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MASTERCLASS

Artificial intelligence and Machine Learning approaches in sports: Concepts, applications, challenges, and future perspectives

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Abstract
Background: The development and application of Artificial Intelligence (AI) and Machine Learning (ML) in healthcare have gained attention as a promising and powerful resource to change the landscape of healthcare. The potential of these technologies for injury prediction, performance analysis, personalized training, and treatment comes with challenges related to the complexity of sports dynamics and the multidimensional aspects of athletic performance.
Objectives: We aimed to present the current state of AI and ML applications in sports science, specifically in the areas of injury prediction, performance enhancement, and rehabilitation. We also examine the challenges of incorporating AI and ML into sports and suggest directions for future research.
Method: We conducted a comprehensive literature review, focusing on publications related to AI and ML applications in sports. This review encompassed studies on injury prediction, performance analysis, and personalized training, emphasizing the AI and ML models applied in sports.
Results: The findings highlight significant advancements in injury prediction accuracy, performance analysis precision, and the customization of training programs through AI and ML.

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However, future studies need to address challenges such as ethical considerations, data quality, interpretability of ML models, and the integration of complex data.
Conclusion: AI and ML may be useful for the prevention, detection, diagnosis, and treatment of health conditions. In this Masterclass paper, we introduce AI and ML concepts, outline recent breakthroughs in AI technologies and their applications, identify the challenges for further progress of AI systems, and discuss ethical issues, clinical and research opportunities, and future perspectives.

Introduction

Engaging in regular physical activity is important for all ages.[1,2] The reasons why people seek a physically active lifestyle vary and may include leisure, competition, socialization, maintenance and improvement of fitness and health.[3] Sports practice is an important way for achieving an active lifestyle. However, physical activity- and sports-related injuries are considered major 'adverse events' of such practice. Data from an emergency department in Ireland, showed that sports injuries accounted for 14% of all attendances over 6 months, yielding a negative impact in people's lives and long-term consequences.[4] Furthermore, approximately 4.3 million nonfatal sports or recreation-related injuries are seen annually in the emergency department in the US, specifically affecting children and adolescents.[5]

The balance between optimal athletic performance and prevention of sports-related injuries is of primary importance for sports staff members and society.[6] However, understanding the interaction and contribution of several factors (e.g., biophysical, social, psychological, cultural, and environmental) to sports-related injury etiology as well as developing, evaluating, and implementing prevention strategies remain major challenges in the field of Sports and Exercise Medicine (SEM).[7] In general, individual factors are assumed to have a linear and unidirectional contribution to sports injuries.[7,8] This narrow approach relies on correlation and regression analyses and, despite the vast effort to predict sports injuries, it has been limited in its ability to successfully identify predictive factors.[7] Recently, complex systems approaches have been suggested to aid in understanding the multifactorial complex nature of sports injuries.[7] Complex systems consider that a phenomenon (e.g., injury) occurs not from the linear interaction between isolated factors, but from the complex, dynamic, and non-linear interaction among a web of determinants (for a review see Fonseca et al.[7] and Bittencourt et al.[8]). In this sense, sports injuries occur in dynamic environments and can be referred to as complex problems.[9]

With the advances in processing power, memory, storage, and real-time data acquisition, computers can help to solve complex problems. In this aspect, artificial intelligence (AI) is widely accepted as a technology offering an alternative way to tackle complex problems. AI is a branch of computer science that is broadly defined as "*mimicking human cognition using machines and/or computer science techniques*".[10] Machine Learning is a subdiscipline of AI in which computer algorithms learn from large datasets and identify interaction patterns among variables without human interference.[11] AI is gradually changing the landscape of healthcare and biomedical research, especially in prediction and diagnosis, but also regarding treatment efficiency and outcome prediction, drug discovery and repurposing, epidemic outbreak prediction, and precision health.[12] Thus, there is a plethora of opportunities for AI in the fields of 'Sport Sciences' and SEM. In fact, some leagues such as the National Football League (NFL), Major League Baseball (MLB), and German Football League (DFL) have been hosting several 'competitions' on Kaggle website (www.kaggle.com), looking to solve real-world problems using AI or Big Data analytics. In this masterclass, we aim to introduce the concepts, applications, challenges, and future of AI in the context of sports.

Concepts and terminology of AI and Machine Learning

The term AI is not new. The first use of the term AI was in a Computer Science Conference in 1956.[13] Although there is no well-endorsed definition in the literature, AI can be understood as a technology with the ability to respond to environmental information (or new data) and then change its operation to maximize performance mimicking the problem-solving and decision-making capabilities of the human mind.[13]

Recent interest in AI has been driven by advances in Machine Learning. Machine Learning is a subfield of AI that develops algorithms (using mathematics, statistics, logic, and computer programming) with the ability to identify patterns in data that automatically improve from experience, that is, without being specifically programmed.[13] Machine Learning approaches fall into four categories: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Learning methods, definitions, and models are presented in Table 1.

Claudino et al.[14] reviewed the literature on Machine Learning models used in sports to predict injury risk and sport performance and found 171 publications in the field of signal processing, 161 publications in the field of image processing, 151 on modelling and planning, and 57 on user interaction. Artificial Neural Network was the most common technique used in both injury risk (representing 10%) and sports performance (representing 26%) models. The decision tree classifier and support vector machine were the next most commonly used techniques, each representing 5% of injury risk assessment. Regarding sports performance prediction, the decision tree classifier was used in 17% of cases,

Table 1 Machine Learning techniques.

Learning category	Definition	Target variable	Methods	Examples of techniques
Supervised	Supervised learning works by collecting many 'training' cases and the desired output labels. By analyzing the patterns in all labelled input—output pairs, the algorithm learns to produce the correct output for a given new case.[13]	Labeled (known output) Variable type: continuous	Regression	• Simple and multiple linear regression • Polynomial regression • LASSO and Ridge regression
		Labeled (known output) Variable type: categorical	Classification	• Naive Bayes • Linear Discriminant Analysis • Logistic regression • K-nearest neighbors (KNN) • Support vector machine (SVM) • Decision tree • Random forest • Adaptive Boosting (AdaBoost) • Extreme gradient boosting (XGBoost) • Stochastic gradient descent (SGD) • Rule-based classification
		Labeled (known output) Variable type: numeric, dichotomous, categorical	Artificial Neural Network and Deep Learning	• Multilayer Perceptron • Convolutional Neural Network • Long Short-Term Memory Recurrent Neural Network
Unsupervised	Unsupervised learning analyzes unlabeled datasets without human interference. It is used for extracting generative features, identifying meaningful trends and structures, groupings in results, and exploratory purposes.[13]	Unlabeled (unknown output)	Clustering	• Partitioning methods • Density-based methods • Hierarchical-based methods • Grid-based methods • Model-based methods • Constraint-based methods • K-means clustering • Density-based spatial clustering of applications with noise (DBSCAN) • Gaussian mixture models (GMMs)
			Association Rule Learning	• Artificial immune system (AIS) • Apriori • FP-Growth • ABC-RuleMiner
			Dimension Reduction and Feature Learning	• Feature selection • Feature extraction • Variance threshold

Table 1 (*Continued*)

Learning category	Definition	Target variable	Methods	Examples of techniques
				• Pearson correlation • Analysis of variance (ANOVA) • Recursive feature elimination (RFE): • Model-based selection • Principal Component Analysis (PCA)
Semi-supervised	It combines supervised and unsupervised learning (e.g., situations where collected data presents labeled and unlabeled outputs).[13]	Labeled and unlabeled data	Classification	• Naive Bayes • Linear Discriminant Analysis • Logistic regression • K-nearest neighbors (KNN) • Support vector machine (SVM) • Decision tree • Random forest • Adaptive Boosting (AdaBoost) • Extreme gradient boosting (XGBoost) • Stochastic gradient descent (SGD) • Rule-based classification
			Clustering	• Partitioning methods • Density-based methods • Hierarchical-based methods • Grid-based methods • Model-based methods • Constraint-based methods • K-means clustering • Density-based spatial clustering of applications with noise (DBSCAN)Gaussian mixture models (GMMs)
Reinforcement	In reinforcement learning, an agent needs to take an action in a given environment. The agent evaluates the optimal behavior based on immediate reward. The goal is to increase long-term reward and reduce the risk.[14,15]	Interaction with the environment	Positive Reinforcement Negative Reinforcement	• Monte Carlo techniques • Q-learning • R-learning

while the Markov process and support vector machine were used in 9%. Soccer had the highest percentage of studies (12%) applying AI for injury risk assessment, followed by basketball, American football, Australian football, and team handball (each with 3%). Basketball had the highest percentage (19%) of studies using AI for performance prediction, followed by soccer (14%) and volleyball (9%).

Artificial intelligence applications in sports

Clinical opportunities

The wealth of data now available, including personal, clinical, and real-world data, together with continuous biometric monitoring, Internet of Things (e.g., wearables), cloud storage, computing capabilities, and the super-fast speed of data processing are ideally suited to enhance AI-generated predictive models, complex system analyses, and decision-making support. These opportunities may have particularities regarding their applications when considering research and/or sports/clinical practice. In what follows, we summarize possible applications of AI in sports.

Prediction of injuries and poor performance

In general, explaining sports practice phenomena is challenging due to their complicated or complex nature.[7,8] AI methods, based on training load, performance techniques, biokinetics, physiological and psychological data, and non-modifiable metrics such as anthropometric measurements, injury history, and genetic markers, can be used to tailor training programs to individual requirements, to reduce the risk of injuries, and to enhance overall athletic performance. In addition, AI models are now capable of continuously analyzing incoming data, thereby alerting athletes or clinicians when the risk of injury and/or performance reaches a predetermined threshold. Studies in the literature show the use of sensors to: (i) monitor variables (e.g., force, displacement, and velocity) to improve sport technique; (ii) to develop an in-game decision-making that calculates probabilities and selects optimal strategies; and (iii) to monitor mental health.[15,16]

Enable a complex systems approach to SEM

A complex systems approach may be considered the 'next step' in 'model development and validation' in the fields of 'Sport Sciences' and SEM,[7,8,17] because of the recognition of the complexity related to sports performance,[18–20] management,[18,21,22] and the athletes' health.[18,23–26] Plsek and Greenhalgh[27] defined a complex system as "*a collection of individual agents with freedom to act in ways that are not always totally predictable, and whose actions are interconnected so that one agent's actions changes the context for other agents*". Characteristics of complex systems include non-linearity, non-holonomic (fuzzy) constraints, unpredictability, hierarchy, interaction, emergence, internalized rules and asymmetry, adaptability, self-organization, and overall pattern.[7,8,28,29] Characteristics such as 'emergence', 'adaptability', and 'self-organization' may refer to a sort of 'intelligence' of complex systems. Therefore, efforts to develop and/or to validate sports phenomena under the complex systems approach may benefit from AI methods, especially those related to machine/deep learning algorithms. Other computational methods that may be used to model complex systems in sports include 'agent-based modelling' (ABM) and 'systems dynamics' (SD).[29]

Identification/diagnosis of sports injuries

A lot of attention has been placed toward the identification and/or diagnosis of sports injuries in the field of SEM. Monitoring,[30] classification,[31,32] prediction,[33,34] and imaging[35,36] are examples of AI application to the field. Imaging may be the most promising application regarding the identification and/or diagnosis of sports injuries, because existing algorithms have shown similar identification/diagnostic capabilities compared to human experts.[35,36] Moreover, providing model predictions to experts may improve experts diagnostic capabilities compared to not providing model predictions to experts.[36]

Data analysis from wearables

Wearables may create opportunities for AI research in 'Sport Sciences' and SEM fields mainly in two ways: (1) collecting, monitoring, and providing data[24]; and (2) providing real time feedback based on collected data.[15,37] Therefore, wearables may help in Big Data development and also in communicating information to the athletes, coaches, health professionals, and/or stakeholders. Depending on the way this communication is performed, behavior change related to sports may be achieved.[38]

Automation of individual monitoring

A very desirable application of AI is the automation of processes due to its ability to save time, human work, and resources especially for repeated tasks. Because people usually increase their engagement in physical activity or prevention programs when monitored, this process could be automatized by the integration of chatbots based on natural language processing. In addition, the automation and integration of linear and predictable processes with data collected from chatbots and wearables can be applicable for training management and advice,[39,40] performance,[14] injury risk assessment,[14,41] and injury prevention.[42–45]

Real-time body movement feedback

A significant innovation in clinical practice through AI is the development of digital therapies. The use of computer vision or sensors to measure body movement can be employed to analyze video recordings of athletes' exercise. In this application, algorithms are employed to meticulously track body movements, posture, and alignment. This allows for the provision of real-time feedback on the athletes' exercise technique enhancing the accuracy of the exercises performed.[15,46] Digital therapies are promising applications, mainly for personalizing sports injury prevention and rehabilitation programs.

Model development and validation

Explaining sports practice phenomena is challenging due to their complicated or complex nature, in general.[7,8,17,21,23] One approach to achieve such purpose would be 'simplifying' or reducing the levels of complexity to generate simple and specific 'rules' that could resemble the actual phenomenon under investigation when combined. Although considered a 'reductionist' approach, it contributes to a large extent in building knowledge when there is no substantial prior knowledge on the actual phenomenon under investigation. This approach has been employed when researchers begin to study and/or to explore, for example, classification problems,[31] risk factors,[47] etiology models,[48] prediction models,[49] etc. Therefore, emerging new exercises/sports or understudied sports areas could benefit from such methods during the first stages of building knowledge in a specific topic.

Broader applications in sports

The application of AI in sports is of interest to all sports industry segments,[50] and the AI sports industry market has been growing.[51] The main purpose of using AI in sports and/or clinical practice is to provide information and/or knowledge for helping in the decision-making process. There are plenty of opportunities for AI applications in sports/clinical practice, such as: stadium/facilities industry (e.g., systems for athletes and/or fans monitoring, camera systems for broadcasting, fans statistics); sports competition industry (e.g., match/events outcome prediction, tactical decision-making, players investments, tracking using wearables, eSports); sports training industry (e.g., monitoring, automation, real-time feedback, tailored counselling, wearables, systems integration for data summary from different sources); sports media industry (e.g., journalism, chatbots, robots controlling sports media coverage, audience content creation/recommendations/management, audience engagement, augmented audience experience, message optimization, content management); sports education (e.g., sports training systems, monitoring, automated feedback).[35,36,51–56] However, to tackle these opportunities it is necessary to have a qualified work force and personnel. The sports research and sports industry growth has created a demand for sports biostatistician, data scientists, and other related professionals, also creating job opportunities and providing career paths.[50]

We provide examples of potential applications of AI based on learning category and methods in Table 2.

Research opportunities

A fruitful field for opportunities in AI for 'Sport Sciences' and SEM is the research field. Future research on sports AI-based technologies should concentrate efforts in: (1) developing and making available Big Data database structures and procedures for data mining and storage; (2) model development and validation to a specific context, and adaptation to new/different contexts (external validity); (3) complex systems investigation; (4) enhancing the accuracy on the identification and/or diagnosis of sports-related injuries, including clinical data and imaging; (5) developing and investigating automation of processes, including training management and sports injury prevention; (6) the development and validation of wearable technologies; (7) technology acceptability and usability by coaches, athletes, and stakeholders; (8) Machine Learning model explainability; (9) developing a frameworks/checklists for the assessment of Machine Learning models by non-specialized professionals; (10) fostering research-industry collaborations to leverage existing industrial data resources for sports science research. This includes partnering with sports technology companies and fitness industries to access, utilize, and analyze their datasets for advancing sports-related AI applications and innovations.

Challenges and ethical considerations

Although the use of AI-based solutions in sports is growing, there are diverse challenges to their successful implementation. AI systems have complex life cycles, including data acquisition, training, testing, clinical implementation, ethical, and social issues. This section explores some challenges that may be paramount to the appropriate and optimal use of AI.

Table 2 Examples of possible clinical applications according to Machine Learning techniques.

Examples of possible clinical applications	Example of AI learning category (Method)
Injury Risk Prediction: Estimating the likelihood of injuries based on athlete's training load, previous injury history, and physical fitness levels (e.g., the model considers each player's training load, history of previous injury [types and frequencies of past injuries], and physical fitness levels [strength, flexibility, etc.]). For a player who has recently increased their training load and has a history of injuries, the model might predict a higher risk of re-injury.	Supervised (Regression)
Athlete Health Status: Identifying athletes at risk of overtraining or stress-related conditions (e.g., if athlete's data show unusually high training loads, poor sleep quality, and signs of psychological stress, the model could classify them as at higher risk of overtraining).	Supervised (Classification)
Movement Analysis: Assessing athletes' movement patterns to predict and prevent potential injuries.	Supervised (Artificial Neural Network and Deep Learning)
Athlete Segmentation: Grouping athletes based on performance metrics or injury risk profiles to tailor training and rehabilitation programs (e.g., athletes could be grouped based on their agility test scores, history of ankle injuries, and training load data and, as a result, the team might identify a cluster of players with higher agility but also with higher risk of ankle injuries).	Unsupervised (Clustering)
Heatmap Generation: Analyzing player movement data to create heatmaps that visualize player density and positioning during games, aiding in tactical analysis.	Semi-supervised (Clustering)

AI: Artificial Intelligence.

The first challenge is data availability. In general, Machine Learning methods heavily depend on the nature and the characteristics of data collected to work effectively and efficiently.[57] In addition to the need of sufficient data to work properly, Machine Learning requires external validity and continuous availability of data with progressively larger datasets.[58] Thus, monitoring performance and retraining of Machine Learning models (robustness) should be considered from the beginning. Considering that the availability of data may be expensive, there is a need to advance data shareability and reusability. Shareability and reusability can contribute to transfer learning (i.e., due to similarities among some sports, a model trained on a sport-specific data can be tested in another).[59,60] Biases on data (unfairness) have been reported and it can lead to biased trained Machine Learning models.[61] In these cases (e.g., racial bias), minorities are underrepresented contributing to lower prediction performance. To mitigate biases in data, particularly those affecting underrepresented groups, it is proposed: (i) to determine the availability of diverse populations; (ii) to consider diversity in model design while framing hypotheses; (iii) to use recommended preprocessing bias mitigation techniques; (iv) to perform regular assessment of model performance across different demographic groups; (v) to engage with diverse domain experts, multidisciplinary teams, and community members; and (vi) to maintain transparency in reporting data sources.[62] Also, most of the available Machine Learning studies in the literature have poor methodological quality. Efforts to improve the design, conduction, reporting, and validation of Machine Learning studies are necessary to bridge the gap towards its application in clinical practice.[63]

Explainability of Machine Learning models (i.e., results of a used method must be interpretable for humans) is another challenge.[64] Currently, many Machine Learning models may be considered 'black boxes.' The lack of transparency of 'black box' approaches hinders independent evaluation of model performance, interpretability, utility, and generalizability prior to implementation.[65] To enhance the explainability of Machine Learning models in sports AI, researchers can integrate techniques such as model simplification and employ explainability frameworks such as Local Interpretable Model-Agnostic Explanations (LIME) or SHapley Additive exPlanations (SHAP) to provide insights into model decision processes. Furthermore, incorporating visualizations, practical examples, and interpretable reports in model outputs can aid non-expert users in comprehending the results.[66,67]

Regulatory guidance, liability, legal responsibility, and ethical considerations must be in the mind of those in charge of designing, conducting, and implementing AI-based applications in any field, thus also in sports. Some standard and general ethics considerations applicable to AI include[68]: (1) honesty; (2) truthfulness; (3) transparency; (4) benevolence and non-malevolence; (5) human dignity, autonomy, privacy, and safety; and (6) justice. However, moral values and ethical standards are context-specific and, therefore, they might differ among populations, such as countries, regions, ethnic groups, etc.

Context-specific ethical aspects beyond those described here might be worth consideration, and the sports professionals and researchers must be aware of such aspects and preferably they should discuss AI-related ethical issues with other collaborators, stakeholders, coaches, health professionals, athletes, and/or end-users, when applicable, to ensure that AI applications comply with the required ethical standards. Therefore, it is essential to adopt comprehensive measures for protecting sensitive information, such as: (i) evaluating transparency and effectiveness in obtaining user consent for data collection and processing activities; (ii) ensuring AI systems comply with laws and regulations governing personal data privacy; (iii) data minimization, anonymization, and de-identification techniques; (iv) implementing robust access controls and encryption mechanisms; and (v) conducting privacy impact assessments to identify and address privacy risks.[69,70]

Future perspectives

Industry 4.0, often referred to as the fourth industrial revolution, integrates intelligent digital technologies into manufacturing and industrial processes. It represents a transformative shift in how technology is embedded in industries, enhancing efficiency and connectivity.[71] This concept, first introduced in Hanover, Germany, in 2011, serves as a model for subsequent initiatives like Health 4.0.[72] Health 4.0 integrates innovative technologies such as the Internet of Health Things (IoHT), medical CyberPhysical Systems (medical CPS), health cloud, health fog, Big Data analytics, Machine Learning, and blockchain to enhance individualized prevention, diagnosis, treatment, and public health.[73]

Similarly, Sports 4.0 has the potential to tailor and implement foundational principles from Industry and Health 4.0, including: (i) interoperability (allowing different devices and systems to connect); (ii) virtualization (creating digital models of systems and processes); (iii) decentralization (enabling self-governing systems); (iv) real-time capability for prompt data gathering and analysis; (v) service orientation to develop software for interacting with devices; and (vi) modularity (enhancing specific components for meeting new requirements and reusing available modules to build new sports systems).[74] These features in Sports 4.0 could change the SEM field by supporting personalized injury prevention, diagnosis, management, training, and rehabilitation, focusing on a coordinated and individual-centric care to optimize health outcomes and encourage physical activity.

Declaration of competing interest

The authors declare no competing interest.

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