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مراجعة لاستخدام خوارزميات الذكاء الاصطناعي في التنبؤ بالإصابات والأداء لدى لاعبي كرة القدم

هيثم جواد كاظم [1]* مأب فتحي حمزه [2] محمد لطيف حسين [3]
[1] وزارة التربية ، مديرية تربية بغداد الكرخ الثانية، العراق.
[2] كلية التربية البدنية وعلوم الرياضة ، جامعة بغداد ، العراق.
[3] وزارة التربية ، مديرية تربية بغداد الكرخ الاولى، العراق.
haitham.ali2404p@cope.uobaghdad.edu.iq
maab@cope.uobaghdad.edu.iq
Mohamed.rko91@gmail.com

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ملخص البحث:

تهدف هذه الدراسة إلى البحث في الخوارزميات الذكاء الاصطناعي المستخدمة في لعبة كرة القدم، لا سيما فيما يتعلق بتوقع أداء اللاعبين والوقاية من الإصابات. لتحقيق هذا الهدف، تم استخدام مصادر أكاديمية مثل Google Scholar و ResearchGate و Springer و Scopus لإجراء مراجعة منهجية للأبحاث المنشورة خلال السنوات العشر الأخيرة (2015 – 2025). من خلال عملية منهجية شملت جمع البيانات والمصادر، واختيار الدراسات بناءً على معايير محددة، وتصنيفها وفقًا لتطبيقات وخوارزميات الذكاء الاصطناعي المستخدمة في لعبة كرة القدم، وتقييم المشكلات البحثية الرئيسية والاتجاهات والفرص المستقبلية، تم العثور على ما يقرب من خمسين ورقة بحثية وتحليلها. تسلط الدراسة الضوء على ثلاثة محاور رئيسية: تلخيص تطبيقات الذكاء الاصطناعي في كرة القدم فيما يتعلق بتوقع الأداء والإصابات، التنبؤ بالإصابات وتحليل المخاطر المرتبطة بها، وتقييم أداء اللاعبين باستخدام نماذج الذكاء الاصطناعي. تؤكد هذه الدراسة على دور الخوارزميات الذكية في المجال الرياضي، لا سيما في توقع الإصابات والتنبؤ بأداء الفرق أو اللاعبين في كرة القدم.

الكلمات المفتاحية: الذكاء الاصطناعي(AI) ، تعلم الآلة(ML) ، الشبكات العصبية العميقة(DNN) ، التنبؤ بالأداء، الوقاية من الإصابات.

A Review of the Use of Artificial Intelligence Algorithms for Predicting Injuries and Performance in Football Players

Haitham Jawad Kadhim[1], Maab Fathi Hamzah[2*], Mohammed Lateif Hussain[3]

Abstract
The purpose of this study is to investigate the research on artificial intelligence algorithms in football, specifically in relation to player performance prediction and injury prevention. To accomplish this goal, scholarly resources including Google Scholar, ResearchGate, Springer, and Scopus were used to provide a systematic examination of research done during the last ten years (2015–2025). Through a systematic procedure that included data collection, study selection based on predetermined criteria, categorisation based on AI applications in football, and assessment of major research problems, trends, and prospects, almost fifty papers were found and analysed. Summarising AI applications in football for performance and injury predictions, predicting injuries and analysing related risks, and evaluating player performance using AI models are the three main topics highlighted in the study. This study highlights the use of AI algorithms in the sports field to predict injuries and predict team or player performance, especially in football.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Deep Neural Networks (DNN), Performance Prediction, Injury Prevention.

1 Introduction

Artificial intelligence can be defined as a neural network that mimics human action [1]Artificial intelligence has become available in many aspects of our daily lives and people use it extensively on a daily basis, such as ChatGPT from OpenAI, Alexa from Google, Siri from Apple [2][3][4] .AI technologies increase productivity by automating tasks with less time and effort, especially in the sports field [1] as is the case with the semi-automated offside system used in the 2022 FIFA World Cup in Qatar in football [5]. In recent years, artificial intelligence (AI) algorithms and applications have become an essential part of the sports field such as football [6][7] [8] Such as machine learning (ML) and deep neural networks (DNN) because of their ability to analyze large amounts of data and identify patterns that help in decision-making [6][7] In football, AI is used to analyze performance and predict injuries based on player data in matches and training.

AI algorithms enable coaches, especially fitness trainers, to improve training programs aimed at reducing injuries and improving performance based on relevant data [9] AI in sports is important because it can enhance the quality of training, reduce injury rates, and provide reliable information to help management and coaches make data-driven decisions. It also helps develop players’ fitness by improving performance and avoiding injuries by setting specific training programs for each player [1]. The adoption of AI has become an important tool and should be used due to the increasing reliance on technology by sports teams and federations.

However, the use of various algorithms that actively learn from data transforms machine learning into a complex process. The core function of these algorithms is to provide more accurate data, as long as new information continues to be incorporated [10]. The use of various algorithms that interactively learn from data transforms machine learning (ML) into a complex process. The core purpose of these algorithms is to provide more accurate data as long as new information is continuously integrated [8]. In conclusion, machine learning algorithms may be divided into two categories: (i) supervised learning, which includes techniques like regression and classification, and (ii) unsupervised learning, which solely uses input data [8]. Random forests [10] , support vector machines [11]. and decision tree classifiers are a few of the most popular machine learning prediction models. In football, however, a wide variety of alternative techniques are being investigated for talent identification, performance prediction, and injury prediction [12].

Given the substantial advancements since the first machine learning models were introduced in football [13], it is still crucial to summarise and extract a set of conclusions to decide when to make decisions. The use of predictive techniques in different team sports (e.g., basketball, baseball, football, cricket, and soccer) has been summarised in some narrative reviews up to this point [7], and there have been recent developments in the use of machine learning and statistical methods for predicting maximum oxygen consumption [14]. Furthermore, to the best of the authors' knowledge, the application of AI in team sports has only been compiled in two systematic reviews. While Herold et al. .[3] concentrated their systematic review on current applications and future directions of predictive models in the attacking phase of the game, Cludino et al. [8] compiled the use of machine learning in a number of team sports (including basketball, American football, Australian football, volleyball, soccer, and handball) for injury risk and performance analysis. Nevertheless, no study has thoroughly examined the application of machine learning in football for talent discovery, performance prediction, and injury prevention.

Therefore, the purpose of this paper is to review recent work on artificial intelligence applications in football, focusing on performance prediction and injury prediction algorithms. The study aims to evaluate the accuracy of these models, implementation challenges, and the future development scope of these models. Articles were collected from reliable academic sources such as Google Scholar, ResearchGate, Springer, and Scopus, with an emphasis on research published between 2015 and 2025. The studies were classified and analysed based on their applications in football, such as player performance prediction, player injuries prediction, in order to identify important research trends and provide a comprehensive perspective on the topic.

2 Material and Methods

This type of review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [15] [16] and the standards for performing systematic reviews in sport sciences [17]

2.1 Information Sources

Up to February 2, 2025, databases including Google Scholar, ResearchGate, Springer, and Scopus were searched for pertinent research.

2.2 Search Strategy

The title, abstract, or keywords had a variety of keyword and synonym combinations, including: (Football or Soccer) AND ("deep learning" or "machine learning" or Artificial Intelligent. To find any studies that were missed by the computerized searches, the reference lists of the papers that were obtained were also manually reviewed. In order to make sure no studies were missed throughout our search; an outside expert was contacted to confirm the final reference list that was part of our scoping study. Every study that was included had any potential mistakes examined as well.

2.3 The extraction of data

The inclusion criteria were evaluated using an Excel sheet, which was then tested for each of the chosen papers. Discussions were held to settle any disputes over study eligibility, and the procedure was carried out independently. The reasons for any full-text articles that were not included were noted. The datasheet contained all the records.

2.4 Information Items

The following data was taken from the original papers that were included: (1) Participants (the quantity of teams, games, and attempts); (2) Source/technology of data collecting; (3) Attributes, variables, or characteristics; (4) Prediction goal; (5) Machine Learning problems (method, algorithms, and prediction percentage); and final thoughts and forecasts.

3 AI Algorithms used in Football

Nowadays, artificial intelligence (AI) is used in many aspects of football, including performance monitoring, injury prediction, and tactical strategy optimisation. Machine learning algorithms and deep neural networks are utilized to analyse player data collected from GPS tracking devices, biometric sensors, and analytical videos, providing precise insights for coaches and managers. AI is used in the field of sports, especially in football, in terms of predicting match results, analysing player performance, predicting injuries, and opposing team strategies based on previous data recorded by devices such as global tracking devices (GPS) due to their role in tracking player movement, which contributes to developing both individual and team performance. AI algorithms in sports need an amount of data to make more accurate and reliable predictions. A variety of sources, including video recordings and GPS tracking devices, are available to collect data during matches and training. Given the importance of AI in football, which enhances the quality of training and reduces sports injuries, knowing the causes of sports injuries helps avoid future injuries and decision-making, thus raising the level of performance of the team. Table 3 shows some types of AI algorithms used in the sports field:

Table 3. Type of AI algorithms used in the Performance and injuries predictions.

Type	Description
ML	Machine learning is one of the most popular AI techniques in football, using large amounts of data to predict athlete performance. It is also used in diverse areas such as analysing opposing team strategy, predicting match results, and evaluating player performance. Such as support vector machines (SVMs), random forests, and decision trees.
DNN	Deep neural networks are complex networks that use several layers of neurons and handle vast volumes of data to replicate human behaviour. it is uses in physical performance analysis, player movement tracking, and picture and video analysis all make use of them. Long short-term memory networks (LSTMs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs) for image and video processing are a few examples.
RL	It is one of the most advanced artificial intelligence algorithms because it can make decisions based on previous experiences and can interact with the environment, so it is used in designing robots that simulate players' performance. This type enhances sports applications in football because it facilitates decision-making based on reliable data.

4. AI prediction in Football:

In This review paper will discuss the research in two clustering were created to study their characteristics as follow:

3.1 AI for Performance Prediction in Football

One of the most well-known uses of artificial intelligence in football is player performance prediction, which gives fitness coaches the ability to assess players and make tactical choices based on precise information. These forecasts are based on an analysis of a number of factors, including heart rate, acceleration, deceleration, sprint distances, and distances travelled. To find trends pertaining to player and team performance, deep learning methods and machine learning algorithms like logistic regression and random forests are employed. In order for coaches to understand training loads on players and create individualised training regimens to improve their physical performance, monitoring devices like GPS tracking systems are essential for gathering data during practice and games. Additionally, by projecting future performance based on previous data, artificial intelligence makes it possible to anticipate player performance and minimise injuries. Teams may enhance training quality and obtain a competitive edge during games by utilising historical data analysis and closely tracking player performance. (Table 4) illustrated the researches of AI in performance.

Table 4. Comparison between the researches that predicted football performance using AI.

Ref.	Year	Participants	Technology for acquiring data	Aim	AI algorithm	Practical application from predicting
[18]	2019	20 English Premier League professional teams, with a season-long total of 380 games.	Observation	Match outcome (win, draw, loss)	Supervised/ K-means Clusters Decision trees	Scoring first is the most crucial factor in match outcome prediction, and its impact is influenced by the calibre of the opposition.
[19]	2020	Five top-tier European football matches (715 unsuccessful assaults and 380 successful ones)	Tracking system	Which game conditions are most likely to result in successful assaults (the ball is less than 25 meters from the opponent team's goal)	Deep reinforcement learning	Positional data may be utilised to assess multiplayer positioning using the deep reinforcement learning that has been given. They reasoned that this model may be useful for determining what kind of attack—a counterattack or a cross pass—could be most successful, in addition to playing pace and passes.
[20]	2020	16 U15 from a professional team in Italy	Anthropometric measurement tools and timing gates for yo-yo, the 90º change of direction test, the 10 and 20 m sprint, and CMJ	intended to use anthropometric factors to predict performance.	Extra tree regression	Anthropometric characteristics may be crucial for forecasting success in the yo-yo test and the 10/20 m sprint. Features of the upper body, such as the circumference and arm muscle area, may be utilised to forecast performance in a 10–20 m sprint. The yo-yo test performance may be affected by the lower body characteristics of the right and left suprapatellar girths. It is not appropriate to use anthropometric characteristics to predict performance in the CMJ and change of direction tests.
[21]	2021	7918 observations after data cleaning during 2013–2018 seasons	RPE and wellness surveys + GPS	Aimed to predict training load from wellness questionnaires	Classification tree Regression tree Random Forest	Fluctuations in wellness status responses can lead to predicting an influence in athlete´s performance
[22]	2019	46 non-professional players during 2 seasons (61 training sessions)	GPS + Heart rate devices	Session RPE	Gradient Boosting Machines	eTL indicators (mainly total distance covered) are the stronger RPE predictors, although including a broad range of variables, other than ELIs, may be useful.
[23]	2018	38 players from the first division in the Netherlands during two seasons.	RPE survey + GPS + MEMS	RPE	ANN LASSO	A wide range of e TL factors may be used to predict RPE using LASSO and ANN. Accelerations were crucial eTL factors in predicting RPE.
[24]	2019	13 elite females in a shuttle run test	MEMS (accelerometer, gyroscopes, and barometer)	Direction of turn Speed (both prior to and following a turn) mechanical strain when turning	Regression using linear models Encouragement regression with vectors Enhanced decision trees ANN	We demonstrated that a data-driven method may yield valuable information on turn kinematics and energetics from inertial units, even though models can be extended to other angles.
[25]	**2024**	Football players (strikers, midfielders, defenders)	Biometric parameters	to use supervised machine learning algorithms to predict football players' performance that is above team average.	Random Forest, with optimization through grid search and two versions of the whale-optimization algorithm (including a proposed version using Euclidean distance).	The method helps football teams' staff monitor players, make tactical decisions, design customized training sessions, and guide market choices. The prediction of performance indicators with over 90% accuracy enables the optimization of training and performance evaluations based on player roles.
[26]	**2024**	Football players	Wearable technology, optical tracking systems, biological parameters, location data, and event data	to talk about the use of AI and ML in football from the standpoint of performance analysis.	Machine Learning (ML)	Use AI techniques, including ML, for player performance analysis. Theoretical guidance is provided using ecological dynamics. A case study on a spatial-temporal indicator, "density zone," is presented.

[27]	**2025**	players		To review and analyse the research trends, hotspots, and status of youth football through a bibliometric analysis of 1637 articles	-	Provides an overview of global research trends and hotspots in youth football, including areas such as sports monitoring, injury risk, talent development, and youth training systems.
[28]	**2025**	Liverpool FC, Arsenal FC, Manchester City FC	Statistical Chi-squared tests on football data, AI collaboration on football tactics	To evaluate the effectiveness of predictive AI in suggesting prescient ideas in football, particularly corner kick tactics.	Artificial Intelligence (AI)	Study on AI's predictive capacity regarding corner kick tactics and goals scored/conceded, evaluating performance trends across multiple football clubs over different seasons.

4.2 AI for Injury Prediction in Football

Predicting injuries is an essential tactic in football to safeguard players and reduce the chance of harm. Player data gathered from several sources, including GPS tracking devices and past injury records, is used by artificial intelligence systems. To analyse data like heart rate and anticipate injuries before they happen, machine learning techniques like support vector machines (SVMs), random forests, and deep learning are employed. By using this approach, coaches may take preventative actions like modifying training schedules, lessening the physical load on ailing players, and creating customised programs based on player data.
As data analysis methods continue to advance, AI has emerged as a critical tool for improving player health and prolonging their careers. By ensuring players' readiness and reducing downtime due to injury, it gives teams a competitive advantage. Researches clustering AI and injuries is illustrated in (Table 5)

Table 5. Comparison between Researches that predicted football performance using AI.

Ref.	Year	Participants	Technology for acquiring data	Aim	AI algorithm	Practical application from predicting
[29]	**2020**	75 high school academies' players (17 games)	Video capture combined with MEMS (accelerometer).	Changes in the brain brought about by these acts.	Tree-based Extreme Gradient Booster (XG Boost) classifier	Using longitudinal machine learning methods, the quantity of head hits may forecast alterations in the brain.
[8]	**2019**	355 young people (ages 10 to 18) in a single season.	Instruments for biomechanical testing	Injuries to the neuromuscular	Decision trees and supervision: J48 consolidated. An alternative decision tree. minimises the mistake trimming tree.	The most common factors that predict injury rates include anthropometrics, Y-balance, 75% hop distance and stick, asymmetry in single leg CMJ, and tuck jump knee valgus.
[30]	**2019**	26 experts throughout the course of one season (931	Both GPS and MEMS are provided by STAT Sports.	Overuse or severe injuries.	Decision tree regression under supervision	When training HSR exceeds 112 meters, an injury may recur. Training HSR > 112 m and monotonous of total distance ≥ 1.78 times. The player's average

		sessions over 23 weeks)				distance is 2.5 times lower than the training HSR > 112 m and total distance.
[31]	**2024**	Athletes	Cassandra (Big Data Storage), Wearable technology, medical records, Performance data	To predict injuries in professional sports using machine learning, specifically Support Vector Machines (SVM), and Big Data Analytics (BDA) for player health management	Support Vector Machines (SVM)	Helps in predicting injuries to assist in early detection, taking preventive measures, and improving player performance. Uses big data analytics for player health and resource management.
[32]	**2023**	813 youth football players, ages 10-18	Injury registration forms, weekly training, and match exposure data	to learn more about the prevalence, kind, and location of growth-related sports injuries (GRSI) among young professional football players to assess the severity and impact of injuries.	-	Provides data on GRSI incidence and severity, useful for injury recognition, management, and prediction of time loss for youth football players.
[33]	2025	players	Cite Space (visual bibliometric software), Web of Science (WOS), China Knowledge Infrastructure Project (CNKI)	To analyse the trends, hotspots, and status of youth football research by reviewing 1637 articles and identifying key research areas	-	Provides a comprehensive view of the research landscape in youth football, identifying major trends and areas for further investigation.
[34]	**2024**	-	AI technologies in sports science (load management, injury prevention, etc.)	To examine how AI is advancing sports science, particularly in team sports, by improving training load management, performance, and player well-being	Various AI models for training load optimization, injury prevention, talent scouting, etc.	AI enhances team sports by optimizing training loads, preventing injuries, aiding in return-to-play protocols, improving performance, identifying talent, and managing athlete health (sleep, menstrual cycle).
[17]	**2019**	363 players from FC Barcelona across ten leagues in	-	Tendinopathy injuries	Support vector machine Random Forest	It is possible to predict tendinopathies by analysing genes. In the fibrillin 2 gene, which codes for fibrillin 2, rs10477683 was one of the most stable single

		various team sports, including football (55% injured)				nucleotide polymorphisms.

5. Result and Discussion

A total of 50 searches were found through database searching (Google Scholar, ResearchGate, Springer, and Scopus). After removing duplicates, 46 articles were screened for relevance based on their title and abstract. As a result, 25 full texts were assessed for eligibility, with 10 of them deemed unsuitable for review. However, through the references of 15 suitable articles, three additional studies were found. Consequently, a total of 18 articles were included in the review. The reasons for excluding the remaining articles were as follows: articles related to team playing styles, other sports, academies, books, dissertations, and other types of non-peer-reviewed documents. Additionally, some articles were excluded due to their incompatibility with the study's objective, while others were excluded due to the unavailability of the full text (Figure 1). After that, Mendeley Reference Manager 2.112.2 was used to export these studies., a reference manager program. This review paper's objective was to find original research that used AI on football data, emphasising the potential of ML, DL, AI, and its potential uses in the future. The main conclusions were that the best predictions of injury occurrences are obtained from pre-season screening, training load, genetics, and risk factor surveys (which encompass psychological, neuromuscular, and personal components). Algorithms like decision trees can be used to forecast the likelihood of injuries. AI algorithms are used in three fields to predict performance:

- Predicting outcomes: Notational analysis and positional data can help predict match outcomes or even league rankings.
- Physical/physiological performance: ML approaches help identify key contributors and factors that determine player wellness and training load, offering valuable insights to coaches.
- Technical/tactical performance: Technical and tactical data can reveal passing effectiveness and classify team styles.

Lastly, by primarily employing positional and technical data, AI algorithms may help determine the optimal lineup for a tournament and forecast the performance of successful players in teams. In soccer, the fitness coaches often make decisions based on intuition, despite being informed by objective data, due to the unpredictability of events. Technological advancements have led to the development of prediction algorithms (e.g., AI), which leverage the large amount of data collected by GPS devices and stored, enabling "learning" processes. These processes help predict future events, focusing on two main aspects: (1) performance, and (2) injury prevention.

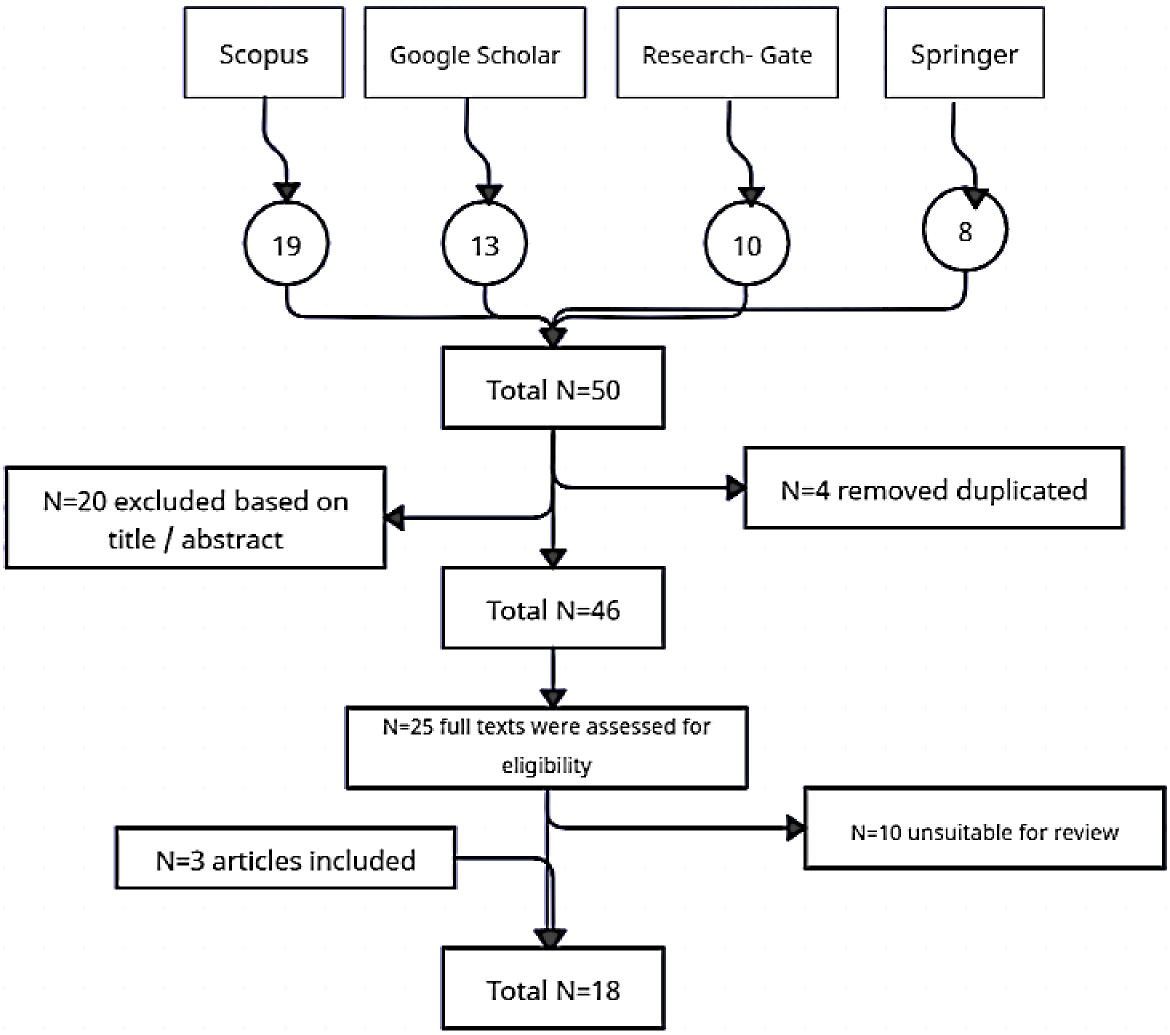

Figure (1): Literature search flowchart according to the PRISMA guide

In the field of predicting sports performance and injuries in football, deep learning and traditional machine learning algorithms exhibit varying levels of accuracy and effectiveness, depending on the nature and size of the data used. The accuracy of AI models can be determined using Equation 1.

$$\text{Accuracy}= \frac{TP+FP}{TN+TP+FN+FP} \qquad (1)[34]$$

Which expresses the ratio of correct predictions to the total number of predictions, In equation (1) the true negative is denoted by (TN), the false negative by (FN), the false positive by (FP), and the true positive by (TP).Also the accuracy can be increased using hyperparameter tuning techniques, increasing the size of training data, and increasing the amount of data collected from tracking devices. We found that the best algorithms used in research are illustrated in table (6):

Table 6: illustrated the best algorithms used in the Researches with the implementation challenges and estimation accuracy.

Type		Description	Estimated accuracy percentages	Implementation Challenges
Deep Learning (DL)	Deep Neural Networks (DNN)	Used to discover complex patterns in player tracking data.	85%	High computational cost, difficult to interpret results.
	Recurrent Neural Networks (RNN)	Used to analyze GPS data and predict fatigue and injuries based on past performance.	82%	Requires sequential data, prone to vanishing gradient problem.
	Convolutional Neural Networks (CNNs)	Effective in analyzing video data and recognizing movement patterns.	88%	High data processing demand, requires large labelled datasets.
Machine Learning (ML)	Random Forest	Effectively used to classify performance levels and predict injuries based on variables such as distance covered and maximum speed.	80%	Less effective with highly imbalanced data.
	Support Vector Machines (SVMs)	Effective in predicting injuries and classifying fitness levels based on multivariate data.	78%	Computationally expensive for large datasets.
	XG Boost	This is considered one of the best algorithms for classification and prediction, boasting high accuracy and effectiveness in handling complex sports data.	90%	Requires parameter tuning, sensitive to noisy data.

Although artificial intelligence offers numerous benefits in analysing sports performance and predicting injuries, some algorithms are more effective for injury prediction, such as LSTM, Random Forest, and XG Boost, which are among the most used due to their ability to analyse temporal data and complex variables. For performance prediction, deep learning algorithms demonstrate high effectiveness when dealing with video data and GPS tracking devices, such as CNN and RNN. In contrast, SVM and Logistic Regression are less accurate compared to deep learning when handling large datasets.

Based on recent research, deep learning algorithms are preferred for processing temporal data, such as tracking player performance throughout the season, while machine learning is used when a robust and precise model is needed to identify factors influencing injuries. Despite the advantages of AI in sports performance analysis and injury prediction, several challenges remain, including the availability of accurate and large-scale data. AI applications that process big datasets can be expensive for teams with limited funding. Moreover, the use of AI in football is also hindered by ethical and legal constraints, such as player data privacy and preventing the unlawful use of data.

As a result of the development of artificial intelligence technologies and the widespread use of its applications in the sports field, especially in football and for all age groups, men and women, football is expected to witness development in performance analysis and prediction of future injuries for sports teams. It is possible to use diverse and huge data in deep learning algorithms to increase the accuracy of prediction models. As a result, the coach will be able to make better judgments about managing the training load and player performance and develop customized training plans for individual or collective players. Artificial intelligence can become a more effective tool by simulating match conditions and making decisions in real time using virtual reality and augmented reality. Integration with IoT technology will also improve the collection and analysis of real-time player data, allowing for accurate monitoring of vital signs and physical performance. It is anticipated that intelligent decision-making technologies will develop further, helping coaches refine their tactical plans through in-game data analysis. As artificial intelligence advances and teams' ability to enhance performance and reduce injuries increases, professional football administration will alter significantly in the future.

6. Conclusion

Through this Article review, we aimed to summarize the current scientific knowledge regarding the use of artificial intelligence algorithms in football. Machine learning algorithms, deep neural networks, and reinforcement learning have enabled advancements in performance analysis, injury prediction, and tactical decision-making. The integration of big data and tracking devices with AI algorithms enhances prediction accuracy and aids in developing personalized training programs. However, challenges remain regarding model interpretability, data quality, and the costs associated with large-scale implementation. According to previous research, deep learning and traditional machine learning algorithms exhibit varying levels of accuracy and effectiveness. Moreover, LSTM, Random Forest, and XG Boost are among the most used algorithms due to their ability to analyse temporal data and complex variables. In performance prediction, CNN and RNN demonstrate high effectiveness when processing video data and GPS tracking information. Lastly, SVM and Logistic Regression were found to be less accurate compared to deep learning when handling large datasets.

It is also suggested that researchers, AI experts, and sports coaches work together more to create solutions that better suit the real requirements of sports teams. Future research opportunities include the potential for a major change in player training and performance analysis due to the proliferation of technologies like interactive AI, augmented reality, and the Internet of Things. Football performance management may become more sophisticated and accurate with the creation of hybrid models that use various AI approaches. These models may also aid increase prediction accuracy and lower injury rates.

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