensors (Özdemir and Barshan, 2014), or from an integrated data collection system such as inertial sensor and Bluetooth nodes data captured on a smartphone (Santoyo-Ramón et al., 2018). Sensor data from both a smartwatch and a smartphone is shown to work better than either one individually (Weiss et al., 2019). The smart home prides itself in capturing data real-time and device-free, utilizing wi-fi enabled IoT platforms (Yang et al., 2018). Finally, radar data from continuous-wave radar systems can be used for activity recognition and fall detection providing an unobtrusive solution for data collection and posing no privacy concerns (Wu Q. et al., 2015), (Seyfioglu et al., 2018). CapSense sensing technology uses KEH capacitor voltage traces to recognize among five different activities with an accuracy of over 90% (Lan et al., 2017). In subsequent work, the accuracy was improved by using two capacitors, one in the sole of a shoe and one in front (Lan et al., 2020). The overall system energy usage was also reduced by 75% since the conventional machine learning algorithms such as NB or KNN used accumulated voltage data as input, reducing the computational load of the system. Future work will make these sensors fully self-powered and battery-free and address activity recognition accuracy and user experience issues.
Datasets: Royal Institute of Technology (KTH) (Jaouedi et al., 2020) and University of Central Florida (UCF) (Perera et al., 2019).

Low-cost, automatic activity recognition and fall detection accuracy, minimizing false alarms, thus providing accurate, flexible and versatile systems (see Taborri et al., 2021). Threshold Pedestrian Dead Reckoning (PDR) algorithm (Mathis et al., 2018) designed four schemes for indoor positioning. They found that WiFi Pseudo-Odometry integration with a combination of topology-constrained KNN and a multi-threshold Pedestrian Dead Reckoning (PDR) algorithm achieves higher accuracy with a smaller number of particles when a floor map is used. Other researchers (Tariq et al., 2017) found that RF performs best out of all the Weka ML collection algorithms using capacitive sensors for indoor person localization. Robertson et al. (2013) achieve SLAM using distortions of the local magnetic field. A foot-mounted sensor, for instance, can serve to localize a moving person or robot and generate a map of the indoor space while exploiting odometry. Low-cost 2D LiDAR has been recommended to preserve user’s privacy in human tracking (Hasan et al., 2020) (See Table 6).

### 5 TRACKING HUMAN POSE

Applications of gait analysis to indoor environments include indoor positioning and localization algorithms. Wang et al. (2015) designed four schemes for indoor positioning. They found that WiFi Pseudo-Odometry integration with a combination of topology-constrained KNN and a multi-threshold Pedestrian Dead Reckoning (PDR) algorithm achieves higher accuracy with a smaller number of particles when a floor map is used. Other researchers (Tariq et al., 2017) found that RF performs best out of all the Weka ML collection algorithms using capacitive sensors for indoor person localization. Robertson et al. (2013) achieve SLAM using distortions of the local magnetic field. A foot-mounted sensor, for instance, can serve to localize a moving person or robot and generate a map of the indoor space while exploiting odometry. Low-cost 2D LiDAR has been recommended to preserve user’s privacy in human tracking (Hasan et al., 2020) (See Table 6).

### 6 GAIT BASED BIOMETRICS

Gait is a soft biometric feature enabling the identification of people by their gait. The individuality of the gait pattern persists over time (Horst et al., 2017) and many pathologies. The main applications of gait recognition are person identification, person re-identification, person authentication, gender recognition, age estimation (Dindorf et al., 2020a), occupancy sensing (Yang et al., 2018), crowd density estimation (Zhou et al., 2018), crowd monitoring and anomaly detection for video surveillance applications (Sun et al., 2017), and multi-player tracking and identification (Zhang R. et al., 2020). We will look into the first four categories in more detail in sections 6.1 through 6.4.

### 6.1 Person Identification

Human identification is the process of determining an individual’s identity. Methods include but are not limited to those based on vision, identification cards, and biological data. Human gait-based identification is the process of determining an individual’s identity by their distinctive walking style. Person identification and re-identification through gait recognition have a growing importance in security systems and video surveillance in public spaces such as airports, banks, shopping malls, etc., since gait provides a non-invasive biometric feature. The task includes identifying a subject from a camera and matching him/her to persons in the other cameras with non-overlapping fields of view, an operation known as “tag-and-track” (Wu et al., 2015c). These gait recognition systems face challenges due to variable parameters that influence the size and quality of video and image inputs, such as camera viewpoint, lighting, occlusion, image resolution, and the subjects’ dressing and carrying conditions. For this reason, most papers we reviewed tried to address one or more of these difficulties by improving previously studied and implemented algorithms. To validate their work, authors conduct experiments to analyze the performance of their algorithms against benchmarks using public datasets. For instance, when CNN was first proposed for gait recognition (Wu et al., 2017), the authors evaluated their proposed algorithm on the CASIA-B (Yu et al., 2006), OU-ISIR (Iwama et al., 2012), and USF (Sarkar et al., 2005).

Most person identification SG systems deal with the case when gait data is extracted from video. These systems are model-based (Hu et al., 2012), (An et al., 2020), or appearance-based (Guan et al., 2012; Zhang W. et al., 2019), also called model-free. Gait Energy Image (GEI) is an average of all the human body silhouette images in one gait cycle (Han and Bhanu, 2005). It is widely used in appearance-based person identification algorithms because it allows for a simple representation of gait.

### Table 5

| Reference          | Algorithm            | Data Collection/Input                                      | AI Task/Output                                                                 |
|--------------------|----------------------|------------------------------------------------------------|---------------------------------------------------------------------------------|
| Taborri et al. (2021) | Linear SVM 96%       | N = 39, inertial sensors, and optoelectronic bars         | ACL risk prediction in female basketball players via LESS score                 |
| Johnson et al. (2021) | CNN, not enough accuracy | Wearable accelerometer                                     | predict near real-time GRF/Ms from kinematic data                               |
| Nguyen et al. (2020)   | CNN                  | 7 IMU’s                                                   | Gait classification: athlete vs. foot abnormalities                             |
| Guo and Wang, (2021)    | TS-DBN               | Public datasets of videos KTH and UCF                      | HAR/sports behavior recognition                                                 |
| Gholami et al. (2020)  | CNN                  | shoe-mounted accelerometer                                | Abnormal running kinematics Activity recognition                                |
| Cronin et al. (2019)   | DeepLabCut           | single GoPro camera                                        | Markerless 2D kinematic analysis of underwater running                         |
| Kang et al. (2018)     | FFT                  | Smartphone (unconstrained)                                | Detects walking, counts steps, irrespective of phone placement                 |
| Onodera et al. (2017)  | ANN with IG          | infrared cameras and force plates                         | Influence of shoe midsole resilience and upper structure on running kinematics and kinetics |
| Sundholm et al. (2014) | KNN with DTW          | pressure sensor mat                                        | Exercise detection and exercise count                                           |

Legend: Fast Fourier Transform (FFT), Time-Space Deep Belief Network (TS-DBN), Landing Error Score System (LESS), Ground Reaction Forces and Moments (GRF/M), DeepLabCut as in (Mathis et al., 2018).

Datasets: Royal Institute of Technology (KTH) (Jaouedi et al., 2020) and University of Central Florida (UCF) (Perera et al., 2019).
data, removing noise while preserving relevant gait information. It strikes a good balance between reducing computational cost and maintaining a good gait recognition rate. On the other hand, GEI is sensitive to appearance variations such as camera view angles and whether a subject is wearing a coat or carrying a bag, and it loses temporal information. There have been efforts to replace GEI with a representation that preserves more of the temporal gait information such as Chrono Gait Image (CGI) (Wang et al., 2011) or to fuse GEI features with temporal features (Liu et al., 2018). Chao et al. (2019) proposed GaitSet, which uses unordered sets of equally sized gait silhouettes as the input to a CNN architecture with set pooling, providing an effective way to preserve spatial and temporal information without the sequential constraints. Argued that not all body parts contain discriminative information for gait recognition tasks, and they proposed GaitPart, a part-based and micro-motion model that preserves spatial and temporal information without the sequential constraints. An et al. (2020) acknowledges the challenges of appearance-based models and proposes a pose-based model approach for gait recognition. The gait poses are

**TABLE 6 | Fall detection and human activity recognition.**

| Reference | AI Algorithm Best Achieved accuracy | Data Acquisition | Task |
|-----------|-------------------------------------|------------------|------|
| Chang et al. (2021) | HMM with OpenPose | Two cameras | Fall risk assessment. Evaluation of imbalanced gait |
| Shiori et al. (2021) | SVM, 79% | micro-Doppler radar | Classification of gait differences associated with fall risk |
| Lu et al. (2021b) | SOT, improved accuracy by 6% | Public HAR datasets UCI-DSADS, UCI-HAR, USC–HAD, PAMAP2 | Cross-domain HAR, utilizing transfer learning from auxiliary labeled data |
| Mori et al. (2020) | NN | 11 men, TW, induced disturbances | Predict falls caused by an unexpected disturbance in time for CD to deploy |
| Chelli and Pätzold, (2019) | ANN, KNN, QSVM, EBT, fall detection = 100%, false alarms = 0, ARA = 97.7% | Wearable sensors Public datasets (Anguita et al., 2013) and (Ojetola et al., 2015) that record falls, near-falls, and 7 ADL | Estimation of Gait Parameters for Elderly Care from 3D Pose |
| Kondragunta et al. (2019) | OpenPose for 2D pose estimation | Kinect images and sensor gait data from 250 subjects, 4 times, over 3 years | Continuous biometrics authentication and identification on smartphones or smartwatches. |
| Weiss et al. (2019) | RF, DT, KNN with K = 5, EER = 9.3 by RF, RF performs best in most of the sensor combinations | 51 subjects, 18 ADL. Smartphones in right pocket and smartwatch on the dominant hand | Wearable Fall Detection System |
| Santoyo-Ramón et al. (2018) | SVM, KNN, NB, DT, Error 14.162% by SVM. | Inertials. 19 subjects at home, 3 falls and 11 ADL | Own data. 200 fall events and 385 normal activities |
| Yang et al. (2018) | CSVD-NMF, 96.8% occupancy detection. 90.6% activity recognition | WIFI-enabled CSI measurements of 5 ADL | Device-Free Occupancy Sensing and activity recognition |
| Yu et al. (2018) | Gaussian HMM, Sensitivity of 0.992. Positive predictive value of 0.981 DOAC vs. CNN, SVM, AE. | Own data. 200 fall events and 385 normal activities | Fall detection system |
| Seyfoğlu et al. (2018) | ARA = 97.35% by GK-SVM, FD: sensitivity 98.70% and specificity 98.59% by GK-FDA. | micro-Doppler signatures | Radar-based activity recognition |
| Xi et al. (2017) | HCM-SFS on fused GFR and accelerometer data. ARA> 90% on all 5 ADL. | Force sensors and accelerometers under intelligent tiles. 6 subjects, 5 ADL | Automatic activity recognition and fall detection |
| Hakim et al. (2017) | SVM, NN, DT, DA. 99% by SVM. | Smart phone IMU. 8 healthy subjects, 4 fall events, 6 ADL | Fall detection and ADL recognition in independent living senior apartments |
| Gao et al. (2017) | SVM | WiFi CSI measurements | ADL recognition and threshold-based fall detection |
| Wu et al. (2015a) | Sparse BC+RVM. | 2 falling, 6 ADL. Spectrograms from continuous-wave radar smartphone | Device-free wireless localization and activity recognition |
| (Wannenburg and Malekian 2017) | KNN, kStar, HMM, SVM, DTC, RF, NB LR, ANN | 10 young subjects, intentionally falling, and 6 ADL | Radar-based Fall Detection |
| Ngo et al. (2015) | SVM, KNN | inertial sensor | Recognition for similar gait action classes |
| Semwal et al. (2015) | k-means and KNN ANN + PCA | vision and sensor-based gait data | Abnormal gait detection |
| Ma et al. (2014b) | Variable-length PSC+ELM, 91.15% sensitivity, 77.14% specificity, and 86.83% accuracy | 10 young subjects, intentionally falling, and 6 ADL | Shape-based fall detection that is invariant to human translation, rotation, scaling and action length |
| Özdemir and Barshan, (2014) | KNN, LSM Over 99% | Kinect depth camera | Automated fall detection system |
| (Mannini and Sabatini, 2012) | HMM | 14 subjects, 20 falls, 16 ADL, 6 wearable sensors | Gait phase detection and walking/jogging discrimination |

Legend: Quadratic SVM (QSVM), HCM (Histogram Comparison Method), Sequential Forward Selection (SFS), Least squares method (LSM), Gaussian Kernel Fisher Discriminant Analysis (GK-FDA), Non-Negative Matrix Factorization (NMF), Class Estimated Basis Space Singular Value Decomposition (CSVD), Equal Error Rate (EER), Relevance Vector Machine (RVM), Gaussian Kernel SVM (GK-SVM), Substructural Optimal Transport (SOT), Channel State Information (CSI). Datasets: UCI-DSADS (Anguita et al., 2012) UCI-HAR (Barshan and Yüksek, 2014), USC–HAD (Zhang and Sawchuk, 2012), PAMAP2 (Fleiss and Stricker, 2012).
TABLE 7 | Tracking human pose.

| Reference | AI Algorithm Best Achieved accuracy | Data Acquisition | Purpose |
|-----------|-------------------------------------|-----------------|---------|
| Vandersmissen et al. (2018) | Deep CNN. Error 21.54% | Low-power Radar. IDRad dataset made publicly available | Indoor PI invariant to the exact radar placement, room setup, and walking direction |
| Tatır et al. (2017) | Weka collection ML classifiers. 0.05 localization error. Accuracy > 93% | 4 Capacitive Sensors in load mode | Indoor Person Localization |
| Li et al., (2015) | Improved PDR algorithm The best achieved accuracy is within 2 m | Samsung Galaxy Note3 and Bluetooth beacons | PDR algorithm integrated with Bluetooth beacons for indoor positioning without additional infrastructure |
| Robertson et al. (2013) | MagSLAM Achieves a position accuracy of 9–22 cm | Foot mounted IMU sensors. Low-power radar device. No a priori map | Dynamic positioning (SLAM) of indoor pedestrians derives a multi-floor indoor map |

extracted from video using deep learning techniques AlphaPose (Fang et al., 2017) and OpenPose (Cao et al., 2017). Tracking the 3-D pose of walking pedestrians in video surveillance systems in cases where multiple people move together and cast a shadow or cause occlusion has also been attempted (Rogez et al., 2014).

Besides video, gait data can come from depth sensors, force plates, radar, Wi-Fi-enabled IoT devices, and IMU sensors. Radar-ID, a radar-based human identification algorithm (Cao et al., 2018), employs a CNN with architecture similar to that of AlexNet (Krizhevsky et al., 2012) to learn the necessary features from raw micro-Doppler spectrograms directly without a need to explicitly design the features. This algorithm has excellent anti-noise performance, and it can identify one person amid up to 20 other people. Similarly, Vandersmissen et al. (2018) use radar device data for indoor person identification and intruder detection. Costilla-Reyes et al. (2019) propose a footstep recognition system that can differentiate between the legitimate users (clients) and the impostor users of a biometric system from sensors on the floor. Biometric recognition by gait makes it possible to identify intruders since gait is difficult to fake. Deep CNN architectures that utilize footstep representations extracted from GRFs serve as automatic continuous person identification and verification systems with applications in security and anomaly detection at airports, workplace environments, and smart homes.

Zhong and Deng (2014) propose a gait representation using accelerometer and gyroscope data invariant to sensor orientation. Haque et al. (2016) present a method for human identification when given only depth images. Zou et al. (2018) propose Auto-ID, a human identification system that collects CSI measurements data from WiFi-enabled IoT devices referred to as shapelet “signatures” of human identification. Yang et al. (2018) also use the CSI curve of the human body for occupancy sensing and activity recognition. This system is good for anomaly detection, such as identifying intruders in a smart home automatically. A person walking in a smart space equipped with RFID devices affects the radio frequency (RF) signals. The effect can be captured by Received Signal Strength Indicator (RSSI) and the phase of the RF signal and then used for person identification. A system that employs TSNet, a tag selection deep reinforcement learning algorithm, PCA for feature reduction, and an attention-based LSTM algorithm performs RFID-based gait recognition that can easily be integrated into a smart home or smart office environment (Luo et al., 2020).

Person identification studies have benefitted from the developments in computer vision, established benchmarks, and public datasets. The code proposed in the studies is often made public, encouraging continued and collaborative research (Chao et al., 2019). Recent studies employ deep learning approaches that extract gait representations directly from raw gait data and learn discriminative features for human identification (see Table 8).

6.2 Person Re-Identification

Human reidentification is the task of identifying images of the same person from non-overlapping camera views at different times and locations. A re-identification problem has three major components: identifying which human parts should be compared, constructing invariant features to represent those parts, and computing an appropriate similarity metric between them. (Saghafi et al., 2014). SG as a soft biometric feature allows continuous tracking and behavior analysis of a person over a large camera network for forensics, surveillance, and security applications. Traditional ReID methods usually focused on building robust feature representations of the gait and estimated the similarity between a probe and gallery image by calculating their Euclidian distances. This method faces challenges in cross-view and cross-walking conditions, such as when the gait pair is in different camera viewpoints and carrying and dressing conditions (Wu et al., 2017). Wu et al. (2015c) proposed that current classifiers be enhanced with a combination of Pose Prior (PP) algorithm and subject-discriminative feature selection algorithm to construct a view-invariant ReID system.

One solution is to view the ReID task as a link probability prediction problem where each person represents an instance node in a graph structure. The ReID algorithm computes the likelihood of the link between the two (Liu H. et al., 2021). Another solution, suggested by Chtourou et al. (2021), includes an offline and an online phase. During the offline phase, an optimized GEI feature representation is constructed combining a dynamic selection of most relevant parts and a transformation of the probe or the gallery image, so the two of them have the same view before a matching score is calculated. This offline phase serves to train the Part View Transformation Model (PVTM), which will be used online to transform the gallery image to the same view as the probe image before classification.

ReID algorithms involve feature learning and metric learning. They learn gait features attributable to a person and then learn a similarity measure which should be greater if a gait pair belongs to different people than when it belongs to the same person. Song et al. (2018) introduced binary segmentation masks and region-
level contrastive learning. Joint feature learning and similarity measure learning have also been attempted to perform both tasks well. The algorithm simultaneously extracts local convolutional features and enhances the discrimination capability by focusing only on distinct regions when looking for similarities between videos. It jointly learns features and similarity values for a pair or triplet of values (Wu L. et al., 2019). A deep Siamese attention mechanism can learn spatiotemporal representations and similarity metrics and learn to discriminate which local spatial representations are relevant (Wu L. et al., 2019). With large datasets of gait images, one faces the issue of multiple pedestrians having similar appearances. Chen et al. (2015) observed that the similarity metric was larger for images of the same pedestrian than for two different pedestrians Multiple deep metric learning utilizing multiple stacked auto-encoder networks and classification networks has been used to characterize different pedestrian images belonging to the same person based on multiple similarity probabilities (Xiong et al., 2019). These deep learning networks have integrated the feature learning and dissimilarity learning tasks of the traditional ReID systems into a unified deep neural network that learns representations robust to variations in image quality, background clutter, camera viewpoint and subjects’ carrying and dressing conditions directly from raw gait images at pixel level. (See Table 9)

### 6.3 Person Authentication

Proper authentication includes user authentication: whether the user has authorized access, and person identification: who the current user is (Liang et al., 2020). Sensor-based user authentication uses biological features categorized in physical, physiological, and behavioral (Hernández-Álvarez et al., 2021). Gait provides behavioral biometric-based authentication, which by comparison with knowledge-based (passwords, personal identification number (PIN)) and physiological biometric-
based (face recognition, fingerprint) is unobtrusive, continuous, less prone to attacks, and easily tracked through wearable devices, videos, and smartphones in the context of IoT environments. Gait-based authentication is studied either by itself (Qin et al., 2018) or as part of an authentication system that uses multiple modalities (Hirn et al., 2019) (Acien et al., 2019) (See Table 10). Authors (Acien et al., 2019) showed that the fusion with behavioral data improves the authentication system results.

6.4 Gender Recognition
SG performs gender recognition reliably and unobtrusively (See Table 11). The gender classification task is usually conducted alongside human identification, and human re-identification tasks (Lu et al., 2014) since a person’s gender can serve as a soft feature in identifying a person. For instance, gender classification is done first to prune a subset of subjects before human identification is performed (Castro et al., 2017), (Meena and Sarawadekar, 2020). Gender classification is also done first to improve the accuracy of a subsequent age estimation algorithm (Zhang et al., 2019). Gender and age classification, in certain commercial and electronic consumer applications specifically, can be sufficient to enhance user experience (Duan et al., 2018).

The authors have explored different input features for this task. Joint Swing Energy (JSE) is a static feature extracted from the skeleton, namely the distance of the body joints from anatomical planes. It can be easily extracted from gait data and performs well with various classifiers to recognize someone’s gender (Kwon and Lee, 2021). Histogram of Gradient (HG) method reduces the three-dimensional (3D) accelerometer and gyroscope data from smartphones into 1D temporal descriptors, used as input for a bootstrapped DT algorithm (Jain and Kanhangad, 2018). Small walking speed variations do not affect the classification accuracy, but larger variations do, suggesting that spatial features are probably better suited for gender recognition tasks using conventional classifiers. Authors (Wazzeh et al., 2019) suggested that extracting features that are invariant to walking speeds variations could improve the performance of their gender recognition algorithm. Castro et al. (2017) proposed a CNN-based end-to-end approach that uses optical flow maps extracted from very low-resolution video to represent each person by their gait signature and recognize their gender and identity with high accuracy. A multi-task CNN setup, where the deep network learns multiple attributes simultaneously, improves the accuracy further (Zhang et al., 2019).

Some authors focus on recognizing gender from gait data when subjects walk in different directions (Lu et al., 2014), at different walking speeds (Jain and Kanhangad, 2018), carrying a bag, wearing a coat (El-Alfy and Binsaad, 2019), etc. SG for gender recognition is non-intrusive, does not require the subject to cooperate, and has better performance invariant to carrying and clothing conditions, even with the low-resolution quality of videos.

7 SMART GAIT DEVICES AND ENVIRONMENTS
This section reviews systems that incorporate ML, IoT, and advanced sensing and textile technologies for automatic, real-time gait data processing to perform an intelligent task with health, sports, entertainment, and security applications.

7.1 Smart Gait Devices
The domain of smart gait devices and environments is exciting, brave, creative, extensive, and ever-growing (See Table 12). SG devices include wearable shoes (Zou et al., 2020), socks (Zhang et al., 2020), knee pads and anklets (Totaro et al., 2017), insoles (Low et al., 2020), as well as devices attached to the body, such as smartphones (Poniszewska-Maranda et al., 2019), smartwatches (San-Segundo et al., 2018), (Sigcha et al., 2021), etc., implantable medical devices such as ActiGait (Sturma et al., 2019), wearable robotics (Shi et al., 2019) such as prosthetics (Gao et al., 2020) orthotics (Zhang et al., 2020e), (Choo et al., 2021), assistive devices such as smart walkers (Jimenez et al., 2018), and environmental devices such as smart tiles (Daher et al., 2017). SG devices use gait data to facilitate health monitoring, including passive mental health assessment (Rabbi et al., 2011) and transfer data to control devices for health, sports, security, and entertainment applications. For instance, UbiHeld (Ubiquitous Healthcare for Elderly) incorporates gait and other data from a smartphone as well as additional data from an inexpensive Kinect camera to keep a status of the overall health, location, and activities of the elderly at home (Ghose et al., 2013).

The requirements for soft smart wearable garments can be conflicting: stretchable, entirely conformable to the body, designed ergonomically and esthetically pleasing, small size and weight, flexible, washable, robust, unobtrusive, reliable, and durable (Yang and Yin, 2021). Person identification is an integral part of smart gait devices due to the need for customized user experience, which introduces the need to preserve users’ privacy. Additionally, continuous, seamless user authentication is vital to prevent malicious attacks on users’ medical records without the burden of frequently entering a personal identification number (PIN) (Xu et al., 2021). Finally, other requirements include water-proof capability, mechanical durability, and connectivity with other smart devices and environments depending on the specific use (Zou et al., 2020).

To accommodate these requirements, the main focus of the research is on sensing technology. Sensors for wearables are IMUs, capacitive sensors (Lan et al., 2020), KEH (Xu et al., 2017; Xu et al., 2018), (Ma et al., 2018), solar cells (Sandhu et al., 2021), resistive sensors, stretchable conductive micro fluids (Low et al., 2020), and TENGs (Zhang et al., 2020g).

There is generally a trade-off between the complexity of sensing technology in smart gait devices and the accuracy of the intelligent task they perform (Khademi et al., 2019). Depending on the task and granted sufficient accuracy, one can stop the chase for performance and focus on patient comfort (Di Nardo et al., 2020). A multi-object optimization (MOO) technique is implemented (Khademi et al., 2019) to navigate this trade-off: it selects an optimal feature subset that maximizes accuracy while minimizing sensing hardware. Fusing different bio-signals in hBCI systems for gait applications improves classification accuracy and the number of control
TABLE 9 | Human Re-Identification.

| Reference                  | Dataset                                      | Proposed method for ReID |
|----------------------------|----------------------------------------------|--------------------------|
| Liu et al. (2021a)         | Market1501, DukeMTMC-reID and CUHK03         | PrGCN; Graph based method. Predicts the link probability of the node pair. |
| Chtourou et al. (2021)     | CASA-B                                       | PVfTM; Transforms gallery image to the same view as the probe and uses only most informative human gait parts. |
| Wu et al. (2019b)          | iLIDS-VID, PRID 2011, and MARS.              | Deep Siamese Attention Network. Joint learning of spatiotemporal features and similarity metrics. |
| Zhang et al. (2019c)       | PRID 2011, iLIDS-VID, and SDU-VID            | Multiple CNN networks. Compact appearance representation of selected frames rather than whole sequence. |
| Liu et al. (2019a)         | MARS and iLIDS-VID                           | D3DNet, Deep metric learning. |
| Xiong et al. (2019)        | VIPeR, CUHK01                                | Stacked Auto-Encoders. Deep metric learning of multiple similarity probabilities. |
| Song et al. (2018)         | MARS, Market-1501 and CUHK03                | MGCM; Binary segmentation mask and region-level triplet loss; Contrastive Learning. |
| Wang et al. (2018)         | VIPeR, PRID 450S, and CUHK01                 | Fine-tuned CNN with MCM; Metric learning of discrepancy matrix instead of characteristic vector. |
| Zhao et al. (2017)         | VIPeR, ETHZ, SAVT-SoftBio, and iLIDS MCTS    | KNN, SVM ReID by saliency learning and matching. |
| Wu et al. (2015c)          | VIPeR, ETHZ, SAVT-SoftBio, and iLIDS MCTS    | Improved RDC, RankSVM and PCCA by using pose priors, image rectification and online person-specific weights. |
| Chen et al. (2015)         | VIPeR, GRID, ILIDS MCTS, and CAVAR4REID      | RMLLC ReID as image retrieval task using relevance metric learning. |
| Tao et al. (2015)          | VIPeR and ETHZ                              | MCE-KISS Improved KISS metric learning by MCE and a smoothing technique. |
| Ma et al. (2014a)          | GRID and VIPeR                              | MTCMCL; multi-task learning. Designed multiple distance metrics. |
| Zheng et al. (2013)        | ETHZ, ILIDS MCTS, and VIPeR                 | Ensemble RDC model, Relative Distance Comparison Learning. |

TABLE 10 | Person authentication (PA).

| Reference                  | AI Algorithm                  | Dataset/Data Modality | Purpose                        |
|----------------------------|-------------------------------|-----------------------|--------------------------------|
| Zhang et al. (2020b)       | SVDD and PCA for illegal user detection, LSTM for PI | BrainRun dataset. Own dataset of gait and other behavioral features from smartphones, 100 subjects. | PI and illegal user detection. |
| Li et al. (2020)           | Two-stream CNN with SVM       | BrainRun dataset. Own dataset of gait and other behavioral features from smartphones, 100 subjects. |SCANet: Continuous PA, distinguishes legitimate vs impostor users. |
| (Zhang et al., 2021b)      | Multi-layer LSTM and Extreme Value Statistic | ZJU-GatAcc, 3D accelerations from smartphones | PI and PA of the learned user, reject unauthorized user. |
| (Wu et al., 2018; Hintze et al., 2019) | Deep CNN | Own IDRad Dataset: micro-Doppler signatures, 5 subjects | Multisensor PA, HAR. |
| Vandervissen et al. (2018) | Semi-supervised ML, Isolation Forest | Tracking current vs. known usage of the device and motion sensor data from phone | Automatic intruder detection, indoor PI. |
| Joqueria Valero et al. (2018) | Dense clockwork RNN | HMOG, Google Abacus Dataset: time series of inertial measurements | Adaptive and continuous PA system, anomaly detection distinguishes legitimate vs impostor users. |

Legend: Probability Graph Convolutional Network (PrGCN), Dense 3D-Convolutional Network (D3DNet), Mask-guided Contrastive Attention Model (MGCM), Discrepancy Matrix and Metric Matrix (DMM), Relevance Metric Learning with Listwise Constraints (RMMLC), Minimum Classification Error (MCE) Keep it simple and straightforward (KISS) Metric Learning, Multi-task Maximally Collapsing Metric Learning (MTCMCL), Relative Distance Comparison (RDC), Support Vector Ranking (RankSVM), Pairwise Constrained Component Analysis (PCCA). Datasets: VIPeR (Gray and Tao, 2008), CUHK01 (Li et al., 2012), iLIDS-VID (Wang et al., 2014), PRID 2011 (Hirzer et al., 2011), and MARS (Zheng et al., 2016), SDU-VID (Liu et al., 2015), Market1501 (Felzenszwalb et al., 2008; Zheng et al., 2013), DukeMTMC-reID (NIST, 2016), CUHK03 (Li et al., 2014), PRID 450S (Roth et al., 2014), GRID (Loy et al., 2009), iLIDS MCTS (Zheng et al., 2009), and CAVAR4REID (Cheng et al., 2011). ETHZ (Schwartz and Davis, 2009), SAVT-SoftBio (Blaikowski et al., 2012).

commands. Still, it introduces the problem of channel configuration, information transfer rate, and temporal synchronization between the modalities (Khan et al., 2021).

SG devices will be an integral part of smart cities, smart buildings, smart homes, smart transportation, smart factories, energy grids, and e-Healthcare and are poised for tremendous growth in the future as IoT in the 5G framework will facilitate better and faster inter-connectivity between the devices (Chettiri and Bera, 2019), end-to-end deep learning algorithms will provide real-time intelligence, and sensing technology will be embedded more comfortably into our everyday objects and clothing.

7.2 Smart Homes
A smart home environment is defined as one that acquires and applies knowledge about its residents and their physical surroundings to improve their experience in that setting (See Table 13). The smart home sensors, the wearable sensors, and the classifying algorithms in the CASAS smart home (Cook et al., 2015) serve to perform health monitoring, early detection of...
TABLE 11 | Gender recognition (GR).

| Reference                     | AI Algorithm Best Achieved accuracy | Dataset/Input features                                                                 | Task                        |
|-------------------------------|-------------------------------------|----------------------------------------------------------------------------------------|-----------------------------|
| Kwon and Lee (2021)           | KNN, SVM, NB, DT, 100% multi-task CNN, AE; MAE = 5.47, GR: 98.1%                        | UPCVgaikK1, UPCVgaikK2                                                                 | GR and AE                   |
| Zhang et al. (2019b)          | Bootstrap DT 94.44%                  | 1D HG extracted from Smartphone in the front pocket                                      | GR                          |
| El-Alfy and Binsaadoon, (2019)| 1D CNN F:77%, M:96%                  | TUM-GAID: extracted from low-resolution video streams recorded with MS Kinect            | automatic PI and GR         |
| Jain and Kanhangad, (2018)    | Bootstrap DT 94.44%                  | Own dataset: DSCAWD USF and CASIA-B C-AGI instead of GEI from MS Kinect                  | PI and GR                   |
| Castro et al. (2017)          | CNN F.77%, M.96%                     | Own dataset: DSCAWD USF and CASIA-B C-AGI instead of GEI from MS Kinect                  | PI and GR                   |
| Lu et al. (2014)              | AP clustering + SRML PI: 87.6%       | Own dataset: DSCAWD USF and CASIA-B C-AGI instead of GEI from MS Kinect                  | PI and GR                   |
| Sandhu et al. (2021)          | Bootstrap DT 94.44%                  | 1D HG extracted from Smartphone in the front pocket                                      | GR                          |

Legend: Sparse Reconstruction-based Metric Learning (SRML), Cluster-based Averaged Gait Image (C-AGI), Affinity Propagation (AP), Optical Flow (OF), Person Identification (PI). Gender Recognition (GR), Age Estimation (AE), Fuzzy Local Binary Pattern (FLBP), Linear Kernel SVM (LK-SVM). Datasets: UPCVgaikK1 (Kastaniotis et al., 2013), UPCVgaikK2 (Kastaniotis et al., 2016), OULP-Age (Iwama et al., 2012), CASIA-B (Yu et al., 2006), TUM-GAID (Hofmann et al., 2014), USF Gender Recognition (GR), Age Estimation (AE), Fuzzy Local Binary Pattern (FLBP), Linear Kernel SVM (LK-SVM).

TABLE 12 | Smart gait devices.

| Reference                     | AI Algorithm | AI task                                      | Sensing Technology | Application                   |
|-------------------------------|--------------|----------------------------------------------|--------------------|--------------------------------|
| Yang and Yin (2021)           | LSTM with CAE| estimating joint torque for motion intent prediction | three soft pneumatic sensors two 3D IMUs | soft smart shoes               |
| Xu et al. (2021)              | attention-based LSTM RF | gait recognition while preserving privacy of users human activity recognition wrist-worn solar cell | KEH                | PriGait, a KEH-equipped wearable device SolAR, a solar self-powered wearable device |
| Sandhu et al. (2021)          | 1D CNN NB, RF, DT, KNN | gait and human activity recognition human activity recognition textile TENGs two capacitors and two transducers built-in motion sensors | built-in motion sensors | powered transfemoral prosthesis |
| Zhang et al. (2020g)          | RNN          | imitation learning for real-time prosthetic control classification of EMG signals to activate an event-driven controller | EMG sensors        | SAFE orthosis                  |
| Lan et al. (2020)             | RL           | assist-as-needed control for robot-assisted gait training | built-in motion sensors | SAFED-B, a KEH-equipped wearable device |
| Gao et al. (2020)             | DONN         | classification of EMG signals to activate an event-driven controller | EMG sensors        | mobile lower limb active orthosis |
| Zhang et al. (2020e)          | RL           | classification of EMG signals to activate an event-driven controller | EMG sensors        | mobile lower limb active orthosis |
| Liolerte-Vidrio et al. (2020) | DONN         | classification of EMG signals to activate an event-driven controller | EMG sensors        | mobile lower limb active orthosis |

Legend: Deep Differential Neural Networks (DNNN), Stevens Ankle-Foot Electromechanical (SAFE), Reinforcement Learning (RL).

disease, health care, and treatment. The smart home integrates wearable sensing technology, AI technology, and sensor fusion technology to automatically control home appliances via a gesture recognition algorithm, to turn lights on and off via an indoor positioning algorithm, and to set the alarm off via a fire detection algorithm (Hsu et al., 2017). With a focus on XAI, a numerical score of anomaly level is output on the monitor along with natural language explanations (Khodabandehloo et al., 2021). The privacy and security of health data are major concerns of smart homes. With the recent advancements in blockchain technology and its wider acceptance, a possible solution is to build smart blockchain networks to securely store and share health data (Taralunga and Florea, 2021) (Cernian et al., 2020). Of interest in this discussion is the project HABITAT (Home Assistance Based on the Internet of Things for the Autonomy of Everybody) that had only four key AI applications at the time this paper was written: an indoor localization system, smart armchair, smart belt, and a wall panel and mobile devices as the user interface (Borelli et al., 2019). The smart home embeds smart objects into objects of everyday life. The belt, which assesses body movement, is of interest to this study since it captures postural transitions and gait biometric data. The AI modules follow the Event Calculus (EC) modelling approach, which makes it easy to define the properties of the system. The system is expandable, more smart devices can be incorporated into it, and is an example of what is possible when activities and objects of our daily lives become “smart.” In summary, AI algorithms take care of the “smart” part of the home. Instead of being a passive recipient of care, the patient becomes an active agent of an intelligent health ecosystem (Najafi and Mishra, 2021). SG extends beyond the context of smart home and will play a major role in the future smart cities (Lozano Domínguez and Mateo Sanguino Tde, 2021), smart factories (Pech et al., 2021), smart retail stores (Zhang et al., 2019a), smart rehabilitation labs (Sessoms et al., 2015), and smart devices (Lozano Domínguez and Mateo Sanguino Tde, 2021).
TABLE 13 | Smart home applications.

| Reference       | AI Algorithm | Data Acquisition                                                                 | Purpose                                                                                     |
|-----------------|--------------|----------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------|
| Borelli et al.  | AI algorithms are built into smart objects. The smart armchair and the smart belt perform activity recognition algorithms. The wall light sends input to a fall detection algorithm. | Wall light for indoor localization. Armchair for sitting posture monitoring. The belt for movement information. The wall panel and mobile devices are the user interface. | This paper provides a complete description of the HABITAT project regarding methodology, architecture, design, and smart objects development. |
| (2019)          |              |                                                                                 |                                              | Design and implementation of a smart home system that integrates wearable intelligent technology, artificial intelligence, and sensor fusion technology to complete these tasks: Automated household appliance control. Smart energy management. |
| Hsu et al.      | 3D gesture recognition: 95.3% using PNN and 10-fold CV. Pedestrian navigation: distance and positioning accuracies were 0.22 and 3.36% of the total distance traveled in the indoor environment. Home safety and fire detection: classification rate 98.81%. | Wearable IMU on wrist tracks hand gesture and on feet walking data and energy management Environmental sensors. Experimental smart home testbed. Web camera. Multisensory circuit module for home safety and fire detection. | In home health monitoring for early detection of changes associated with PD and MCI and evaluation of treatment. |
| (2017)          |              |                                                                                 |                                              |                                                                                                     |
| Cock et al.     | PNN, DTW, SVM, LDA, PDR, PCA-PNN. DT, NBC, RF, SVM, AdaDT, AdaRF are tried out, and AdaDT provides the best classification accuracy. PCA is used to reduce features k-Means clustering and random resampling are used to add features in smaller (individual activities) datasets. | Fire detection and home safety. CASAS smart home and wearable sensors. Analysis 1: N = 75 PD = 25 HC = 50. Analysis 2: N = 52, PD ann No MCI = 16, PD with MCI = 9, HC = 18, MCI and no PD = 9. Subjects perform IADL tasks in a CASAS smart home testbed. |                                                                                                     |
| (2015)          |              |                                                                                 |                                              |                                                                                                     |

Legend: Pseudo-odometry (P-O), Adaptive Boosting (Ada), Probabilistic Neural Network (PNN), Mild Cognitive Impairment (MCI), Instrumental ADLs (IADLs), Dynamic Bayesian Network (DBN).

8 ANIMATION AND VIRTUAL ENVIRONMENTS

For this review, we consider studies requiring and using gait data and implementing an ML algorithm to create animated characters for movies, video games, and virtual reality environments. These studies include research in gait modeling, motion reconstruction, and character control. (See Table 14)

In Virtual Reality (VR) applications, the virtual character is controlled real-time by the user’s behavior. The task of the AI algorithm is to correctly recognize the user’s gait phases, with no delay, for a good real-time visual representation of the avatar’s motion. In video games, deep reinforcement learning is the algorithm of choice where the policy controls the action at each step. The policy is defined carefully to positively reward the desired action at each step, such as maintaining balance, tracking pose and orientation, alignment, mimicking the reference motion, surviving perturbations, and negatively rewarding actions such as falls. The avatars must be real-looking, preserving both the motion extracted from the skeleton features and the shape (Loper et al., 2014), (Huang et al., 2015).

Responsiveness to user demand, quality of visual representation, robustness to different walking styles and terrains, system runtime performance, adaptation to disturbances, maintaining balance, and retargeting to different morphologies are some of the key goals of these systems. Usually, motion data is extracted from expensive high-quality multi-camera motion capture systems. Authors have studied the possibility of retrieving high-quality representations from low-cost video clips recorded with pervasive monocular videos such as YouTube clips (Peng et al., 2018b) and reconstructing human pose from inertial measurements, in the case when direct-line-of-sight camera recording is not available due to occlusion for instance (Huang et al., 2018).

9 DISCUSSION AND FUTURE TRENDS

In this study, we reviewed different applications of the smart gait with a focus on the various tasks artificial intelligence algorithms perform across many industries and disciplines, such as health and wellness, security, forensics, and energy management. We further identify four emerging trends in the SG research: 1) population-scale health data will be available and empower end-to-end automatic, ubiquitous, and continuous deep learning approaches for big data-driven intelligent systems, 2) Fast-growing innovations in other technologies such as cloud computing, smart textiles, blockchain, and 5G will offer new opportunities and pose new challenges for SG systems and demand fast congruent growth, 3) SG systems will need to address concerns about user privacy, safety, comfort, and experience captured by the paradigm, “human-in-the-loop” (Sedighi Maman et al., 2020); these will be enforced by human rights advocates and regulatory bodies, and 4) the need for AI in health applications to benefit from the fast, low-cost, and accuracy of “black box” intelligent systems while still being transparent and understandable, as captured by the paradigm of XAI. SG is a valuable tool in kinetic and kinematic analysis, disease monitoring, diagnosis, and rehabilitation, sports performance, fall risk assessment, detection and prevention, gait-based biometrics for person identification, re-identification and continuous automatic authentication, age and gender recognition, physical skill and mobility assessment, fitness tracking, gait modeling and simulation, crowd monitoring and anomaly detection, human pose estimation, indoor tracking, and localization. SG is often integrated with other smart systems that...
TABLE 14 | Animation and virtual environments.

| Reference                  | AI Algorithm/Characteristics                                                                 | Data Acquisition/Inputs                                                                 | Task                                      |
|----------------------------|---------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|-------------------------------------------|
| Feigl et al. (2020)        | THIR, COR, SVM and BiLSTM, tested - COR has the best accuracy for real-time VR applications (low delay) | N = 6, head-mounted accelerometer data                                                    | Motion reconstruction                     |
| Bergamin et al. (2019)     | DiReCon: motion matching and deep RL - responsive to user demands, natural-looking. Trained on flat terrain | Unstructured motion data from mocap                                                        | Real-time physics-based character control for video games |
| Peng et al. (2018b)        | OpenPose/HMR and DRL - Learning from inexpensive video clips, robust                       | Simulated character model and YouTube video clip                                          | Learning dynamic physics-based character controllers from video clips |
| Peng et al. (2018a)        | DeepMimic: DRL - Diverse skills/terrains/morphologies, realistic response to perturbations    | Character model, kinematic reference motion from video clip                                | Physics-based character controllers from video clips |
| Huang et al. (2018)        | SMPL body model and BiLSTM - Useful when camera-based data is not available due to occlusion, fast motion, etc | 6 IMUs                                                                                   | 3D human pose reconstruction from a sparse set of IMUs |
| Holden et al. (2016)       | CAE - Capable of fixing corrupt data, filling in missing data, motion interpolation along the manifold, and motion comparison | CMU Motion Capture Database ³                                                                | Unsupervised learning of a human motion manifold |
| Huang et al. (2015)        | SMG and part-based Laplacian deformation - Simultaneously captures both motion and appearance for video-like quality | Three 4DPC datasets ⁴                                                                    | A data-driven approach for animating 4DPC character models |
| Ding and Fan, (2015)       | Multilayer JGPMs/topologically constrained GPLVMs - diversity of walking styles, motion interpolation, reconstruction, and filtering | CMU Motion Capture Database + Simulated data                                               | Human gait modeling                        |
| Alvaraez-Alvarez et al. (2012) | FFSSM with automatic learning of the fuzzy KB by GA - Fuzzy states and transitions are still defined by experts, interpretable, generalizes well for each person’s gait | N = 20 Accelerometer attached to the belt                                                 | Human gait modeling                        |

Legend: Threshold Based Method (THIR), Pearson Correlation-based Method (COR), Data-Driven Responsive Control (DiReCon), Human Mesh Recovery (HMR), Deep Deterministic Policy Gradient (DDPG), Skinned Multi-Person Linear (SMPL), Joint Gait-Pose Manifolds (JGPMs), Fuzzy Finite State Machines (FFSM), Knowledge Base (KB).

Datasets: ³ http://mocap.cs.cmu.edu/⁴ http://cvssp.org/cvssp3d.

utilize biomedical signals such as electrocardiograms, body parameters such as temperature, blood pressure, respiration rate, energy expenditure, and heart rate, and environmental signals such as room temperature and humidity. SG is often part of a smart IoT framework embedded with sensors, monitoring devices, and AI-enabled actuators that are all connected and in continuous communication. SG is everywhere, in our smart devices, smart homes, classrooms, cars, stores, cities, and energy grids. Smart Gait research will continue to grow fast in the future and will benefit from advancements in other technologies such as sensors, blockchain, IoT, textiles, 5G, cloud computing, and big data. These new technologies will also pose new demands and offer new opportunities for smart gait research. SG research will continue to address user privacy issues, security of health data, patient comfort, worker safety in the workplace, enhanced user experience, fatigue monitoring and injury prevention in sports.

We also identify these three needs for the SG research community: 1) inter-disciplinarity 2) the need for SG to become an organized field of study with specific definitions and good practices in place, and 3) the need for open competition and collaboration. Looking into the future, digital technologies such as smartwatches, headbands, and smartphones will be exploited to collect population-wide scale data to facilitate health monitoring and early detection of various diseases. One aspect of such systems is the multimodality of the data (Frey et al., 2019), (Abeysekara et al., 2020). Their integrated approach will demand cross-disciplinary research and collaborations. The gait research teams will need to include experts across many disciplines. We see the collaborative culture becoming more prevalent in the future both, within the SG community and between the SG community and the larger research community across many fields. With the recent development of programming languages and the open research community around them on Github, Kaggle, and other online and app-based forums, it is possible and important that the Smart Gait research community is open and the datasets, AI code, and suggested strategies for improvement are available for future collaborative work. For instance, some authors have made the data and the ML toolbox public and available for other researchers (Baghdadi et al., 2021) and (Horst et al., 2019). Wherever such open and collaborative efforts have flourished in the past, the results have been outstanding. Computer vision studies have seen tremendous results by reducing the cost of entry to new research and encouraging collaboration and competition towards a goal. The authors of this paper are excited to see similar growth in the SG research community.

10 CONCLUSION

The utilization of AI in gait analysis is a growing field. In this paper, we refer to it as the Smart Gait. It is compellingly multi-disciplinary, drawing from cutting-edge research in multiple mathematical and
engineering fields, and it continues to welcome new approaches and new data-capturing methods. With the constant advances in wearable sensors technology, cloud computing, and new advances in ML, the progress is formidable. Coupled with the growing realization of real-world applications such as non-invasive person identification, person re-identification, intruder detection, medical diagnosis and treatment, advanced fall detection, etc., will keep the demand for new gait detection and analysis methods high and keep AI at the forefront of the research. The field should only grow and expand in scope over the next 10–15 years. From smart home devices to smart grids and smart cities, AI is here to stay, and it will become very pervasive. AI-driven gait-based systems will take the shape of a chair you sit on, shoes you wear, a mat you exercise on. The smart door of your home will open as it recognizes your walk via a continuous SG authentication system, and the phone will lock itself in the hands of the thief as the abnormal gait is recognized. A crowd density algorithm will warn you of high Covid-19 risk when you enter a store.

With the growing demand and promising results, accessibility remains a limitation. ML is a tool, and as such, it should be in the hands of those who need it; early detection of PD in the hands of the clinician, monitoring of treatment in the hands of the caregiver, occupancy sensing in the hands of a family who cares about energy management in their home, indoor tracking and localization in the hands of the police in your town police station, kinematic analysis in the hands of a competing athlete. For ML systems to be more accessible, the technology will need to become easy to understand and implement. It must become less expensive and more scalable. XAI is a trend that will continue. The experts in related fields and the general population will continue to become more AI savvy. In a not-too-distant future, knowing how to use an opensource Python library or write your line or two of code in R will be as common a task as writing an email today. With that will come privacy concerns, ethical concerns, and a need to adjust our laws and regulations as a society.

**AUTHOR CONTRIBUTIONS**

EH conducted the systematic review of the papers. I-HK helped with the review of the papers and the writing of the manuscript. ED planned the systematic review, helped with the review of the papers, and contributed to the writing.

**FUNDING**

The work has been supported by the California State University Small Faculty Grant.
Cao, Z., Simon, T., Wei, S.-E., and Sheikh, Y. (2017). A Machine Learning Approach to Detect Changes in Gait Parameters Following a Fatiguing Occupational Task. *Ergonomics* 61, 1116–1129. doi:10.1080/00140139.2018.1442936

Baker, R., Eskenazi, A., Benedetti, M. G., and Desloovere, K. (2016). Gait Analysis: Clinical Facts. *Eur. J. Phys. Rehabil. Med.* 52, 560–574.

Barbosa, I. B., Cristani, M., Del Bue, A., Bazzani, L., and Murino, V. (2012). A Machine Learning Approach to Detect Changes in Gait Parameters Using Body-Worn Sensor Units. *Computer J.* 57, 1649–1667. doi:10.1093/comjnl/bxt075

Bahlkem, A. N., Jamil, N., Palmer, J. A., Oubbi, S., and Chen, C. (2020). Brain Computer Interfaces for Improving the Quality of Life of Older Adults and Elderly Patients. *Front. Neurosci.* 14, 692. doi:10.3389/fnins.2020.00692

Bergamin, K., Clavet, S., Holden, D., and Forbes, J. R. (2019). DeCon: Data-Driven Responsive Control of Physics-Based Characters. *ACM Trans. Graph.* 38, 206. doi:10.1145/3355089.3356366

Bhattacharya, U., Mittal, T., Chandra, R., Randhavane, T., Bera, A., and Manocha, D. (2020). “Step Spatial Temporal Graph Convolutional Networks for Emotion Perception from Gait,” in Proceedings of the AAAI Conference on Artificial Intelligence, 1342–1350.

Bialkowski, A., Denman, S., Sridharan, S., Fookes, C., and Lucey, P. (2012). “A Database for Person Re-identification in Multi-camera Surveillance Networks,” in 2012 International Conference on Digital Image Computing: Techniques and Applications (DICTA) (Fremantle, WA, Australia: IEEE), 1–8.

Bilgin, S. (2017). The Impact of Feature Extraction for the Classification of Amyotrophic Lateral Sclerosis Among Neurodegenerative Diseases and Healthy Subjects. *Biomed. Signal Process. Control* 31, 288–294. doi:10.1016/j.bspc.2016.08.016

Bin Tariq, O., Lazarescu, M. T., Iqbal, J., and Lavagno, L. (2017). Performance of Machine Learning Classifiers for Indoor Person Localization with Capacitive Sensors. *IEEE Access* 5, 12913–12926. doi:10.1109/access.2017.27221538

Borelli, E., Paolini, G., Antoniazzi, F., Barbiroli, M., Benassi, F., Chesani, F., et al. (2019). HABITAT: An IoT Solution for Independent Elderly. *Sensors* (Basel) 19, 1258. doi:10.3390/s19051258

Bossard, L., Guillaumin, M., and Van Gool, L. (2013). “Event Recognition in Photo Collections with a Смотрежков Time MM,” in Proceedings of the IEEE International Conference on Computer Vision, 1193–1200.

Bot, B. M., Sover, C., Neto, E. C., Kellen, M., Klein, A., Bare, C., et al. (2016). The mPower Study. Parkinson Disease mobile Data Collected Using ResearchKit. *Sci. Data* 3, 160011. doi:10.1038/sdata.2016.11

Burdack, J., Horst, F., Giesebelbach, S., Hassan, I., Daffner, S., and Schollhorn, W. I. (2019). Systematic Comparison of the Influence of Different Data Preprocessing Methods on the Classification of Gait Using Machine Learning. *arXiv preprint arXiv:1911.04335*.

Burdack, J., Horst, F., Giesebelbach, S., Hassan, I., Daffner, S., and Schollhorn, W. I. (2020). Systematic Comparison of the Influence of Different Data Preprocessing Methods on the Performance of Gait Classifications Using Machine Learning. *Front. Bioeng. Biotechnol.* 8, 260. doi:10.3389/fbioe.2020.00260

Cao, P., Xia, W., Ye, M., Zhang, J., and Zhou, J. (2018). Radar-ID: Human Identification Based on Radar micro-Doppler Signatures Using Deep Convolutional Neural Networks. *IET Radar, Sonar & Navigation* 12, 729–734. doi:10.1049/iet-rsn.2017.0511

Cao, Z., Zhu, C., Zhou, Y., Wang, Y., Chen, M., Ju, Y., et al. (2021). Risk Factors Related Balance Disorder for Patients with Dizziness/vertigo. *BMJ* 21, 186. doi:10.1136/bmj2021-0021887-00

Cao, Z., Simon, T., Wei, S.-E., and Sheikh, Y. (2017). “Realtime Multi-Person 2d Pose Estimation Using Part Affinity fields,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 7291–7299.

Castro, F. M., Marin-Jimenez, M. J., Guil, N., and De La Blanca, N. P. (2017). “Automatic Learning of Gait Signatures for People Identification,” in International Work-Conference on Artificial Neural Networks (Berlin, Germany: Springer), 257–270.
Zhang, H., Deng, K., Li, H., Albin, R. L., and Guan, Y. (2020a). Deep Learning Identifies Digital Biomarkers for Self-Reported Parkinson’s Disease. Patterns 1, 100040. doi:10.1016/j.patter.2020.100040
Zhang, H., Liu, J., Li, K., Tan, H., and Wang, G. (2020b). Gait Learning Based Authentication for Intelligent Things. IEEE Trans. Veh. Technol. 69, 4450–4459. doi:10.1109/tvt.2020.2977418
Zhang, J., Lockhart, T. E., and Soangra, R. (2014a). Classifying Lower Extremity Muscle Fatigue during Walking Using Machine Learning and Inertial Sensors. Ann. Biomed. Eng. 42, 600–612. doi:10.1007/s10439-013-0917-0
Zhang, L., Zhang, L., Tao, D., and Du, B. (2015). A Sparse and Discriminative Tensor to Vector Projection for Human Gait Feature Representation. Signal Process. 106, 245–252. doi:10.1016/j.sigpro.2014.08.005
Zhang, M., and Sawchuk, A. A. (2012). “USC-HAD: a Daily Activity Dataset for Ubiquitous Activity Recognition Using Wearable Sensors,” in Proceedings of the 2012 ACM conference on ubiquitous computing, 1036–1043.
Zhang, Q., Wang, D., Zhao, R., Deng, Y., and Yu, Y. (2019a). “ShopEye: Fusing RFID and Smartwatch for Multi-Relation Excavation in Physical Stores,” in Proceedings of the 24th International Conference on Intelligent User Interfaces (Marina del Ray, California: Association for Computing Machinery).
Zhang, R., Wu, L., Yang, Y., Wu, W., Chen, Y., and Xu, M. (2020c). Multi-camera Multi-Player Tracking with Deep Player Identification in Sports Video. Pattern Recognition 102, 107260. doi:10.1016/j.patcog.2020.107260
Zhang, S., Yang, W., and Li, A. (2019b). “Gait-based Age Estimation with Deep Convolutional Neural Network,” in 2019 International Conference on Biometrics (ICB), 1–8. doi:10.1109/ichb45723.2019.8987240
Zhang, W., Hu, S., Liu, K., and Zha, Z. (2019c). Learning Compact Appearance Representation for Video-Based Person Re-identification. IEEE Trans. Circuits Syst. Video Technol. 29, 2442–2452. doi:10.1109/tcsvt.2018.2865749
Zhang, Y., Pan, G., Jia, K., Lu, M., Wang, Y., and Wu, Z. (2014b). Accelerometer-based Gait Recognition by Sparse Representation of Signature Points with Clusters. IEEE Trans. Cybern 45, 1864–1875. doi:10.1109/TCYB.2014.2361287
Zhang, Y., Huang, Y., Yu, S., and Wang, L. (2020d). Cross-View Gait Recognition by Discriminative Feature Learning. IEEE Trans. Image Process. 29, 1001–1015. doi:10.1109/tip.2019.2926208
Zhang, Y., Li, S., Nolan, K. J., and Zanotto, D. (2020e). “Reinforcement Learning Assist-As-Needed Control for Robot Assisted Gait Training,” in 2020 8th IEEE RAS/EMBS International Conference for Biomedical Robotics and Biomechatronics (BioRob), 785–790.
Zhang, Z., He, T., Zhu, M., Sun, Z., Shi, Q., Zhu, J., et al. (2020f). Deep Learning-Enabled Triboelectric Smart Socks for IoT-Based Gait Analysis and VR Applications. npj Flexible Electronics 4, 1–12. doi:10.1038/s41528-020-00092-7
Zhang, Z. X., He, T. Y. Y., Zhu, M. L., Sun, Z. D., Shi, Q. F., Zhu, J. X., et al. (2020g). Deep Learning-Enabled Triboelectric Smart Socks for IoT-Based Gait Analysis and VR Applications. npj Flexible Electronics 4, 29. doi:10.1038/s41528-020-00092-7
Zhao, N., Zhang, Z., Wang, Y., Wang, J., Li, B., Zhu, T., et al. (2019). See Your Mental State from Your Walk: Recognizing Anxiety and Depression through Kinect-Recorded Gait Data. PLoS one 14, e0216591. doi:10.1371/journal.pone.0216591
Zhao, R., Oyang, W., and Wang, X. (2017). Person Re-identification by Salience Learning. IEEE Trans. Pattern Anal. Mach. Intell. 39, 356–370. doi:10.1109/tpami.2016.2544310
Zheng, L., Bie, Z., Sun, Y., Wang, J., Su, C., Wang, S., et al. (2016). “Mars: A Video Benchmark for Large-Scale Person Re-identification,” in European Conference on Computer Vision (Springer), 868–884.
Zheng, L., Shen, L., Tian, L., Wang, S., Wang, J., and Tian, Q. (2015). “Scalable Person Re-identification: A Benchmark,” in 2015 IEEE International Conference on Computer Vision (ICCV), 1116–1124.
Zheng, W.-S., Gong, S., and Xiang, T. (2009). “Associating Groups of People,” in British Machine Vision Conference, 1–11.
Zheng, Y., and Deng, Y. (2014). “Sensor Orientation Invariant mobile Gait Biometrics,” in IEEE International Joint Conference on Biometrics, 1–8.
Zhou, B., Song, B., Hassan, M. M., and Alamri, A. (2018). Multilinear Rank Support Tensor Machine for Crowd Density Estimation. Eng. Appl. Artif. Intelligence 72, 382–392. doi:10.1016/j.engappai.2018.04.011
Zhou, Y., Romijnders, R., Hansen, C., Campen, J. V., Maetzler, W., Hortobágyi, T., et al. (2020). The Detection of Age Groups by Dynamic Gait Outcomes Using Machine Learning Approaches. Sci. Rep. 10, 4426. doi:10.1038/s41598-020-61423-2
Zhu, Y., Xu, W., Luo, G., Wang, H., Yang, J., and Lu, W. (2020). Random Forest Enhancement Using Improved Artificial Fish Swarm for the Medial Knee Contact Force Prediction. Artif. intelligence Med. 103, 101811. doi:10.1016/j.artmed.2020.101811
Zou, H., Zhou, Y., Yang, J., Gu, W., Xie, L., and Spanos, C. J. (2018). “Wi-fi-based Human Identification via Convex Tensor Shapelet Learning,” in Thirty-Second AAAI Conference on Artificial Intelligence.
Zou, Y., Libanori, A., Xu, J., Nashalian, A., and Chen, J. (2020). Triboelectric Nanogenerator Enabled Smart Shoes for Wearable Electricity Generation. Research 2020, 7158953. doi:10.34133/2020/7158953

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher’s Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Copyright © 2022 Harris, Kho and Demircan. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.