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Artificial Intelligence in Human Gait and Sports Biomechanics: A Review of Methods and Applications and Future Directions

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Abstract

Sports biomechanics and human gait are crucial for understanding movement disorders, optimizing athletic performance, and preventing injuries. Conventional biomechanical analysis relies on laboratory-based tools, such as force plates and optical motion capture systems, which are costly and limited to controlled settings. Biomechanical assessment is now portable and real-time thanks to recent developments in wearable sensors and artificial intelligence (AI). The sensing modalities and AI techniques used in gait and sports biomechanics over the past 20 years are compiled in this review. Support vector machines, convolutional neural networks, long short-term memory networks, and other deep learning and classical machine learning techniques are covered. Highlighted are important application areas, including sports performance optimization, rehabilitation monitoring, injury risk prediction, and gait classification. The issues include sensor placement, inter-subject variability, and data scarcity. The key applications of these techniques, including gait analysis, injury risk assessment, rehabilitation analysis, and sports performance optimization, are presented. In addition, key challenges, such as data availability, subject variation, sensor location problems, and lack of generalizability, are mentioned. The upcoming trends, including sensor-minimal systems, digital twins for biomechanics, and explainable AI are presented.

Keywords: Human Gait, Sports Biomechanics, Wearable Sensors, Artificial Intelligence, Machine Learning, Deep learning.

1. Introduction

Gait analysis is a practical clinical and biomechanical procedure for assessing human locomotion patterns and diagnosing movement disorders. In sports biomechanics, movement and gait analysis are employed for studying motion effectiveness and fatigue, which could enhance athletic performance and prevent injuries [1]. The precise measurement of movement patterns helps sports practitioners in gaining quantitative information for well-informed decision-making in athletic performance training [2].

Conventional biomechanical analysis tools usually comprise optical motion analysis laboratory, force platforms, and surface electromyography signals (EMG). These tools are capable of providing very accurate kinesthetics and kinesthetics data, but the main drawback is that they are quite expensive, difficult to calibrate, and there are certain limitations in working environments as well [3]. Moreover, it has been considered that laboratory-based analysis might not be reflective of reality, especially in outdoor sports and activity analysis tasks.

Artificial intelligence (AI) and wearable sensor technologies have become viable substitutes for laboratory-based biomechanical systems over the last 20 years [4]. The use of wearable sensing technology facilitates real-time analysis of gait and motion under actual conditions. The purpose of this review is to present a structured synopsis of AI-based approaches that have been explored for human gait and sports biomechanics analysis [5].

The rising global incidence of neurological conditions such as stroke and Parkinson's disease, as well as sports injuries, requires a constant and objective monitoring of individual movement, independent of a hospital setting [6]. The big volume of high-frequency biomechanical information generated from the use of wearable sensor technology makes it very difficult to process this information using statistical analysis. The rising demand for objective information on movement has transformed the field of biomechanics from being descriptive to predictive, focusing on personalized models of movement, where AI technology is of paramount importance. There remains a challenge of standardized protocols during sensor placement, processing, and performance assessment [7].

2. Gap in Research

Although a considerable amount of progress has been made within the area of artificial intelligence-related gait and sport biomechanics, there remain several imperatives for improvement [8]. Primarily, a large number of models have generally underperformed in terms of their generalization ability on varied subjects, since the models have largely been trained on a homogeneous dataset and have a substantial deterioration in their accuracy when applied on a different person. Secondly, the models have largely emphasized the utilization of multiple sensors [9].

Third, while accuracy is high with deep learning techniques, most of these studies conduct offline analysis on existing datasets, while little attention is paid to real-time analysis on wearable/Embedded systems [10]. Fourth, the current state of technology is centered either on classification or estimation of parameters, while there are no personalized biomechanical digital twin systems with the ability to examine the motion behavior of each individual for prognosis, rehabilitation, and performance analysis [11]. Lastly, the existing black box of deep learning hinders clinical acceptance, since explanatory and interpretable artificial intelligence is not combined within gait and sports biomechanics systems [12].

2.1. Standardization of Data

The lack of standardized approaches to collecting, labelling, and exchanging biomechanical data used in the training of artificial intelligence has hindered the ability to produce reproducible models and compare results from different studies [13]. As a result, biomechanical data from different studies is often stored in different formats, with little to no standardization when it comes to the way it is collected and labelled [14]. For example, the difference between the motion capture systems used by Vicon (250 Hz) and Opti Track (120 Hz), as well as the number of kinematic markers used in the different protocols as 39 markers in the Plug-in Gait protocol compared to 22 markers in a sports-specific setup, and the differences in the way that each company's IMU accelerometers are calibrated, lead to a lack of interoperability among biomechanics researchers [15-19]. The majority of the biomechanical datasets used for training AI models are collected from either a laboratory-specific or a proprietary format, which creates a situation where models do not generalize, creating challenges when applying to heterogeneous populations and sports [20]. The implications of this lack of standardization are inflated accuracy claims and the inability to implement a federated learning model [21]. In the development of an AI Biomechanics Hub as a repository of open access, multi-sports databases, many researchers have proposed the inclusion of standard data sets, with 10,000 gait cycles per age group/gender, which is augmented with additional metadata containing details regarding environmental factors, surface type, type of footwear, for each gait cycle, which will conform to the International Society of Biomechanics (ISB) validated protocols [22]. To validate and relate new AI-Driven marker-less systems to the performance of Optoelectronic Systems, researchers must perform a rigorous benchmark to establish the validity of marker-less systems using random sampling of 250 randomly selected participants performing various dynamic sport-related tasks [23-25]. Unfortunately, most current validation protocols are inconsistent and occur in a random pattern. As an example, while many studies indicate planar joint angles between marker-less systems and their gold-standard counterpart, nearly every marker-less study indicates a complete breakdown of the marker-less system once three-dimensional multi-limb movement is introduced [26]. Thus, there exists an opportunity for longitudinal studies comparing hybrid marker-less and gold-standard marker systems under real-world sport conditions and measuring error propagation from kinetic estimates between the two.

2.2. Interpretability of the Model

The difficulty of interpreting a model, the high level of interpretability in black-box models such as CNNs and Transformers for Gait Anomaly Detection, is due to the opaque nature of the decision-making processes of these models [27]. For example, classifying ACL injury from stride kinematics cannot be traced back to specific biomechanical inputs, for example hip adductor movements or ground contact times [28-30]. Most dominant models use the approach of treating gait as an image-like stream of depth camera footage, achieving high AUCs but failing to meet the requirements for SHAP and LIME post-hoc explanations that clinicians need to develop trust in their models, especially when false positives could lead to unnecessary sitting of athletes [31-32]. Common pitfalls of these high-AUC models consist of saliency maps that highlight regions of the image with no relevance to the interpretation that the model produces. In the case of sports applications, models will likely fail to capture the temporal hierarchies present in the stance and swing phases of the gait cycle, as well as the biomechanical priors associated with particular athletic movements such as spike biomechanics in volleyball [33].

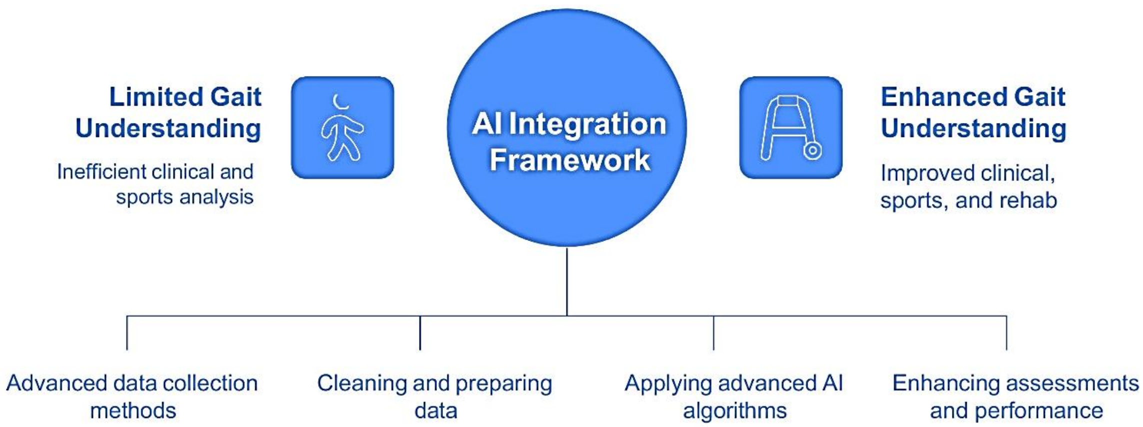

Figure 1: AI-Powered Gait and Biomechanics Analysis

Several researchers, consider developing XAI frameworks such as attention-based LSTMs that include biomechanical fidelity scores and have been evaluated on rehabilitation datasets to demonstrate the causative nature of the assessment and to establish the validity of this framework through clinician surveys indicating a >70% trust in the outcome of these assessments [34].

2.3. Real-World Validation

Real-world validation is necessary to test AI models in real-world settings such as outdoor training tracks, practices, and competitions. The impact of these environmental factors on the neural network is significant [35]. Numerous examples of successful applications of machine learning are stated in the literature, including 85% sensitivity of random forest models predicting reinjuries for hamstring strain through prior kinematic data [36-40]. However, these applications are limited by the lack of researcher-derived longitudinal tracking or longitudinal data. While athlete-specific baseline measures could have significantly improved reinjury prediction rates, the overall number of published studies of reinjuries is limited to small pilot studies [41]. On top of that, the vast majority of available literature is focused on individual sports and does not address the complexities of team dynamics and the constraints introduced by sports equipment [42]. A publishable study would look like a multi-site randomized control trails (RCT) deployed to collect data on 200 athletes over two seasons, quantify changes from lab to field, and incorporate contextual covariates using Bayesian networks to improve the accuracy of predictions [43].

2.4. Accessibility and Ethical Issues

All AI training data are biased towards elite, younger males; for example, 80% of AI datasets are made up of Caucasian runners, leading to lower levels of performance for diverse groups; for instance, elderly South Asian individuals experience a 25% reduction in their accuracy when using gaits [44]. Concerns around issues such as data privacy regarding the use of wearables and algorithmic discrimination regarding talent identification also remain unexamined [45]. Accessibility barriers for amateurs' slow adoption rates due to the relatively high cost of the motion capture lab and workflow barriers for average coaches, despite the use of AI dashboard technology [46]. Our research agenda is focused on directing equity audits that will assess the presence of bias in AI training data using fairness metrics as well as suggesting the development of mobile phone-based low-cost federated learning as a means to enhance equity & inclusion for participants around the world, and providing systematic resource pathways developed and tested in low-resource contexts [47].

2.5. Emerging Modalities

Real-world validation is necessary to test AI models in real-world settings such as outdoor training tracks, practices, and competitions. The impact of these environmental factors on neural networks is significant. Numerous examples of successful applications of machine learning are stated in the literature, including 85% sensitivity of random forest models predicting reinjuries for hamstring strain through prior kinematic data [48-50]. However, these applications are limited by the lack of researcher-derived longitudinal tracking or longitudinal data. While athlete-specific baseline measures could have significantly improved reinjury prediction rates, the overall number of published studies of reinjuries is limited to small pilot studies [51]. On top of that, the vast majority of available literature is focused on individual sports and does not address the complexities of team dynamics and the constraints introduced by sports equipment [52]. A publishable study would look like a multi-site RCT deployed to collect data on 200 athletes over two seasons, quantify changes from lab to field, and incorporate contextual covariates using Bayesian networks to improve the accuracy of predictions [53].

3. Materials and Methods

This review adopted a systematic literature analysis approach to identify, categorize, and synthesize research studies related to artificial intelligence applications in human gait and sports biomechanics. The review process was designed to ensure scientific rigor, transparency, and reproducibility. Relevant literature was collected from major scientific databases including IEEE Xplore, PubMed, Scopus, ScienceDirect, and Google Scholar. Keywords and Boolean search combinations such as artificial intelligence, machine learning, deep learning, gait analysis, biomechanics, sports performance, and motion analysis were used to ensure a comprehensive search. The search spanned publications, focusing on peer-reviewed journal articles, conference proceedings, and review papers written in English.

The selection process followed three main stages:

1. **Identification:** Screening titles and abstracts to identify AI-based studies in gait and sports biomechanics.
2. **Eligibility:** Evaluating full texts to include only studies involving computational modelling, data-driven techniques, or biomechanical performance optimization.
3. **Inclusion:** Categorizing the selected papers based on AI methods and their specific applications in gait assessment, injury prevention, performance analysis, and rehabilitation.

Data were extracted systematically from the selected studies, summarizing information such as dataset characteristics, AI techniques used, biomechanical parameters analyses, and key outcomes. The extracted data were then organized into thematic categories to identify existing research trends, methodological gaps, and emerging directions in the integration of AI and biomechanics.

3.1. Search Strategy

A literature search was conducted in scientific databases such as IEEE Xplore, PubMed, Scopus, and Web of Science. The articles considered for the literature search comprise those published between the years 2005 and 2025 [54]. The literature search has been conducted by using combinations of the following keywords:

1. Gait Analysis
2. Sports Biomechanics
3. Wearable Sensors
4. Artificial Intelligence
5. Machine Learning
6. Deep learning

The search was conducted only on journal articles and proceedings papers of international conferences, restricting to papers that focused on AI-based analysis of human gait patterns or sports biomechanics [55]. The search, to exclude papers unrelated to AI, human gait pattern analysis, or sports biomechanics, was first conducted at the title and abstract levels, leaving only their full texts to be screened [56].

3.2. Inclusion and Exclusion Criteria

Inclusion Criteria

1. Peer-reviewed articles in journals or conference proceedings that report experimental work.
2. Research studies with human participants, either in gait, sport performance, and/or rehabilitation settings.
3. Using inertial measurement units, pressure insoles, surface electromyography, or smart textiles [57].
4. Use of artificial intelligence and/or machine learning for gait classification, joint angle prediction, injury prediction, fatigue monitoring, and assessment of rehabilitation [58].
5. Comparison of results with gold standard systems, such as optical motion, force plates, or expert opinion.
6. Articles written in English, published from 2005 to 2025 [59].

Exclusion Criteria

1. Research conducted on non-human gait and sports biomechanics, simulation studies, or robotic mannequins.
2. Papers that do not use any artificial intelligence or machine learning analyses.
3. Theoretical articles that lack experimental support.
4. Hardware engineering studies of the design only, without implementation for gait or sports biomechanics [60].
5. Review articles, editorials, theses, book chapters, and non-peer-reviewed literature.
6. Research not related to gait analysis, sports biomechanics, and rehabilitation tracking [61].

4. Data Extraction

Extracted variables included study characteristics, sensing configuration, artificial intelligence methodology, and validation outcomes. Study characteristics include publication year, study objective, participant demographics, sample size, and experimental environment (laboratory or real-world) [62]. Details on sensing configuration include the type of wearable or laboratory system, the number and placement of sensors, sampling frequency, and measured biomechanical parameters

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such as space-time gait metrics, joint angles, and muscle activity [63-65]. Details on artificial intelligence methodology include feature extraction techniques, type of learning model used, including support vector machines, random forests, convolutional neural networks, long short-term memory networks, training strategy, and approach to performance evaluation [66]. Validation outcomes include measures of classification accuracy, regression error metrics, computational latency, and comparison against gold-standard systems such as optical motion capture or force plates. Limitations, challenges, and recommendations for future studies are also documented to facilitate identification of gaps in current research [67].

A total of approximately 120 papers were chosen to be reviewed extensively [68]. The papers were assessed, classified, and identified based on the technology being utilized, the method of artificial intelligence, the intended application, the level of performance, and the limitation clearly stated within each paper reviewed [69]. The data collected from the assessed papers were then presented through narrative and tabular forms to determine the prevailing trends, the shortfalls, and the research voids within the field [70].

Table1: Summary of Key Studies Applying Artificial Intelligence in Sports Biomechanics and Human Gait Analysis (2005-2025)

Author & Year	Study Type	Sensors/ Data	AI/ML Methods	Application/ Outcome	Key Findings	Gaps/ Limitations
Begg et al., 2005	Experimental	Force Plates, Optical motion capture	Support Vector Machine (SVM)	Automated gait classification (young vs elderly)	SVM achieved strong classification; better than NN in some feature combinations	Focus on age groups only; not broader pathologies
Begg & Kamruzzaman, 2005	Experimental	Motion Capture System	SVM classification	SVM used on temporal/kinetic/kinematic features	High classification accuracy; good generalization potential	Small sample; limited real-world conditions
Wu & Wang, 2006	Conference Research	Wearable accelerometer	Kernel methods related to ML	Pattern recognition of walking gait	Kernel methods improve classification vs simple classifiers	Conference; slightly outside the strict period
Bartlett, R. (2006)	Narrative Review	Video analysis, motion capture	Expert systems, Artificial Neural Networks (MLP, Kohonen SOM), evolutionary computation	Sports biomechanics technique analysis (throwing, kicking, performance optimization)	Demonstrated early use of AI for diagnosing movement faults, technique classification, and movement optimization; highlighted potential of AI in sports biomechanics	Lack of large-scale validation, limited real-time applications, absence of wearable sensor integration; pre-deep-learning era with low computational power
Wu et al. (2007)	Experimental	In-shoe pressure sensors	KPCA + SVM	Feature extraction & classification	KPCA improved classification vs PCA	Focus on binary groups; limited dataset
Gouwanda & Senanayake *(2008)*	Experimental	Wearable accelerometer (IMU)	Real-time force sensing mat (FSRs + DAQ)	Sports biomechanics & human gait GRF capture	Developed force sensing mat capable of real-time GRF capture with preliminary dataset, demonstrated feasibility	Limited spatial resolution, needs integration with motion/kinematic data for full gait kinematics, no ML analytics presented

Alaqtash et al., 2011	Experimental	Wireless IMU sensors	Fuzzy logic / Fuzzy computational algorithms	Gait analysis using wearable sensor data	Demonstrated sensor-based gait features classification using fuzzy techniques	Pre-deep learning; simpler classifier approaches
Muro-de-la-Herran et al., 2014	Review/ Method Overview	Wearables, Kinect depth cameras	Sensor systems with automated recognition	Overview of wearable & non-wearable gait systems	Summarizes state of gait recognition sensors and early classification methods	Not experimental individual dataset
Kargar et al., 2015	Experimental	Optical motion capture	SVM + Bag-of-Words on Kinect skeleton features	Gait classification for mobility assessment	SVM & feature models discriminate high/low fall risk gait	Small pilot sample; Kinect data limited
Robberechts et al., 2019	Experimental	Wearable IMUs, pressure insoles	Structured ML & RNN	Gait event detection	ML improved stance/time detection	Older dataset, limited sensors
Claudino et al., 2019	Systemic Review	GPS, IMUs, heart rate monitors	Artificial neural networks; decision tree classifier; support vector machines; Markov processes	Injury risk assessment and performance prediction in team sports	Identified prevalent AI applications and most used methods; soccer, basketball, handball, volleyball most studied	Heterogeneous datasets; need for prospective validation; few female athlete data
Chmait & Westerbeek, 2021	Perspective / Review	Wearable, athlete databases	Overview of AI/ML paradigms (supervised, unsupervised, reinforcement learning)	Introduction of AI/ML potential in sports research & analytics	Provided non-technical explanation of AI/ML concepts; surveyed applications and potential future trends in sports performance and business analytics	Not empirical; no original dataset; high-level rather than domain-specific detail
Dindorf et al., 2023	Bibliometric review	Public sports & biomechanics datasets	Bibliometric analysis of AI/ML/DL literature	Mapping trends and conceptual structure of AI in sports research	Exponential growth in AI research; identification of topic clusters such as biomechanics, injury prediction, and algorithms	Focused on bibliometric indicators, not original experimental data; possible database coverage limitations
Molavian et al., 2023	Systemic review	Wearable IMUs, EMG sensors	Neural networks, ML overview	Gait & sports biomechanics	AI handles high-dimensional data	Few large-scale real-world validations
Marimon et al., 2024	Original Research	IMU sensors	ML Feature extraction	Gait kinematics	Identified key features for clinical use	Limited real-world validation
Bauer et al., 2024	Original Research	Inertial sensor	Siamese network	Markerless gait analysis	Effective embedding for gait tasks	Large camera setup required
Benjaminse et al., 2024	Experimental	Optical motion capture, force plate	ML classification & regression models (SVM, nearest neighbor, ensemble, neural networks, PCA feature reduction)	Predicting knee joint loading (KAM) during agility tasks using kinematic data	Classification models could distinguish high vs low knee joint loads with good AUC (~0.81–0.85); regression less accurate for peak KAM prediction	Limited to female youth football; regression models had suboptimal accuracy; lab setting might differ from true field conditions
Ryoo et al., 2024	Experimental	Athlete Performance	XGBoost, Multilayer	Detecting potential doping suspicions via	Ensemble model achieved	Public dataset limitations; need

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		Passport competition and demographic databases	Perceptron (MLP), Ensemble model	performance passport analysis	good identification rates for sanctioned athletes; body weight and performance metrics were key predictive features	richer APP data and sport-specific extensions; varying performance trends across cohorts
Dashore et al., 2025	Experimental	Tennis motion capture	CNN-LSTM + LLM	Athletic action recognition	Better stroke classification + NLP feedback	Still experimental
Souaifi et al., 2025	Scoping Review	IMUs	Machine learning, deep learning, computer vision, Random Forest, CNN	Wearable tech & motion analysis for performance enhancement & injury prevention	CNNs reached ~94% agreement for technique assessment; Random Forest injury prediction ~85% accuracy; integrated AI systems reduced reinjuries by 23%	Inconsistent data standards; need for real-world validation and ethical/interpretability frameworks

(SVM= Support Vector Machine, AI= Artificial intelligence, ML= Machine Learning, SOM= Self-Organizing Map, MLP= Multi-Layer Perception, KPCA= Kernel Principal Component Analysis, PCA= Principal Component Analysis, FSR= Force-Sensing Resistor, DAQ= Data Acquisition, GRF= Ground Reaction Force' RNN= Recurrent Neural Network, DL= Deep Learning, IMU= Inertial measurement Unit, LSTM= Long Short-Term Memory, LLM= Large Language Model, NLP= Natural Language Model, CNN= Convolutional Neural Network)

This table summarizes key foundational and contemporary studies on artificial intelligence applications in human gait and sports biomechanics, spanning experimental work, narrative and systematic reviews, bibliometric mapping, and perspective articles. Across these studies, a wide range of sensing modalities is represented, including optical motion capture, force plates, in shoe pressure sensors, wearable IMUs, EMG, GPS, heart rate monitors, and large athlete databases, reflecting the progression from laboratory-based setups to more ecological, field deployable systems. The AI and ML methods applied range from early support vector machines, fuzzy logic, and expert systems to more recent deep learning architectures such as CNNs, LSTMs, Siamese networks, and ensemble models, targeting tasks such as gait classification, fall or injury risk assessment, joint load prediction, performance analysis, and even doping suspicion detection. Collectively, these works demonstrate that AI can achieve high accuracy in pattern recognition, event detection, and performance or risk stratification, yet they also reveal common limitations, including small or heterogeneous samples, constrained populations, laboratory rather than real world validation, and a persistent need for standardized datasets, interpretable models, and prospective, large-scale studies to confirm clinical and performance utility.

5. Results

The initial database search using the keywords human gait, sports biomechanics, wearable sensor, and artificial intelligence yielded over 1,200 records published between 2005 and 2025. After removing duplicates, non-relevant records, and low-quality sources, approximately 120 peer reviewed articles were retained for detailed narrative synthesis. These studies covered a broad range of experimental designs, sensing technologies, AI methods, and application domains, spanning both clinical gait analysis and sports performance contexts. The synthesized findings are organized below according to sensing technologies, artificial intelligence methods, application domains, performance metrics, and limitations reported across studies.[71].

5.1. Sensing Technologies

Early studies have depended primarily on systems based in the laboratory, such as optical motion capture and force plates, to assess gait and movement patterns. From around 2012, a growing popularity of wearable sensors has occurred, especially IMUs, which are portable, low-cost, and suitable for long-term and real-world monitoring. Smart insoles, pressure sensors, sEMG, and smart textiles have been used in recent years to capture detailed biomechanical parameters and allow for continuous monitoring both in rehabilitation and sports environments [72].

5.2. Artificial Intelligence Methods

Before 2018, classical machine learning algorithms such as SVM, kNN, and random forests had been widely used for gait classification, abnormality detection, and injury risk prediction [73]. Since then, the use of various deep learning methods has grown exponentially. For instance, spatial features can often be obtained through CNNs, while LSTM networks are effective in modelling the temporal dynamics of gait. Sensor fusion approaches, including techniques like Kalman filtering and AI-assisted multi-sensor integration, have also enhanced the accuracy of estimates for biomechanical parameters [74].

5.3. Application Domains

The reviewed literature mainly includes clinical gait analysis, rehabilitation, and sports performance analysis. Although earlier research addressed gait classification and fall risk analysis, more recent studies tend to focus more on sports-related issues such as fatigue analysis, injury prediction, and performance improvement [75]. There are wearable AI systems with real-time feedback, which enable changes to intervention and training sessions.

5.4. Performance Metrics

Laboratory gold-standard validation also indicates a high level of performance of many AI-assisted wearable systems. The classification accuracies vary from 85% to 97%, with error margins between 3° and 6° when it comes to joint angle and spatiotemporal parameter estimation [76]. Result evaluation also indicates a decrease in setup time and portability.

5.5. Limitations Reported across Studies

Despite the promising results, several recurring limitations were identified across the reviewed literature. Many systems still rely on multiple sensors or complex setups, which may reduce user comfort, increase cost, and complicate deployment in routine clinical or sporting environments. A substantial proportion of AI models were trained and evaluated on relatively small, homogeneous cohorts, leading to models that are often subject-specific or population specific and that generalize poorly to new subjects, different sports, or diverse real-world conditions. Furthermore, only a limited number of studies reported truly real time implementations outside laboratory settings, and the integration of explainable AI, digital twin paradigms, and robust domain adaptation methods remains in its infancy. These gaps suggest the need for larger and more diverse datasets, standardized evaluation protocols, interpretable modelling approaches, and long term prospective studies to verify the clinical and performance impact of AI driven gait and sports biomechanics systems [77].

6. Discussion

The review showcases the tremendous advancement that has occurred in the field of gait and sports biomechanics analysis using artificial intelligence in the past two decades [78]. Results clearly indicate the shift from lab-based biomechanics analysis systems towards wearable sensor-based systems based on advanced machine learning models [79]. Initial works concentrated more on the practicality of applying artificial neural networks as well as classical machine learning techniques to classify pathological gait patterns and recognize human movement [80]. These solutions depended greatly on manually designed features extracted from data regarding human movement acquired by means of Motion Capture and inertial sensors. Although these models functioned well within controlled laboratory settings, they were more subject-specific and lacked robustness when applied to real-world settings [81].

The advent of wearable inertial measurement units proved to be an important turning point within the field. Technology based on inertial measurement units led to the ability to continuously monitor outside the laboratory environment, thereby paving the way for the collection of large amounts of data in sports and rehabilitation settings [82]. This, however, was limited by the drift factor, battery life, and the level of complexity involved in the calibration process of the initial wearables [83].

The most recent five years have seen a paradigm shift in Deep Learning Architectures, specifically Convolutional Neural Networks and Long Short-Term Memory Networks [84]. They have shown to better learn the non-linear as well as temporal pattern of gait and thereby minimize feature engineering to a great extent. However, they are Laterally adopted due to the large datasets as well as computational power required [85].

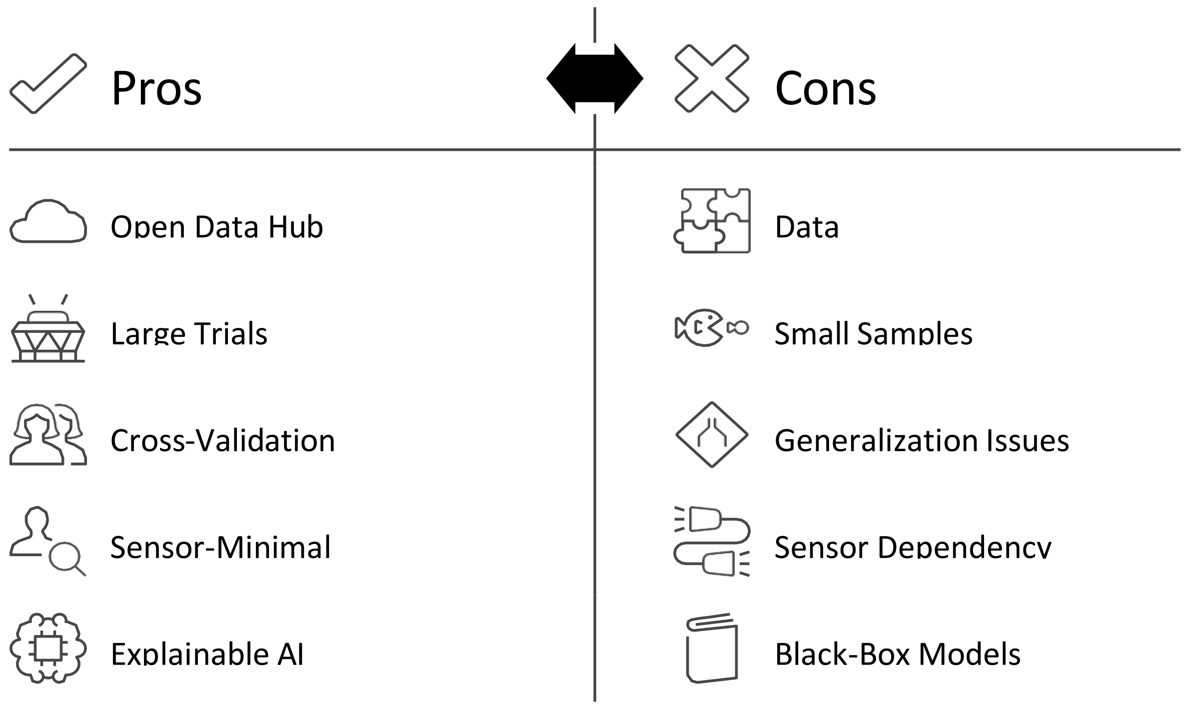

Figure 2: Pros and Cons of AI in Biomechanics

The other prominent emerging field is the fusion of multimodal sensors and digital twins. By integrating kinematic, kinetic, and bio-signal data, there have been improvements in the accuracy of the estimation of biomechanical variables and overall monitoring of athletes. However, very few research works have been conducted in the aspect of explainable AI, thus posing certain concerns over the explain ability and clinical validity of AI-based systems [86].

On the whole, although wearables based on AI technologies hold promise in real-time gait analysis, rehabilitation, and sports optimization, many are still in the prototype phase [87]. Large-scale clinical evaluations, baseline comparisons, and modelling approaches are presently being sought after, thereby emphasizing the requirement for further collaborative studies in the field [88].

6. Conclusion

This narrative review combined the last two decades of literature on the implementation of artificial intelligence with gait or sports biomechanics. The results clearly indicate the advancements that have occurred within laboratory-based systems for motion capture technology to more contemporary examples of sports biomechanics using wearable sensor technology that is now enhanced with the latest machine learning or deep learning concepts. Modern approaches with convolutional layers, long short-term memory networks, or sensor fusion have now allowed for more accurate real-time calculations of biomechanical variables [89].

Despite the progress made, however, several issues are still outstanding. Most existing approaches are based on multi-sensor configurations that do not favor real-world applications, and many models of artificial intelligence generalize poorly across individuals, actions, and conditions. Notably, the area of explainable artificial intelligence, personal modelling, and large-scale clinical validation received little attention so far.

It is recommended that future research should be geared towards designing frameworks using minimum sensors, incorporating digital twin ideas, cross-population validation approaches, and explainable AI models [90]. By such, it will be easy to develop biofeedback systems for gait and sports biomechanics analysis and acceptability of such systems in a clinical setup.

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