Artificial Intelligence Approach in Biomechanics of Gait and Sport: A Systematic Literature Review

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ABSTRACT

Background: Artificial neural network helps humans in a wide range of activities, such as sports.

Objective: This paper aims to investigate the effect of artificial intelligence on decision-making related to human gait and sports biomechanics, using computer-based software, and to investigate the impact of artificial intelligence on individuals' biomechanics during gait and sports performance.

Material and Methods: This review was conducted in compliance with the PRISMA guidelines. Abstracts and citations were identified through a search based on Science Direct, Google Scholar, PubMed, Elsevier, Springer Link, Web of Science, and Scopus search engines from 1995 up to 2023 to obtain relevant literature about the impact of artificial intelligence on biomechanics. A total of 1000 articles were found related to biomechanical characteristics of gait and sport and 26 articles were directly pertinent to the subject.

Results: The extent of the application of artificial intelligence in sports biomechanics in various fields. In addition, various variables in the fields of kinematics, kinetics, and the field of time can be investigated based on artificial intelligence. Conventional computational techniques are limited by the inability to process data in its raw form. Artificial Intelligence (AI) and Machine Learning (ML) techniques can handle complex and high-dimensional data.

Conclusion: The utilization of specialized systems and neural networks in gait analysis has shown great potential in sports performance analysis. Integrating AI into this field would be a significant advancement in sport biomechanics. Coaches and athletes can develop more precise training regimens with specialized performance prediction models.

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Keywords

Artificial Intelligence; Biomechanics; Machine Learning; Performance; Sports

Introduction

Artificial Intelligence (AI) and related technologies have significantly impacted the scientific exploration of sports and human performance in sports biomechanics, whereby computerized scrutiny has been commercially viable [1]. The level of processing capability and technological advancement has significantly increased over the past twenty years, as evidenced by the current extent to which computers are utilized for the biomechanical analysis of sports

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techniques [2]. In recent years, there has been a marked evolution in AI technology to have a significant impact across various sectors. The sports industry has emerged as a beneficiary of the advancements in AI due to the facilitation of a transition from conventional to contemporary practices [3].

The utilization of AI continues to transform sports in multifarious and incalculable ways, surpassing the current level of comprehension. AI is recently implemented to delineate each facet of sports at every conceivable level to facilitate the transformation of statistics and analysis in revolutionizing the approach to strategizing and implementing games on the field. Furthermore, AI has augmented precision in sports as scores, player movements, and fan behaviors can be readily anticipated through its application [3, 4].

The role of human function in the perception of quality life and detection of degradation is paramount, due to precipitation of the onset of aberrations [5]. AI concepts are highly appropriate for creating efficient assessment and feedback structures in the field of sports. Subsequent to the initial upswing observed in the 1970s and 1980s, the implementation of AI techniques has become restricted to distinct domains of application, one of which is sports, in which their use has become essential in evaluating sports data. Recent instances comprise the innovation of mobile monitoring systems that comprise classification algorithms for real-time analysis and feedback generation in sports, such as running [6] or golf [7]. Similarly, the present study investigates the utilization of artificial intelligence techniques in conjunction with innovative measuring devices within the realm of resistance exercise [8].

Specific inquiries, conversely, concentrate on the creation of machine learning techniques to categorize, pattern recognition, and anticipation of the information related to sport, for instance, motion sequences [8]. The use of self-learning algorithms like ANNs in performance analysis is gaining popularity in sports literature, mathematics, and computer science. This is considered a promising application area [9, 10]. Furthermore, alternative classifiers, such as the k-nearest Neighbor (k-NN) algorithm or Support Vector Machines (SVMs) are frequently utilized modeling instruments, presenting advantageous prospects for the examination and identification of sport-specific data patterns [8]. Acikkar et al. [11] employed SVMs in their methodology to prognosticate the aerobic fitness of athletes. Several additional research studies are associated with the act of running to assess the inherent categorization of track inclination and speed parameters [12] or discern variances in kinematic characteristics [13].

Another notable facet impacted by AI is acknowledged as the manner of walking, commonly referred to as gait, emblematic of autonomy and distinctiveness in humans; therefore, any aberration from the norm can significantly diminish the standard of living [14]. Gait analysis, the research pertaining to human walking, is a methodical approach to identify unfavorable variances within the gait pattern and subsequently ascertain their underlying source and consequential impact. Analysis of the Gait is a methodology employed to unveil the intricate mechanisms underlying human locomotion through the quantification of factors that govern the functional presentation of the lower extremities [15, 16]. Dysfunctional locomotion may manifest due to either acute or chronic injury or as a result of inadequate biomechanical functioning [17]. The analysis of variability in gait through the use of kinematic and kinetic characterizations is an empirical and quantitative approach that may prove advantageous to the field of biomechanics. Expertise in this area may benefit from such an approach. The implementation of AI techniques is advantageous in the sport and gait analysis. Such techniques possess the capability to effectively manage and navigate through highly dimensional, temporal, and intricate sets of data [18, 19]. It is beyond the purview of this review study to provide the reader with comprehensive knowledge regarding the AI methodologies expounded upon herein. This paper presents an overview of the concept of Artificial Intelligence. To promote clarity, succinct explications and operational definitions are provided where pertinent [20, 21].

The implementation of AI technology has become ubiquitous across all facets of sports. As an illustration, by means of cameras and wearable sensors, computer systems are capable of precisely acquiring sports data and the physiological data of athletes during both training and competitions. Applying AI technology for the analysis of such data can not only aid coaches in devising tailored training regimens for athletes, but it can also facilitate the development of optimal game strategies [22, 23].

The present study aimed to explore the capabilities of AI methodologies in determining human gait and sports biomechanics through the application of computer-based software. The utilization of AI methodologies in sports biomechanics is a promising and stimulating approach towards future research. Due to the paucity of literature in this sphere and in a bid to investigate possibilities for significant inquiry, this manuscript presents a synopsis of the pragmatic execution of AI in a closely linked discipline, specifically, ambulatory analysis. Thus, it is indispensable to scrutinize the significance of synthetic intelligence in the mechanics of ambulation and athletics.

The present study analyzed previous research on AI in biomechanics of gait and sport. AI is positively impacting sports success. The study focused on evaluating the quality and bias of previous studies. The aim of the review was to determine if AI affects biomechanical function in gait and sport.

Material and Methods

This systematic inquiry was executed in strict adherence to the PRISMA guidelines for systematic inquiry [24].

Eligibility criteria and search strategy

To obtain relevant literature on the impact of artificial intelligence on biomechanics, abstracts, and citations were identified through a search using Science Direct, Google Scholar, PubMed, Elsevier, Springer Link, Web of Science, and Scopus search engines from 1995 up to 2023 articles published. Articles in English and published in reputable journals were considered for review.

Search terms included “Machine Learning”, “Lower Limb”, “Gait Rehabilitation”, “Artificial Intelligence”, “Implementation of AI or Machine Learning (ML) in Gait Analysis”, “Gait Analysis with AI”, “Sport Analysis with AI”, “AI sports biomechanics”, “Gait kinematics with AI”, “AI in sports”, “AI Performance in sport biomechanics”, “AI in Functional biomechanics”, “Deep learning in sport biomechanics” in various combinations.

In the subsequent phase of the screening process, a comprehensive study was conducted on the literature review, comprising a total of 512 research articles, and subsequently eliminating any duplicated research, thereby reducing the number of articles to 298. Non-sport related articles have been removed to ensure the relevance and accuracy of the sports articles published. The subsequent phase entailed a comprehensive examination and assessment of the complete articles, in accordance with the established standards for inclusion or exclusion. A total of 26 articles were selected and subsequently subjected to a comprehensive qualitative analysis.

Through a comprehensive analysis of the complete texts, certain items that failed to satisfy the predefined criteria for inclusion were excluded, resulting in 26 distinct articles.

Exclusion criteria

The articles outside the domain of artificial intelligence, as well as those not in the

English language, were excluded from the study. Furthermore, it was observed that the articles utilizing the data extraction form, formulated with the specific objective of the research, did not align with the intended criteria.

Study selection and Bias

To mitigate potential biases or inaccuracies in study selection, each of the three reviewers individually evaluated the titles, abstracts, and complete texts of the studies in adherence to the inclusion criteria. In the event of any discrepancies, a joint resolution was achieved through a discourse among the three reviewers.

Quality assessment

In this study, the quality of articles was also scored with the Modified Downs and Black checklist [25]. In fact, this checklist was set up to evaluate the methodology of random and non-random articles, based on this checklist, and articles were divided into four levels. If the article score was between 24 and 28, the level was excellent, 19 to 23 was good, 14 to 18 was relatively good, and less than 26 articles were poor. A total of 13 studies scored 21, 7 studies scored 20, and 6 studies scored 19. Any disparities in scoring were rechecked by the author.

Data collection

The pertinent data from the encompassed articles was extracted by a singular author.

Data extraction and assessment of methodological quality

Data from each study were collected and entered manually into Excel: (2019) name of the researchers (year of publication), purpose, subjects, criteria, and results.

Articles were collected and discussed according to the different domains such as machine learning, supervised learning, unsupervised learning, performance prediction, accuracy of parameters, sports, and gait Domain.

Results

Figure 1 shows the process of the screening, which is divided into four consecutive phases,

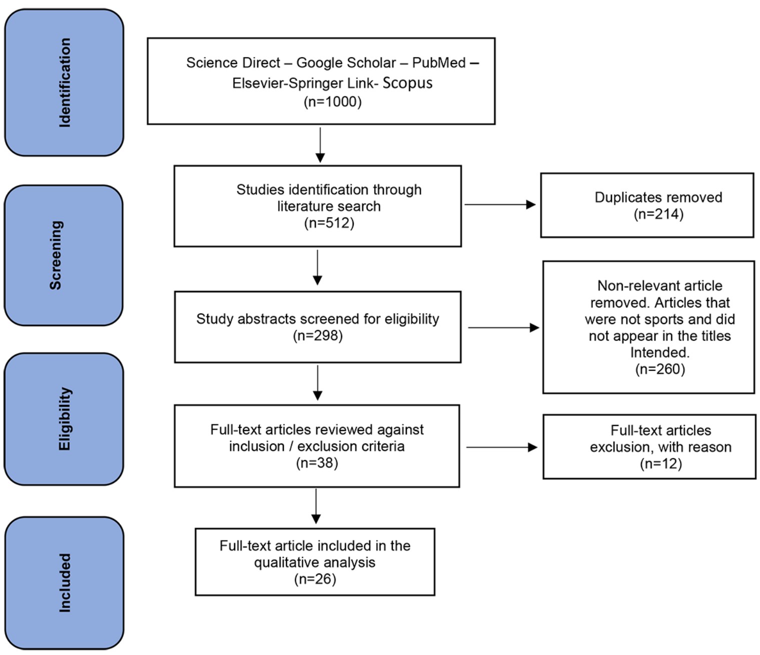

Figure 1: PRISMA flow diagram

including identification screening, eligibility, and inclusion in the review plan. Table 1 shows the results of the quality assessment, demonstrating the total score of the included articles based on the different validity criteria assessment. Table 2 summarizes the characteristics of the included studies. Twenty-six articles were considered for assessing the effect of artificial intelligence on biomechanics of gait and sport functions, and eight articles related to the investigations deep learning [26, 27, 32, 33, 35, 37, 45, 46], eleven studies on unsupervised learning [7, 8, 11-13, 17, 29, 31, 34, 36, 41], three studies on unsupervised learning [38, 39, 42], seven articles concentrated performance-prediction [1, 7, 8, 28, 31, 34, 41], six articles about accuracy of parameters [11-13, 31, 36, 43], six studies on sports domain [7, 8, 11, 30, 31, 41], and three articles on gait domain [40, 43, 44].

Machine learning can be segmented into various categories, including deep learning, and supervised and unsupervised techniques, which respectively rely on classification and clustering methodologies. Table 2 delineated the utilization of machine learning

Table 1: Studies quality assessment based on Downs and Black checklist

Row	Articles	Reporting	External validity	Internal validity-bias	Internal validity-confounding (selection bias)	Total
1	Sah et al. [26]	8	2	6	4	20
2	Ren Hao [27]	9	2	6	4	21
3	Schrapf et al. [28]	9	2	6	4	21
4	Lee et al. [29]	9	2	6	4	21
5	Liu et al. [30]	8	2	7	4	21
6	Tou et al. [31]	9	1	7	4	21
7	Buric et al. [32]	7	1	7	4	19
8	Prakash et al. [17]	7	1	7	4	19
9	Acuna and David [33]	9	2	6	4	21
10	Tumer et al. [34]	8	2	6	4	20
11	Lu et al. [35]	8	2	5	4	19
12	Phinyomark et al. [36]	9	2	6	4	21
13	Pobar et al. [37]	7	1	6	4	19
14	Novatchkov et al. [8]	9	2	6	4	21
15	Zhao et al. [38]	8	2	6	4	20
16	Fischer et al. [13]	9	2	6	4	21
17	Eskofier et al. [7]	9	2	6	4	21
18	Eskofier et al. [12]	8	2	6	4	20
19	Acikkar et al. [11]	9	2	6	4	21
20	Rozumalsk et al. [39]	7	1	7	4	19
21	Kim and Lee [40]	7	2	6	4	19
22	Silva et al. [41]	9	2	6	4	21
23	Xu et al. [42]	8	2	6	4	20
24	Pretorius et al. [43]	9	1	7	4	21
25	Juang ang Jih-Gau [44]	8	2	6	4	20
26	Lapham et al. [1]	8	2	6	4	20

Table 2: Investigations related to the Effects of artificial intelligence in biomechanics.

Authors	Purpose	Subject	Result
Şah et al. [26]	To examine and contrast the effectiveness of traditional techniques, Convolutional Neural Networks (CNNs) with varying image representations, and complex deep learning methods.	Players in field sports	A basic CNN design with image representations yields the highest performance.
Ran Hao [27]	To review a sports video athlete detection system is through deep learning.	Athletes' sports	A nearly 10% improvement in athlete video detection accuracy was compared to traditional convolution network recognition.
Schrapf et al. [28]	To utilize ANN to anticipate the complex I's setting speed and target area in volleyball.	289 rallies of 2nd Austrian Volleyball League Women by one player	The predicted target areas by the ANN were more accurate than those by coaches, with a 2.8% increase in accuracy.
Lee et al. [29]	To determine the feasibility of integrating AI with PE technology.	…	Learners can gain direct experiences through sensory information, and AI can provide objective feedback for physical ability assessment.
Liu et al. [30]	To apply AI and HCI to athletic training for digitalization and intellectualization.	Three participants	The precision of pose reinstatement was enhanced among sportsmen during athletic preparation.
Tou et al. [31]	To find the importance of artificial neural network models to predict sports performance.	…	The artificial neural network model demonstrates a higher level of precision in capturing the functional correlation between the training indices of elite shot-put athletes and their athletic achievements. Furthermore, the model exhibits greater accuracy in prognosticating the special performance of these athletes.
Buric et al. [32]	To present an outline of the latest CNN-based detection techniques and evaluate their effectiveness on handball training and match videos.	Handball players	Mask R-CNN is a superior option for analyzing team sports footage due to the accurate identification of individual players in a group from greater distances with the added advantage of a mask around the detected object. However, it does necessitate more computation power and time.
Prakash et al. [17]	To comprehensively analyze contemporary gait analysis.	Review	Different analysis methods use applications, such as clinical diagnosis, geriatric care, sports, biometrics, rehabilitation, and the industrial sector.
Acuna and David [33]	To create an online detection and tracking pipeline. The tracker depends only on detection from the previous and current frame.	Basketball player	The best accuracy of jump shot was around 33% in the test set.

Authors	Purpose	Subject	Result
Tumer et al. [34]	To conduct a survey on volleyball team ranking prediction using ANN.	Data used to develop obtained from 2013 to 2015 league chart	The most optimum model exhibited a precision level of 98%, showing the artificial neural network model has the capacity to forecast the hierarchical order of teams in a league chart with remarkable precision.
Lu et al. [35]	To present a cascaded CNN that satisfies all three requirements, including accuracy, efficiency, and low memory consumption.	Basketball and soccer players	The approach achieves high accuracy on gaming platforms with fewer parameters compared to traditional CNNs, making it a lightweight alternative.
Phinyomark et al. [36]	To employ PCA and SVM to analyze differences in running gait kinematics between male and female runners.	483 subjects including 263 females and 220 males	Women runners have a higher risk for running-related injuries compared to men. A research study revealed that a significant portion of the data's variability was accounted for by a majority of the principal components. Furthermore, the study showed that classifying female and male runners using SVM resulted in an accuracy of 86.34%.
Pobar et al. [37]	To identify and evaluate the most proficient player in handball by detecting all players present on the court.	Handball players	An evaluation method to assess the performance of the proposed active player detection was proposed, which was successfully tested on a custom handball dataset.
Novatchkov et al. [8]	To illustrate the potential of Artificial Intelligence (AI) techniques in sports	7 Female, 8 Male/ 20-31 years	Artificial intelligence can evaluate weight training equipment performance and provide athletes with quick feedback.
Zhao et al. [38]	To enhance the adaptability control of exoskeletons, leading to successful human-computer coupling.	…	The simulation results of Weka software indicate that the classifier can accurately assess lower limb motion using gait analysis data. Furthermore, cluster analysis can group lower limb motion for various users in different environments and at different times.
Fischer et al. [13]	To examine model classification rates for identifying subjects based on kinematic patterns.	8 male competitive athletes	The optimized SVM performed well in separating data at different velocities and achieved 100% classification rates for identifying subjects, while the ANN had a slightly lower accuracy of 94% to 95.5%.
Eskofier et al. [7]	To introduce a recognition method that identifies important predictors of golf swing technique for improving performance.	396	The SVM performed always better than the k-NN classifier. The best result was obtained using only the club-specific feature set and the SVM. The best classification result was obtained when using only the human-specific feature set and the SVM
Eskofier et al. [12]	To differentiate between three categories of speed and three categories of surface inclination.	…	Surface inclination classification had 67.2% accuracy due to measurement restrictions. Speed classification could be done with up to 89.2% accuracy.

Authors	Purpose	Subject	Result
Acikkar et al. [11]	To support vector machines is introduced to forecast an athlete's aerobic fitness.	27 male athletes / mean 19±4.42 years	Various experiments reveal that curve-fitted data outperforms other data in terms of higher prediction rate, sensitivity, specificity, and shorter training time.
Rozumalsk et al. [39]	To assess significant differences in patterns and underlying causes of various gait deviations within a larger group.	Subjects with Cerebral palsy	The study identifies five clusters in children with excessive knee flexion. A new classification tool can define homogeneous groups in crouch gait. This can guide treatment and outcomes assessment.
Kim and Lee [40]	To adapt the gait of biped robots for different terrains by utilizing a central pattern generator and a leaning mechanism.	…	The biped robot's gait varies with the terrain. The effectiveness of the gait adaptation method was confirmed through simulation.
Silva et al. [41]	To identify explanatory factors for performance events, model performance, and evaluate neural network precision for performance prediction.	(65 males and 73 females)/ the mean age of the males was 15.9±0.4 years and the mean age of females was 13.2±0.4 years	The constructed neural network models had a low mean difference between estimated and true results.
Xu et al. [42]	To examine the identification of the fundamental walking pattern through data analysis.	…	The clustering-based technique can efficiently identify gait patterns and assist with clinical applications.
Pretorius et al. [43]	To compare human prediction ability to an artificially intelligent prediction system.	2015 Rugby World Cup	During a particular rugby tournament, there wasn't enough evidence to support the idea that a human can predict match outcomes more accurately than a machine learning approach.
Juang ang Jih-Gau [44]	To examine the use of Fuzzy neural network methods in generating robot walking patterns.	…	The simulation successfully achieved specific goals, including crossing over a specific clearance, with a desired step length, and walking at a particular speed.
Lapham et al. [1]	To utilize artificial intelligence techniques to elevate the role of computers in decision-making processes within the discipline.	…	Establishment of an expert system catering to a precise and distinct sports technique would present a noteworthy progression in the field of sports biomechanics.

methodologies by emphasizing plausible scenarios, where these techniques could be implemented.

Discussion

AI, a domain of computer science, endows computers to execute tasks that would typically necessitate human intelligence. Further, AI comprises machine learning, an AI subset that enhances computing programs' performance through the automatic learning of data patterns. Machine learning has found success in various domains [39]. The efficacy of AI lies in its adeptness in expeditiously scrutinizing and handling prodigious quantities of data. The techniques for data analysis are continually developing, enabling users to obtain crucial information that is challenging to obtain manually. AI is undoubtedly among the most promising technologies for humankind in the future, and its benefits are reaching the sports world [22]. The present article investigated the concepts of AI approach in Biomechanics of Gait and Sport. A thorough examination of articles published has been proffered in esteemed journals and pertinent conferences. The utilization of machine learning methodologies, namely supervised methods such as neural networks, k-NN, SVM, clustering-based reinforcing learning, rule-based fuzzy logic, evolutionary, and Hybrid approaches, have been recruited for gait analysis and sports.

It has been determined that computational methodologies are presently the most extensively implemented and comprehended. The data pertaining to gait and sports exhibits a notable degree of heterogeneity, high dimensionality, temporal dependence, and variability. Processing of this data poses a formidable challenge. Besides, conventional computational techniques have a limitation in processing data in its raw form. However, AI and ML techniques can handle high dimensional, temporal, and complex data [18, 19].

Machine learning techniques

The primary objective of utilizing machine learning techniques is to create algorithms to obtain knowledge either through experiential learning by means of annotated data or independently detecting significant patterns from designated data points. Techniques, such as statistical and machine learning have been developed to represent and classify data [19]. Multivariate statistical methodologies, including Principal Component Analysis (PCA), may be effectively employed for the purpose of data analysis, referred to as data reduction techniques. However, their utility may be limited when faced with challenges, such as nonlinearity or complexity within the problem domain [17]. The machine learning techniques can be systematically classified into a number of distinct categories, namely, supervised (classification-based), unsupervised (clustering-based), reinforcement, rule-based, evolutionary (Genetic algorithm, particle swarm optimization), probabilistic, and hybrid approaches [17]. The current study conducted a comprehensive analysis of the different techniques employed in machine learning namely supervised (classification-based), unsupervised (clustering-based), and deep learning methods.

Deep learning

The remarkable achievement of deep learning methodologies in the domain of image classification [47, 48] has instigated a forceful impetus for a greater number of researchers to adopt these techniques in their pursuit to tackle a multitude of challenges, including object detection and interception [49, 50], activity recognition and image semantic analysis. The foundation of the architecture of a deep learning network lies in an intricate and extensive neural network, which is trained using a substantial volume of labeled data [51].

The algorithm of the deep learning network asserts that it possesses the capability to attain numerous levels of training whilst concurrently eliminating the requirement of an all-inclusive communication level that consolidates all functionalities into a solitary module, thereby expediting access to data [52].

Some authors used ANN for the study of gait and sport performance [8, 13, 28, 31, 34]. ANNs facilitate the learning process of computers by means of experience and analogy. These computer programs endeavor to construct a mathematical framework of the neurons present in the human brain. An ANN refers to a complex network of simple and adaptable processing elements, commonly known as nodes [31]. The CNN is predominantly employed for the examination of visual imagery [53]. Specialized in the processing of pixel data, these technologically advanced systems are specifically intended for employment in image recognition and processing. Dorschky et al. [45] improved a measured inertial sensor dataset by adding simulated data to train convolutional neural networks for estimating joint angles, moments, and ground reaction forces during walking and running. The addition of simulated data reduced the root mean square error of the test set for joint angles and moments by up to 27% and 6%, respectively, and for Ground Reaction Forces (GRFs) by up to 6%. However, the accuracy of the biomechanical model limited the simulation-aided estimation of joint moments and GRFs. In another study, the estimation of lower limb joint angles and moments was analyzed using a feedforward neural network with Inertial Measurement Unit (IMU) data. The dataset used for this purpose includes both optical motion capture data from previous research and newly collected IMU data. The addition of synthesized data significantly improved joint angle prediction, while the inclusion of noise led to improved prediction accuracy, indicating the potential benefits of augmentation techniques in the context of biomechanical data for machine learning applications [54].

CNNs have gained as a viable and feasible method to detect the athlete's performance. Lu et al. [35] a light CNN architecture is employed to detect football and basketball players in Television camera footage. RGB images are employed in the process of training and testing the Convolutional Neural Network model. Lehuger et al. [46] announced that it is recommended to employ two convolutional layers and Grayscale images in order to detect football players via a television camera. In another comprehensive study, Acuna [33], announced especially focuses on a performance RGB image-based system and You Only Look Once (YOLO) network for real-time detection of basketball players. Pobar and Ivasic-Kos [37] showed that the YOLO was used for optical flow to detect active players during handball matches. Moreover, Buric et al. [32] evaluated the performance of CNNs to detect handball players. Sah et al. [26] also evaluated the efficacy of recent and established techniques for detecting players in field sports. The proposed CNN structures aimed to evaluate the performance of the player utilizing various images. According to the findings, a CNN structure, which is employed in tandem with image representations, attains the most optimal outcomes. Hao Ren et al. [27] developed a system for detecting sports video athletes using deep learning for experimental testing. Additionally, the accuracy of detection improved by nearly 10%, as compared to conventional convolution network recognition algorithms, which underscores the recognition advantages of the system.

Based on the ANN and CNN have shown that the proposed approach can also evaluate the accuracy of parameters, predict performance, and perform clustering.

Supervised learning

Supervised learning is considered a goal-oriented methodology, presenting the input and the desired output. A mathematical framework is formed to depict the inputs in relation to the anticipated outcomes, leading to precisely classifying unobserved data and reducing the probability of erroneous outcomes. In the course of this analysis, healthcare experts are required to assign labels to the data. Supervised learning encompasses a variety of machine learning algorithms, such as Neural Networks, k-NN, SVM, and ANN [17].

The neural network persists in its operation until it achieves a designated minimum error or a predetermined number of epochs, leading to its significant application in normal gait analysis, robotic rehabilitation, sports monitoring and tactics, geriatric care surveillance, and activity recognition [55-62].

The concept of NN is an endeavor to emulate their biological operations through computational means. The initial research was conducted by W. Mculloch and W. Pitts in 1943 to develop artificial neurons. The NN can cause a predetermined minimum error or pre-established epochs. Some studies underscored the extensive utilization of NN in Gait Analysis and sports monitoring recognition [29, 36, 41].

The SVM is a highly resilient classification tool relying on a kernel function to establish the data scatter within the desired state. Several scholars employed the SVM method in the examination of gait and sports [13, 36]. The SVM constitutes an influential classifier for handling small to medium-sized datasets. In situations, in which labeled training data points are available, supervised learning techniques are emerged as a preeminent methodology [36].

The k-NN method is commonly implemented in gait and sport studies [7] and widely recognized as a nonparametric approach for both categorization and regression. This algorithm also operates by the k-NN methods in the feature space as its input to assign class membership to a given entity, which is achieved by examining the predominant characteristics of the entity's neighbors. Here, the value of k represents a positive integer. In the current algorithmic framework, the entity is classified into the category of its closest neighbor, set to one [7].

In supervised learning, data are classified utilizing SVM, while variables are scrutinized through NNs. In the present research, the performance and accuracy of sports and gait is investigated within the framework of supervised learning.

Unsupervised learning

In machine learning, unsupervised learning models do not have access to labeled examples for training to uncover underlying similarities among data points based on their shared characteristics and a metric for measuring similarity. It is important to note that explicit supervision is not provided during the training process.

Using a similarity measure, the data points are classified into distinct clusters, which are predetermined. The similarity measure can have various forms, such as Manhattan, Euclidean, Minkowski, cosine distance, or other related metrics. The main objective of this clustering method is to minimize the distances within clusters (intra-cluster distances) while simultaneously increasing the distances between clusters (inter-cluster distances) [17].

Cluster analysis methodologies, commonly used to group and organize data effectively, play a crucial role in identifying and diagnosing gait irregularities and classifying common physical activities.

Rozumalski et al. [39] conducted a study using clustering methods to identify subpopulations exhibiting different types of pathological. Xu et al. [42] the present study delved into the analysis of k-mean, SOM, and Hierarchical Clustering to distinguish between normal and pathological gait patterns using stride length and cadence as metrics. The findings of this study showed that the clustering-based technique was proficient in identifying gait patterns with efficacy and in clinical applications. Zhao et al. [38] explored the field of gait analysis and showed that the classifier can effectively assess lower limb motion by employing data derived from gait analysis.

Performance-Prediction

Athletic performance refers to the ability of athletes to excel in sports, which is influenced by specific physical attributes that impact their proficiency in various sports skills. The relationship between sports performance and its indicators is intricate and nonlinear. Neural networking, a significant branch of modern nonlinear science, has experienced rapid advancements and widespread application in sports and gait analysis. Researchers have examined the influence of artificial intelligence on athletic performance and gait prediction, serving as the motivation for this study. Conversely, predicting the outcomes of sports competitions poses a complex computational challenge due to the multitude of uncertain factors affecting the result of a match. Probabilities are assigned to every conceivable state, which the game could end, when predictions about such outcomes that this task is generally considered more difficult due to the increased number of potential outcomes.

In the study conducted by Novatchkov et al. [8], similar patterns can be identified when analyzing force characteristics, indicating that supervised machine learning methods are suitable for classification purposes. This research aimed to highlight the significance of AI approaches in sports, particularly in the context of resistance training. Additionally, the modeling results obtained in this study revealed favorable performance and accurate prediction outcomes, showing the practicality and effectiveness of AI techniques in automatically assessing athletic performance on resistance training equipment and providing athletes with timely guidance.

In a study conducted on individuals engaged in swimming, the use of feed-forward NNs enabled the development of four models for predicting performance. The findings of this investigation revealed a small mean difference between the actual and predicted outcomes produced by all four NN models [41].

In the study conducted by Tou et al. [31], the artificial neural network model offered a more accurate representation of the functional relationship between exercise indices of a specific attribute in shot put athletes and their specialized athletic performance. Furthermore, the model predicts the unique performance of shot-put athletes with greater precision. The study also revealed that the specific physical attribute of shot-put athletes plays a crucial role as a foundation for their specialized athletic ability.

The results of the research by Silva et al. [41] demonstrated that the implementation of a feed-forward neural network led to nonlinear analysis, which facilitated the creation of four models for predicting performance. Consequently, the utilization of neural network tools could affect addressing intricate issues, such as performance prediction modeling and talent identification in various sports, most notably swimming. The manuscript authored by Eskofier et al. [7] reports on a study that outlines initial findings pertaining to the establishment of a data-driven pattern recognition method that can successfully discern the key predictors of golf swing technique that are essential to enhancing performance.

In the study conducted by Schrapf et al. [28], on 289 rallies of the 2nd Austrian Volleyball League women, the researchers assessed the agreement between predicted and actual values by measuring the proportion of accurate predictions. The quality of predictions was evaluated by comparing the results produced by the ANN with those provided by expert volleyball coaches. The ANN exhibited a prediction accuracy of 68.1% for the designed area and 79.2% for the setting speed, which significantly surpassed random chance. Additionally, the ANN outperformed the coaches in predicting target areas by 2.8% and showed a remarkable 14.6% improvement in predicting setting speed compared to the coaches' predictions.

The result of the research by Tumer et al. [34] showed that the most optimal ANN method was a single hidden layer 4-neuron model, with “logsig” transfer function, “trainlm” training function, and “learngmd” adaptive learning function. The findings indicate that the precision level of the most advantageous model was 98%, implying that the positioning of a team in a league ranking is predicted with a high degree of accuracy through the implementation of this artificial neural network model.

According to the careful examination and analysis of the empirical evidence presented in this specific section, the fields of AI and ML hold significant potential in enhancing efficiency, performance, and prediction. The predictive capabilities offered by AI and ML can provide invaluable benefits for coaches to refine the athletic skills of their athletes, including the ability to anticipate the strategic moves of opposing teams and develop the abilities of their own setters. Such advancements have the potential to revolutionize the coaching and playing of sports, ultimately elevating the performance levels of athletes across various domains.

Accuracy of Parameters

The accuracy of a positioning system is often inversely proportional to its coverage; accordingly, larger measurement volumes result in lower precision. This limitation is widely recognized as a key factor in the selection of a measurement system. The accuracy and practicality of measurement systems are difficult to evaluate. However, the integration of artificial intelligence enables a comprehensive assessment of algorithm precision. In this section, publications are explored that compare human intelligence with intelligent systems.

Pretorius et al. [43] revealed that an AI approach using machine learning yielded a comparable level of accuracy. In the present investigation, a stochastic classification methodology was utilized to prognosticate the results of the 2015 Rugby World Cup matches. However, there is insufficient evidence to conclude that an individual element is superior to an artificial intelligence-based learning approach in accurately predicting match outcomes for the sport of rugby and within the constraints of a limited tournament duration.

Acikkar et al. [11], demonstrated that the process of classification affects prioritizing variables. It is not advisable to rely solely on VO^2 kinetics for fitness categorization. Hence, it is crucial to consider other time-dependent variables, including but not limited to carbon dioxide emissions, minute ventilation, and heart rate, among others to attain more accurate classifications.

Eskofier et al. [12], showed how much classification affects the accuracy of parameters, and the categorization of surface inclination could only be achieved with a precision of 67.2% due to limitations in measurement. Nonetheless, the data reveal that the classification of speed was viable with a maximum accuracy of 89.2%.

In the comparison of athletes, the optimized SVM demonstrated superior performance in accurately distinguishing data across all velocities compared to the ANN. The SVM achieved a classification rate of 100% for subject identification, while the ANN achieved rates of 94% to 95.5%.

According to the analysis of individuals, who were trained using models with data collected from different speeds, it was observed that the SVM achieved a classification rate of 98.6% (compared to 94% for the ANN). By implementing optimized data separation techniques, the SVM outperformed the ANN in classifying ambiguous data, resulting in a higher classification rate [13].

A methodology was used that combined PCA and SVM classification to examine the differences in running gaits between male and female runners in a large sample of the running population, as well as between two age-based sub-groups. The findings showed that forty principal components explained 84.74% of the variability in the data. Additionally, the SVM achieved an accuracy of 86.34% in accurately distinguishing between female and male runners [36].

Tou et al. [31] indicated that the employment of a neural network prediction model results in significantly decreasing error between the calculated value and actual value of the special results, as compared to the utilization of the multiple linear regression models. This observation underscores the enhanced capacity of the neural network model to fit the quality. Moreover, the fitting accuracy of the functional relationship is notably high between training level and special performance.

According to examination and detailed analysis of the diverse findings from the fields of AI and ML, these techniques possess the capability not only to predict performance but also to assess the accuracy of parameters.

Sports Domain

Sports has experienced significant growth over the past two decades, leading to a pivotal driver for numerous economies and a profound impact on our social and cultural fabric. The complexities involved in predicting and enhancing athletic performance present formidable challenges that have traditionally been addressed by subject matter experts, such as coaches, managers, scouts, and sports health professionals using rudimentary analytical techniques.

The results of the study by Novatchkov et al. [8] revealed that AI methods possess a high degree of effectiveness in the automatic evaluation of weight training equipment performance and the provision of timely guidance to athletes.

Experiments with diverse training and test datasets have demonstrated that utilizing curve-fitted data can result in enhanced performance metrics for athletes. These improvements encompass increased predictive accuracy, heightened sensitivity and specificity, as well as reduced training duration [11].

Silva et al. [41] showed that utilizing neural network models is a viable approach to address complex challenges, such as performance modeling and talent identification in various athletic activities, with a specific focus on swimming.

In the study conducted by Eskofier et al. [7], classification experiments were employed to evaluate the golf swing, and the findings could potentially enhance the understanding of the key factors that influence the successful execution of a golf swing.

The findings of the research conducted by Tou et al. [31], demonstrated that employing an artificial neural network model provides a better representation of the functional relationship between training indices related to the unique qualities of shot-put athletes and their specific athletic performance. Moreover, this advanced model exhibits a higher level of accuracy in predicting the special performance output exhibited by shot put athletes.

The main objective of the study conducted by Liu et al. [30] is to enhance professional sports training by leveraging digitalization and intellectualization techniques. This is achieved through the implementation of motion capture technology based on AI and HCI, leading to the creation of enriched application scenarios. The findings of this research indicate a significant improvement in the accuracy of pose restoration among athletes during sports training.

A comprehensive examination of the multitude of factors contributing to athletic performance holds significant potential for the benefit of coaches, researchers, and athletes. By thoroughly exploring the intricacies and nuances of these variables, a more comprehensive understanding of their impact on athletic outcomes can be achieved. This enhanced understanding can then inform and guide the development of more effective training programs, performance assessments, and overall athletic strategies. Therefore, investing in the analysis of performance prediction and the accuracy of parameters can yield substantial dividends in terms of athletic success and improvement.

Gait domain

Research pertaining to the locomotion of humans is referred to as gait analysis. The methodology of gait analysis involves the quantification of elements that govern the functionality of the lower extremities, thereby exposing the underlying mechanisms of human movement. The study and analysis of human locomotion, commonly known as gait analysis, has a multitude of applications in various fields such as medical diagnosis, safety, virtual reality, trade, and physical activity knowledge [15, 63]. Dysfunctional ambulation may manifest as a result of either acute or chronic injury, or due to inappropriate biomechanics. Healthcare professionals can derive significant assistance from different research types in analyses of gait variability, utilizing kinematics and kinetic parameters, both in predicting the onset of a situation and monitoring the recovery profile of patients in clinical fields [17]. A significant cohort of scholars, who are captivated by this field, have suggested innovative methodologies. This particular group concentrates on the scrutiny of walking patterns with the aim of deliberating on the utilization of machine learning approaches and the influence it has had on the study of gait.

It has been determined that, presently, the most extensively employed and comprehended methods of analysis for gait involve computational techniques. The data pertaining to gait is characterized by marked heterogeneity, high dimensionality, temporal dependence, and variability. Proceeding with this data presents a challenge. Moreover, conventional computational techniques are limited by their inability to process natural gait data in their raw form. However, deep learning architectures offer a wide range of opportunities for identifying, classifying, and detecting abnormalities in gait data. This approach addresses the limitations of manual engineering. Although the available dataset encompasses a wide range of walking environments, it remains insufficient for reliable gait analysis [17].

The examination of human walking patterns, commonly known as gait studies, has made noteworthy contributions to the development of prosthetic limbs and orthotic devices for amputees. Moreover, this research has served as a source of inspiration for the creation of artificial locomotor controllers, which are utilized in exoskeletons and robotics. Juang [44] has suggested a model for synthesizing the gait of robots by employing kinematics principles and utilizing the fuzzy neural network. Kim and Lee [40] used a Hybrid genetic algorithm and neural network to determine joint angles according to the accelerator data. Analysis of gait is a fundamental aspect of studying the natural walking patterns of human-like robots. Various algorithms that utilize artificial intelligence techniques have been developed to facilitate this process [64-66]. Heinen and Osório et al. [67] have explained a scientific method to optimize the gait of humanoid robots. The approach is designed to create and control consistent gaits for legged robots within a physically based simulation environment. Wawrzy ´nski [68] delves into the domain of enhancing the walking pattern of humanoid robots through the application of reinforcement learning with experience. Rozumalski et al. [39] in crouch gait, which can help guide treatment decisions and outcomes assessment.

The incorporation of novel methods has provided clinicians with the opportunity to utilize instrumental gait analysis as a standard clinical practice in order to evaluate the condition, recuperation, and progress of patients with intricate neurological and musculoskeletal disorders, ultimately mitigating the potential propagation of injury through gait analysis.

Conclusion

This paper undertakes an assessment of the inquiries that arise for the artificial intelligence community concerning the field of gait and sports. It endeavors to formulate a methodical framework that can be utilized for prospective research. Through our analysis, we have determined several crucial research domains that provide an extensive outline of the current research and also reveal unexplored areas for future investigation.

In the present research, a comprehensive investigation was carried out on the literature pertaining to the prediction of match outcomes, wherein it was observed that the models employed in this domain still fall short of providing accurate forecasts owing to the inherent unpredictability of sporting events. Nevertheless, a plethora of potential techniques were identified which could be leveraged to enhance the efficacy of existing approaches. In the domain of exercise and walking, several crucial decision-making procedures have been delineated. Subsequently, the prospect of utilizing artificial intelligence methodologies for the enhancement of said procedures was deliberated. Additionally, an appraisal of the literature pertaining to sports revealed that artificial intelligence techniques have demonstrated a notable superiority over a majority of human athletes.

Based on the findings of this investigation, it can be inferred that the implementation of expert systems and neural networks in the realm of gait analysis, as well as their documented accomplishments in experiments and potential advantages, would signify a noteworthy progression in the evolution of sport biomechanics.

Overall, the present investigation provides an overview of the potential effects of AI and ML techniques on the fields of sports and gait, identifying several areas that remain unexplored.

Authors' Contribution

The concept was initially conceived by R. Molavian. The introductory section of the paper was co-authored by R. Molavian, A. Fatahi and D. Khezri. R. Molavian, and D. Khezri provided support in the literature review, as well as contributing to the writing of the related works. The method implementation was carried out by A. Fatahi and H. Abbasi. The Results and Analysis phase was conducted by R. Molavian, A. Fatahi, and D. Khezri. The research work received proofreading and supervision from H. Abbasi and D. Khezri. The final version of the manuscript was reviewed, edited, and approved by all authors.

Conflict of Interest

None

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