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Enhanced Sports Predictions: A Comprehensive Analysis of the Role and Performance of Predictive Analytics in the Sports Sector

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Abstract
Several emerging industries are deploying Artificial Intelligence (AI) and Big Data in many fields. The combination of AI and Big data can benefit sports in many ways. An effective sports prediction model can help athletes improve their sports performance by providing them with an additional training plan and ensuring their health. It is common to use artificial intelligence to predict sports results. Artificial intelligence-enabled predictive analytics can be used to improve an athlete's physical condition and performance. This study attempts to develop a sports predictive analytics system on the basis of AI and big data. This study examines the role of artificial intelligence and big data in the sports industry. The current research status of sports predictive analytics is reviewed through a literature search. Succeedingly, the analysis of the performance of the proposed system is carried out. The result of the study will encourage the use of AI and Big data in sports.

Keywords Artificial intelligence · Predictive analytics · Big data · Machine learning · Pacing behavior of athletes · Performance of athletes

1 Introduction

Training process of athletes which is an integrated multidisciplinary combination of factors, considered necessary for an athlete's growth process and conditions relevant to forms of training system and continuous improvement in performance. The athlete training system is constituted of cooperation and operation factors such as coaches, personnel management and personnel service. The athletes regulate activities such as sleeping patterns, edibles and wearing kits, teaching strategy and range [1]. The goal of incorporating Big Data in sports analysis is to compile data from multiple sources and present it in a cohesive manner, streamlining the decision-making process by providing integrated and accessible information [2]. When it comes to Big Data, sports data collection involves the collection, storage, management, and validation of sports-related information using specialized

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database software tools. These tools are equipped to handle large amounts of data, characterized by its volume, variety, velocity, veracity, and value. The implementation of Big Data services plays a vital role in achieving success in competitions by providing performance evaluation, health monitoring, training statistics, and ongoing supervision. These services are invaluable in helping coaches and athletes optimize their training sessions and develop personalized game strategies [3]. The aim of the study is to explore the advantages of using Big Data and Artificial Intelligence (AI) in sports prediction systems. The study seeks to develop a sports predictive analytics system based on AI and big data, and assess its performance. By reviewing the current research status of sports predictive analytics and analysing the proposed system, the study aims to demonstrate the potential of AI and big data in improving sports predictions. The research also aims to highlight the role of AI and big data in the sports sector, specifically in enhancing athletes' training plans, health monitoring, and overall sports performance. The study's findings are expected to encourage the adoption of AI and big data in the sports industry and promote more accurate predictions across various industries.

1.1 Big Data and Artificial Intelligence

The definition of artificial intelligence encompasses machines' capability to learn from experience, adapt to new inputs, and handle tasks performed by humans. When employed in decision-making processes, AI categorizes roles using a range of approaches [4]. The concept of big data encompasses the integration of structured, semistructured, and unstructured data obtained by organizations. This data is subsequently leveraged for machine learning endeavors, predictive modeling, and other analytical applications. In the age of big data, there is a strong impetus to conduct extensive surveys in order to efficiently manage the datasets obtained. These dataset were accessed for machine learning tasks that focused on research [5].

Big data is necessary for decision-making, business growth, personalization, operational efficiency, innovation and research, risk management, and predictive analytics [1]. It provides valuable insights that enable informed decision-making, foster business growth, enable personalization, improve operational efficiency, foster innovation and research, enhance risk management, and facilitate predictive analytics. Leveraging big data effectively can provide organizations with a competitive advantage and unlock new opportunities in today's data-driven world [3].

The incorporation of big data in the sports industry has become increasingly essential for accurate prediction and informed decision-making [2]. This is due to the data-rich nature of the industry, the need for a competitive edge, the drive for enhanced fan engagement, the development of innovative technologies, and the optimization of operational efficiency [6]. Big data analytics enables the collection, storage, and analysis of diverse data sets, offering valuable insights into player performance, team strategies, and fan preferences. It also provides teams with a competitive edge by identifying patterns, trends, and correlations within the data, helping to predict player injuries, game outcomes, and player performance potential [7]. Additionally, it contributes to the development of innovative technologies, such as wearable devices that monitor player biometrics, smart stadiums that enhance the fan experience, and data-driven decisions to improve player conditioning, enhance training programs, and minimize the risk of injuries [8]. Big data analytics can unlock valuable insights, make accurate predictions, and drive growth in various aspects, revolutionizing the way sports are played, managed, and experienced [9].

The integration of big data in the sports industry prediction is driven by several key factors: enhanced performance, competitive advantage, fan engagement, innovation and technology, and operational efficiency [4]. Big data analytics empowers sports organizations to gain valuable insights from vast amounts of data, such as player statistics, performance metrics, and historical records [10]. These insights enable informed decision-making, leading to improved player performance, optimized training programs, and reduced risk of injuries. Competitive advantage is essential for sports organizations to gain an edge over opponents [11]. Fan engagement is essential for sports organizations to understand fan preferences and behavior. Innovation and technology drives innovation in the sports industry, leading to the development of cutting-edge technologies. Operational efficiency is improved by leveraging data-driven insights to improve player conditioning, enhance training programs, and streamline logistical processes [12].

1.1.1 Big Data Analytics

Sports medicine professionals, including athletic trainers and healthcare providers, utilize big data to gather and analyze biometric information and assess injuries among athletes [7, 9]. Biometric data is collected to measure and statistically analyze the physical and physiological characteristics of athletes. Wearable and non wearable biometric technological devices implemented in sports to optimize performance, maximum recovery and reduce injury conditions of athletes [6].

1.1.2 Artificial Intelligence

Impact of artificial intelligence (AI) on sports as gathering of information as per aspects to meet innovation for frameworks that help players and supporters of sports [8]. The applications of AI in the sports industry are chatbots which are used for answering fans regarding the history of sports. AI consciousness is assigned with a collection of essential information which conveys bits of knowledge for improvement of the sports including players and group specialists with portable application [13].

1.1.3 Predictive Analytics

Econometric and statistical approaches, such as machine learning, classification, and multivariate regression, incorporate predictive analytics as part of their techniques. The analysis of historical data to make prediction based econometric and statistical techniques determines event in the future or outcomes related to rank of player [14].

1.2 Role of Big Data and Artificial Intelligence in Sports Sector

In the sports sector, data collection based on athletes' physical activities and performance. As athletes physical activities and performance is determined as training, diet, sleep duration, healthcare and so on which contributed as details of athletes which are being stored in a database [15, 16]. Big data is a collection of datasets which are relevant to athletes and artificial intelligence is implemented as to predictions related to performance of athletes as algorithms are implemented for comparison for performance and other criteria related to athletes performance or health conditions (as per Fig. 1).

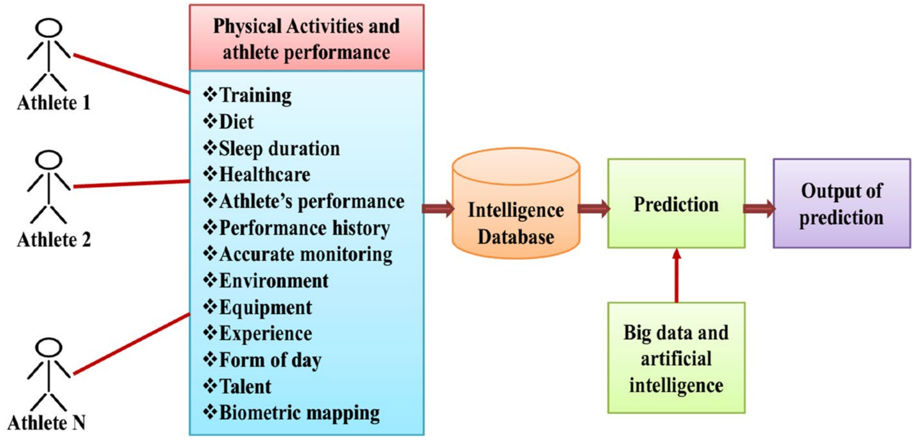


Fig. 1 Implementation of big data and artificial intelligence in sports

As per Fig. 1, athletes' database consists of a dataset of physical activities and their performance. Big data and artificial intelligence algorithms are implemented for prediction related to performance of athletes and output of prediction is improvement or decrement in performance of athletes. A dataset of athletes helps to plan training sessions and diet routines to maintain their health and improve performance.

1.3 Sports and Its Previous Predictive Models

The National Football League's data collection for the first eight rounds of competition utilizes an Artificial Neural Network (ANN) model to focus on key performance indicators such as yards gained, rushing yards gained, turnover margin, possession time, and betting line odds [17]. Using CNN model, data is examined in the form of visual imagery which suggests OCNN classification and SoftMax structure and evaluation of sports medicine in multi-dimensional data analysis [18]. Using a mixed model, the data analyze the relationship between data of the session and injury using generalized estimating equation (GEE) and these analyses can also handle panel data [19]. Using Neural Relational Inference (NRI) model provides an interpretable presentation that underlying system dynamics which is used trajectory forecasting in better way predicting static relations between entities of system [20].

The Gaussian naive Bayes model leverages the principles of conditional probability to calculate the posterior probabilities of data instances being associated with a specific class [21]. Naive Bayes dealing with continuous data assuming Gaussian probability density function class data is distributed [22]. By utilizing kernel tricks for efficient performance, the Support Vector Machine (SVM) model employs a range of supervised learning algorithms that are specifically tailored to handle high-dimensional feature spaces [22]. By leveraging the Random Forest model, a robust machine learning algorithm, intricate nonlinear decision boundaries can be effectively mapped. The algorithm constructs uncorrelated trees, resulting in a decrease in variance [22]. Using Gradient boosting model, the model accuracy is improved with every iteration as sequentially on the entire dataset by boosting classifiers and using model formalization to control over fitting [22]. A comparative Table 1 is given below.

Table 1 Sports and its previous predictive models

Authors	Motive of the model	Methods and algorithm	Features/Findings	Limitations/Scope
Bullock et al. [65]	Evaluation of Sports Injuries prediction models	• Regression methods • Machine learning approaches • Deep learning models	• All research created a prediction model, but none of them externally verified it	• Uses small sample sizes • No models could be suggested for usage in actual applications
Rory & Fadi [17]	To analyze the literature on sports results prediction	• ANN (Artificial neural network)	• Presented a framework called "SRP-CRISP-DM" to forecast sport outcomes • Discovered the drawbacks related to the implementation of sport prediction	• Quite a few features have been employed, although not all of them
Hesheng Song et al. [18]	To assess the sports injuries using deep learning	• Enhanced convolutional neural network • Advanced deep learning architecture • Auto-adjusting Resizing algorithm • Convolution self-coding technique	Constructs and designs an application for in-loop fusion, conducts comprehensive research, and conducts rigorous application testing, delivering technical guidance and hands-on expertise for the practical implementation of in-loop fusion hardware	Going forward, it is important to obtain a successful analysis of the data illustrating sports injuries by incorporating greater neural involvement in the testing of time series data functions
Marcus J Colby et al. [19]	To evaluate the impact of several high risk scenario (HRS)	Sessional workload data Univariate and multivariate Poisson regression models	More than 85% of participants showed very low (0–8 sessions) and very high injury risk (more than 15 sessions)	Playing experience and preseason workload weren't even moderators
Colin Graber & Alexander Schwing [20]	Dynamic nervous system: to identify system relationships amongst its components	Neural Relational Inference	Introduced Dynamic Neural Relational Inference	Examine whether one can further increase performance by using new techniques utilized by contemporary sequential latent variable models

1.4 Working of Sports Prediction Systems

Various stakeholders can enhance their understanding of their prospects for upcoming matches by considering a wide range of factors, such as team performance history, match results, and individual data. Prediction helps clubs and managers in making better choices to win leagues and competitions. Figure 2 shows the steps in prediction systems.

As per Fig. 2, For a game prediction problem, it is key to maintain the original training data sequentially. Training data is used to train the algorithm. Algorithm is used when the type variable has different levels. There is an ever-increasing amount of sports-related information available electronically. Competitive results are generated by predicting models using predetermined features on historical datasets. Competition forecasting is based on various factors.

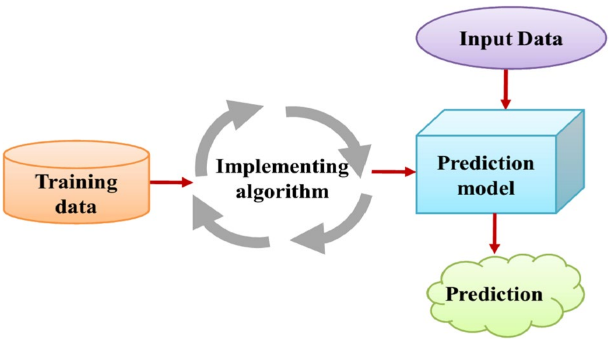
1.5 Training Sessions and Monitoring Health

Sports' training is considered a unique human activity which results in diversification and professionalization of athletes in competitive sports which lead to improved performance of athletes. In order to ensure the constant development of athletes' competitive abilities, sports training require a varied group of individuals to attend, each with specific responsibilities to fulfill, along with a distinct set of goals and challenges [12]. Periodic technical training, unique qualities and functional capabilities requires regular exercises in improving regular skills that includes practicing in segments, sets and supersets [10]. Internet to Things (IoT) is a different application domain that has a tremendous impact on the healthcare transformation which are extended capabilities of e-healthcare that can be considered as smart healthcare. Smart healthcare comprises different fields from the patient's care under medical supervision to well-being practices and factors of healthy lifestyle such as physical activity, food and activity consumption, quality of sleep, stress and social interaction [11, 23]. General purpose sensing is equipped in devices with sensing capabilities and use data for specialized task such as fitness [24].

1.6 Athletes Physical Condition and Performance

Adequate sleep is crucial for optimal athletic performance, cognitive abilities, overall health, and mental well-being. Athletes who struggle with sleep-related issues, such as sleep apnea, may experience negative consequences on their performance. Furthermore,

Fig. 2 Steps in prediction systems



insufficient sleep duration can have detrimental effects on metabolism, endocrine function, athletic performance, and cognitive abilities, leading to an increased sense of exertion during exercise [25]. As the specific nature of the task, factors that athlete is associated with and environment influences pacing behavior of athletes. As adequate pacing behavior developed by coach athletes helps to perform best to their ability staying healthy, engaged and injury-free [26].

1.7 Contribution of This Study

The primary contribution of this research is,

- The study highlighted that these technologies can be implemented across different industries, enabling more accurate predictions and informed decision-making.
- Examined the sports prediction system utilizing Big data and Artificial Intelligence
- Investigated the utilization of Big data and Artificial Intelligence in the analysis of sports predictions
- By analyzing the sports prediction system, the research shed light on how these technologies can be effectively utilized to enhance performance evaluation, talent scouting, strategic planning, and overall decision-making within the sports sector.
- The study opened avenues for further research and exploration in the field of big data and artificial intelligence.

The subsequent sections of the study are organized in the following manner: Sect. 2 presents related terms, Sect. 3 covers the study's methodology, design, and conceptual framework, Sect. 4 reveals the outcome of the hypothesis test, Sect. 5 contains the discussion, and finally, Sect. 6 presents the conclusion.

2 Literature Review

Available datasets are harnessed in conjunction with artificial intelligence and machine learning to foster the development and validation of new techniques in real-world applications. Synthetic environments often serve as the foundation for AI approaches, enabling the assessment of how behaviors are influenced by various entities and external phenomena according to the standard probability distribution [27].

Non linear relationship between observable variables and complex phenomena approached for soft tissue injuries which desire to train artificial models that attempt to model inputs with many variables and signals for complex systems, the human body. To train an injury classifier for the dataset training used by decision tree learners [28].

Continuous medical oversight is provided for an extended period during sports activities, monitoring the physical well-being of athletes. This comprehensive approach utilizes diverse algorithms and technologies to assess various indicators affecting the athletes' functional condition. Targeted determination of a program with real-time guidance is to monitor athletes' in the guiding process on the basis of functions as means for scientific training considered as a dataset for mobile artificial intelligence terminal technology [29].

The huge information which is being collected digitally and stored as a large quantity of information is termed as 'big data'. The technical, tactical and physiological behavior of athletes needs to be understood which is simplified by big data. Interior measurement units

(IMU) which help in improving systems for collecting and analyzing the data such as time motion and kinematics for team or individual sports as external and internal loads [30].

The expansion of sports centers has been made possible through the implementation of a well-rounded service system that focuses on invigilation, reliability, efficient communication, mechanical equipment, live broadcasting, and scoring equipment. By effectively addressing issues such as untimely staff service and space distribution disparities in cultural centers, this system guarantees a stable operation and a balanced financial outcome [31].

Theoretical and practical references are provided by big data that helps in developing sports and improving youth physique. National established sports is a conductor to strengthen national unity handling the relationship between nationalities and stability as ethnic groups gathering considers sports as medium for cultural exchanges [32].

Sports organizations are creating data analytics departments to analyze vast quantities of data collected from different sports, employing predictive analytics and mathematical algorithms as scientific methods to process the extracted information. This analyzed information helps coaches analyze athletes performance and make better decisions that assist better outcome of the game [33].

For improving organizational performance and managerial decision-making processes by implementing predictive analytics and artificial intelligence, an innovative predictive framework uses a combination of predictive analytics and machine learning for identifying the contract signed by athletes [34].

The act of pacing involves making deliberate choices regarding energy expenditure, both during training sessions and in actual competition, which significantly impacts an athlete's performance outcomes [35]. When it comes to pacing decision-making, a significant factor lies in how athletes interact with their surroundings, and their pacing behavior is subject to change depending on the type of event. The decision-making process involved in pacing is shaped by the interdependence among athletes [36].

The extended training sessions of endurance athletes necessitate increased metabolic and nutritional needs. Consequently, athletes tend to follow dietary patterns such as vegetarianism, high-fat intake, intermittent fasting, and gluten-free eating plans [37]. Sport evaluation is a training for athletes that relates to development of theories, techniques and methods for training and performance is influenced by factors contributed in determining the performance in different ways such as quantitative, qualitative and temporal [38].

2.1 Ethical Aspects of AI and Machine Learning in Sports

The ethical aspects of AI and machine learning in sports are crucial to consider, as these technologies have the potential to impact athletes, coaches, and the overall integrity of sports [39]. The use of AI and machine learning algorithms in sports prediction systems has given rise to ethical concerns regarding bias, accountability, and privacy [40]. Safeguarding athlete data privacy and security is crucial to prevent unauthorised access, data breaches, and misuse [41]. It is imperative for AI-driven sports prediction models to address biases in data collection, training sets, and algorithms to ensure equitable and precise predictions. Proactively tackling biases in these processes is essential for fairness, accuracy, and inclusivity in AI-driven sports prediction models. Multiple stakeholders, including data scientists, sports organisations, governing bodies, athletes, and coaches, bear the responsibility of ensuring transparency, explainability, and fairness in the implementation of AI and machine learning algorithms [42]. Upholding accountability standards and mitigating the negative impacts of predictive analytics models require a focus on transparency, explainability, fairness, and continuous monitoring. The utilisation of athlete data in sports prediction systems raises significant privacy concerns that necessitate effective measures for safeguarding sensitive personal information [43]. To protect athlete privacy, stringent data usage policies, informed consent protocols, data minimization, anonymization, and compliance with privacy regulations should be established. While guidelines, regulations, and frameworks have been developed to address the ethical implications of AI and machine learning in various domains, including sports, it is crucial to develop sport-specific guidelines and regulations through collaborative efforts with stakeholders and interdisciplinary expertise [44, 45]. This process will bridge existing gaps and establish comprehensive ethical frameworks for AI in sports. Key steps to be taken include establishing industry-wide standards to ensure fairness, transparency, and privacy protection, increasing transparency and explainability, setting clear protocols for data collection, storage, and usage, and conducting regular audits and evaluations [46]. Moreover, the establishment of ethical review boards and committees can ensure fairness, transparency, accountability, and athlete privacy in the context of AI and machine learning in sports [47].

The ethical concerns surrounding AI and machine learning in sports prediction systems necessitate careful consideration and proactive measures. Safeguarding athlete data privacy, addressing biases, ensuring transparency and explainability, and establishing clear protocols for data collection and usage are paramount. Collaboration among stakeholders, the development of sport-specific guidelines, and adherence to industry-wide standards are essential for fostering fairness, accuracy, and accountability [48]. By prioritizing these ethical considerations, the sports industry can navigate the challenges posed by AI and machine learning, ensuring responsible and beneficial implementation in sports prediction systems while safeguarding athlete privacy and promoting trust.

3 Methodology

This research aims to explore a sports predictive analytics system that utilizes artificial intelligence and big data. The methodology is a set of procedures consisting of a set of methods, rules, and propositions to be used. Quantitative primary sources were used for this study to address the main objectives of the research. The subsequent section provides a detailed explanation of various aspects of the methodology, including hypothesis development, data collection, data interpretation, analysis of findings, and the study's concluding remarks.

3.1 Hypothesis Formulation

By examining previous studies, this study presents a conceptual framework. The study's conceptual framework is visually presented in Fig. 3, highlighting H1a's focus on the precision of sports prediction within the prediction model's implementation. Additionally, H1b explores the wide-ranging capabilities of big data and AI in diverse industries. H2 consolidates the integration of big data and AI to create a sports prediction system. H3 determines the major factor of speed and efficiency in the predictive model. H4a performs the overall satisfaction and expectancy of the prediction system. H4b shows the performance of efficient current trend improvement in prediction systems.

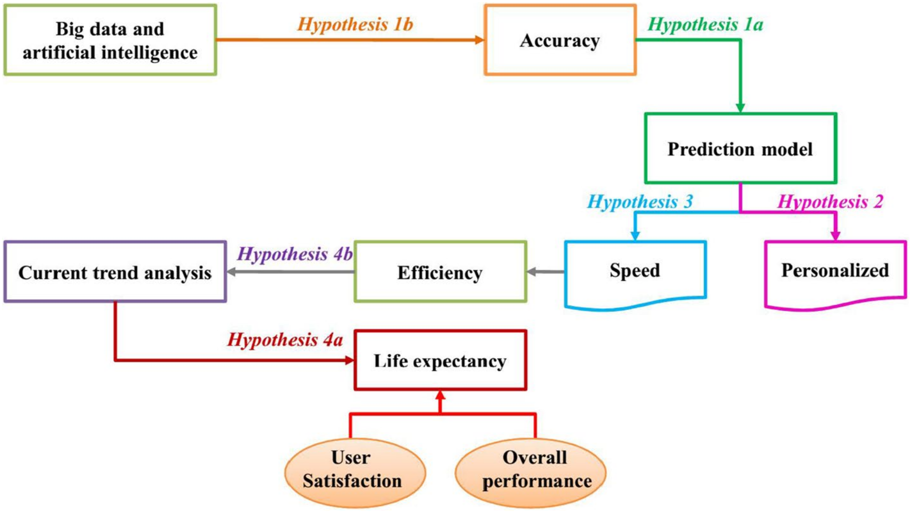


Fig. 3 Conceptual framework

- *The accuracy of sports prediction plays a vital role in implementation of predictive models.*

Sports forecasting is a rapidly expanding field driven by economic and social factors that influence regional development on a global scale. The sporting industry is constantly evolving through the implementation of innovative practices in equipment, techniques, strategies, and training [49]. Sports performance prediction is helpful in developing reasonable sports training programs according to the circumstances of the athletes. It provides guidance for future training so that coaches can reasonably develop competitive goals. Big data processing, artificial neural networks, and other technologies are used in sports performance prediction [50]. The increment level of AI in team sports is increasing, creating a promising future for the sports industry. It helps team players in analysis and data mining skills are used by captains to make changes in team strategy [51]. Therefore the study proposed the following hypothesis.

H1a The accuracy of sports prediction plays a vital role in implementation of predictive model.

- *Big data and artificial intelligence has the capability to make more accurate predictions among all kinds of industries.*

Big data and AI are about creating insights into processes like technologies and machine learning that can be used to make better data-driven decisions that can increase revenue and profitability [52]. Big data with AI to predict and analyze data collected from CCTV footage, GPS-enabled devices, and social media provides customer insights for simpler products. Big data helps in retaining customers from insurance companies. The use of databases with big data in organizations helps AI to deliver better results efficiently [7]. The data in databases can be used to solve problems and human activity.

It doesn't skimp on data analysis. Big data and AI are widely used in activities management, data management, goal management, and context management [53]. Hence the study suggested the following hypothesis.

H1b Big data and artificial intelligence has the capability to make more accurate predictions among all kinds of industries.

- *A personalized service can be provided by the big data and artificial intelligence based sports prediction systems.*

AI and big data have become important in every field and one of them is the sports field where it is used in games, activities, and other sports applications [2]. It is also used for a player's game record, player's performance, and recruitment of tickets. It also improves coaching with analytics on players' strengths, training, performance, deficiencies, and progress in the field of sports. Through big data and AI, the data of all the players are collected individually which enables the analysis of the players and enhances their development [54]. AI helps assess players' fitness, detect injuries, reduce stress, analyze player movements and health variables, etc. By using machine learning combined with big data and AI, a player's real-life situation through weather, team environment, field, player nutrition, sleep, etc., and used to determine measurable physical ability [55]. Therefore the study proposed the following hypothesis.

H2 A personalized service can be provided by the big data and artificial intelligence based sports prediction system.

- *Speed of execution is a major factor that determines the efficiency of the predictive model.*

Sports performance forecasting helps sports training organizations, sports teams, and teams to reflect changes in sports performance [56]. It is also used by coaches and athletes to improve their training improve teaching, and development attributes. AI can strategize and accurately predict games and help players increase their speed in games based on their physical strength [2]. It can also be used to create personalized training plans for players and speed up exercise performance. It helps coaches learn about players' movement, speed, and position. Big data and AI provide incentives for future success in sports by improving speed and performance. AI is a factor that determines the effectiveness and speed of execution of a predictive model [57].Therefore the study suggested the following hypothesis.

H3 Speed of execution is a major factor that determines the efficiency of the predictive model.

- *Life expectancy of a prediction system relies on the user satisfaction and overall performance.*

The longevity of the prediction system depends on the athlete's goal setting, self-talk, effects of emotion regulation, distraction, etc. Performance is sometimes affected by mental factors [58]. And its skills related to processing information and managing emotions are key determinants of athletes' performances. Actions and skills depend on the competitive results of individual-level athletes. Satisfaction is based on the player's own performance [59]. Machine learning can process the data accurately and sometimes the result changes depending on the player's mood. New technologies such as AI and Big data are being used in professional sports to make accurate predictions that players' moods are different and this affects performance [60]. Hence the study follows the hypothesis.

H4a Life expectancy of a prediction system relies on the user satisfaction and overall performance.

- *An efficient prediction system would analyze the current trend and improve the performance accordingly.*

A predictive system is a mathematical process used to analyze patterns in input data to predict future events or outcomes [61]. It helps predict the activity and behavioral trends. Organizations use predictive analytics to make predictions from their data to improve operational efficiency. Forecasting also helps improve the efficiency of financial services to detect fraud and predict credit risk, enabling them to be more efficient throughout the lifecycle of customer engagement with their organizations [62]. Consistently predicts job performance and skill levels in industries. It is widely used for forecasting in the stock market industry. It has become a strategy in education to predict student performance and it can be used to solve learning problems and improve their performance toward success [63]. Therefore the study following hypothesis.

H4b An efficiency prediction system would analyze the current trend and improve the performance accordingly.

3.2 Methods

This study conducted an in-depth investigation into several machine learning algorithms, namely Linear Regression, Logistic Regression, Random Forests, Support Vector Machines (SVM), Neural Networks, and Gradient Boosting. The primary objective of the study was to compare and assess the performance of each algorithm in predicting various aspects of the sports domain, such as game outcomes, player performance, and team dynamics. Through extensive analysis and evaluation, the study aimed to identify the algorithm that outperformed others in terms of prediction accuracy and robustness. Each algorithm was evaluated based on its effectiveness in analyzing vast amounts of sports data and generating accurate predictions.

For instance, Linear Regression, represented by the Eq. (1):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{1}$$

where Y is the dependent variable, β_0 is the intercept, β_1 to βn are the coefficients, and X_1 to X_2 are the independent variables, was examined for its ability to establish a linear relationship between variables.

Logistic Regression, characterized by the Eq. (2):

$$P(Y=1)=\frac{1}{\left(1+e^{-(z)}\right)} \tag{2}$$

where p represents the probability of the positive class, z is the linear combination of the coefficients and predictor variables.

Random Forests utilize an ensemble of decision trees and incorporate techniques such as bootstrapping and feature randomness. The formula for prediction involves aggregating the results of individual decision trees to make accurate predictions for game outcomes or player performance.

For instance, Random Forests utilizes the Eq. (3) to find the impurity in the dataset:

$$G_i=1-\sum_{i=1}^{n}\left(\rho_i\right)^2 \tag{3}$$

where G_i is the Gini index which helps to understand the amount of impurity in the dataset, ρ represents the probability of class.

Support Vector Machines (SVM) employ a kernel function to map data into higher-dimensional space and find an optimal hyperplane for classification. The prediction formula in SVM involves finding the hyperplane equation that maximizes the margin between data points. Support Vector Machines can also incorporate the use of kernel functions to handle non-linear separable data by transforming the input space. The formula with a kernel function can be written in Eq. (4):

$$f(x)=\sum_{i}\alpha_i y_i K\left(x_i,x\right)+b \tag{4}$$

here α_i represents the Lagrange multipliers associated with the support vectors, y_i represents the corresponding class labels, and $\mathrm{K}\left(x_i,x\right)$ denotes the kernel function that measures the similarity between the training data point x_i and the input vector x.

Neural Networks, represented by a set of interconnected nodes (neurons), utilize activation functions to process input data and make predictions. The formula for a neural network involves the calculation of weighted sums and the application of activation functions to obtain output predictions. Gradient Boosting combines weak prediction models and iteratively improves them by minimizing the loss function. The final prediction is obtained by summing the predictions from all weak models. The formula for a single neuron in a neural network can be expressed as follows:

$$z=w_1\times 1+w_2\times 2+w_3\times 3+\cdots+w_n\times x_n+b \tag{5}$$

$$\alpha=f(z) \tag{6}$$

In the above Eq. (5) and (6), z represents the weighted sum of the inputs and biases, w_i to w_n are the weights associated with the input features x_1 to x_n, b is the bias term, which allows the neuron to adjust its output independently of the inputs, a represents the output or activation of the neuron and *f(z)* is the activation function applied to the weighted sum.

By analyzing the strengths and limitations of these prediction models, the study aimed to provide valuable insights into the role and performance of predictive analytics in the sports sector. The findings of this study hold significant potential for the advancement of sports analytics, enabling sports organizations to make more informed and data-driven decisions. These findings contribute to the ongoing progress in sports analytics, fostering the development of more sophisticated and accurate prediction models in the future. This study paves the way for a data-driven revolution in the sports sector, enabling organizations to harness the full potential of predictive analytics for improved performance and success.

3.3 Data Collection

Data collection method includes primary data collection, and it is prepared through systematic procedure. In sports, big data and AI is an important task for data processing. This combination can benefit the game in many ways. The sports prediction model provides athletes with additional training programs to ensure their health and thus improve their sports performance. A primary questionnaire method was used in this study. The primary source of data is predicting the performance of athletes in sports, their performance and their health, through a sports predictive analytics system using AI and big data. The question paper used in this study contained the reliable questions required for the study. In this study, data were collected from participants in sports fields from China and other countries. The research team administered questionnaires to 200 individuals; the respondents included coaches, managers, athletes, forecasters, and predictors. 159 of those who received the question paper had correct answers, 49 had no correct answers and thus 159 were taken for analysis.

3.4 Data Description

To obtain the primary data for the research questionnaire is an essential apparatus. The type of questions in the questionnaire required for the study, the place where the question will be distributed and who the participants will be can be decided by the researcher. The questionnaire received for the study was about the use of artificial intelligence-enabled predictive analytics to improve athlete fitness and performance in sports. The questionnaire received for the study was indicative of the application of artificial intelligence-enabled predictive analytics to improve athlete fitness and performance in sports.

Table 2 provided the description of the study sample. It revealed that 33.96 percent of participants fell within the 25 to 30 age group, while 33.33 percent were aged between 31 and 40 years. Additionally, 32.70 percent of respondents were aged 41 and older. Based on gender, 54% respondents are male and 45.28% of respondents are females.

Figure 4 shows the descriptions of the respondents. According to the nation, 77.36% of respondents were from China and 22.64% of respondents were from other countries. Based on the professions, 55.02% are coaches, 5.03% are Managers, 26.42% are Athletes, 8.81% are forecasters, and 7.55% are Predictors. According to their experience, 29.56% were having Less than 3 years, 55.97% were having 3–10 years, and 14.47% were having greater than 10 years.

3.5 Data Analysis

The statistical analysis of the study was conducted using the SPSS Windows software, which brought the study data to the forefront. The results of various variables in the research questionnaires are likened and analyzed through software. In this study, the collected questionnaire variables were coded before analysis by SPSS. The scale's

Table 2 Sample description

Sample category	Sub-category	Frequency	Percentage
Age	25–30 years	54	33.96
	31–40 years	53	33.33
	41 and above	52	32.70
Gender	Male	87	54.72
	Female	72	45.28
Nation	China	123	77.36
	Others	36	22.64
Profession	Coaches	83	52.20
	Managers	8	5.03
	Athletes	42	26.42
	Forecaster	14	8.81
	Predictor	12	7.55
Experience	Less than 3 years	47	29.56
	3–10 years	89	55.97
	More than 10 years	23	14.47
Marital status	Single	63	39.62
	Married	89	55.97
	Divorced/Separated	7	4.40

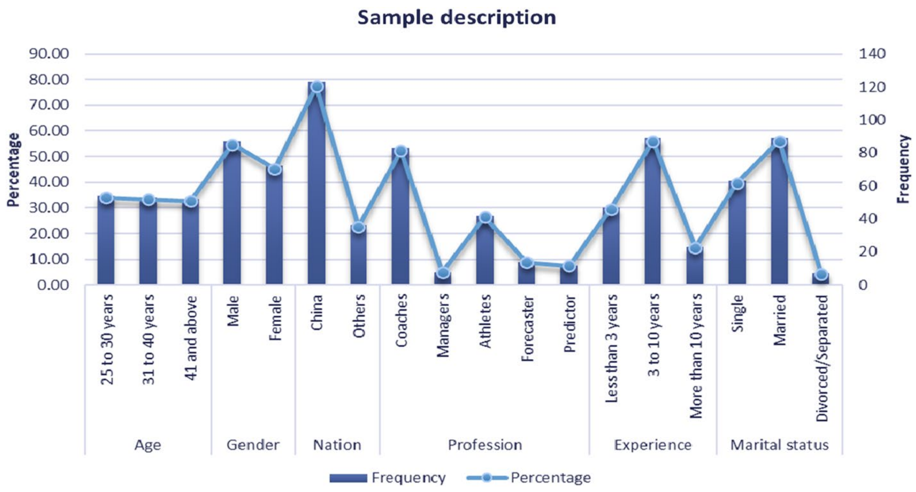


Fig. 4 Sample description

reliability was assessed by testing it against different variables, and the examination included calculating Pearson's correlation coefficient and conducting a t-test.

Pearson's correlation coefficient is an experiment statistic that quantifies the relationship among two incessant variables. It is the best method to measure the interaction in between the variables of interest.

Table 3 shows the scale of Pearson's correlation coefficient. If the correlation is 0.8–1 so the interpretation has very high correlation. The correlation is 0.60–0.79 then the interpretation has high correlation. 0.40–0.59 correlation indicates the interpretation has moderate correlation. if the correlation is 0.20–0.39 hence the interpretation has low correlation. the correlation is 0.1–0.19 then the interpretation has a negligible correlation.

Table 4 indicates the correlation matrix. Correlation between accuracy and capability is 0.611 which is 0.60–0.79 so the interpretation has a high correlation. The correlation among accuracy and personalized is 0.968 that is 0.8–1 therefore the interpretation has Very high correlation. Correlation between accuracy and speed is 0.878 which is 0.80–1 so the interpretation has a very high correlation. Correlation between accuracy and efficiency is 0.779 which is 0.60–0.79 so the interpretation has a high correlation. Correlation between accuracy and Trend analysis is 0.656 which is 0.60–0.79 so the interpretation has a high correlation. Correlation between accuracy and overall performance is 0.923 which is 0.80–1 so the interpretation has a very high correlation. Correlation between accuracy and Life expectancy is 0.748 which is 0.60–0.79 so the interpretation has a high correlation. Correlation between accuracy and user satisfaction is 0.866 which is 0.80–1 so the interpretation has a very high correlation.

Correlation between capability and accuracy is 0.611 which is 0.60–0.79 so the interpretation has a high correlation. The correlation among capability and personalized is 0.757 that is 0.60–0.79 therefore the interpretation has a high correlation. Correlation between capability and speed is 0.865 which is 0.80–1 so the interpretation has a very high correlation. Correlation between capability and efficiency is 0.761 which is 0.60–0.79 so the interpretation has a high correlation. Correlation between capability and Trend analysis is 0.944 which is 0.80 to 1 so the interpretation has a very high correlation. Correlation between capability and overall performance is 0.87 which is 0.80–1 so the interpretation has a very high correlation. Correlation between capability and Life expectancy is 0.671 which is 0.60–0.79 so the interpretation has a high correlation. Correlation between capability and user satisfaction is 0.875 which is 0.80–1 so the interpretation has a very high correlation.

Table 5 states the results of the hypothesis test. The value significance at 5% refers to the *p*-value being less than 0.05 so the hypothesis is accepted. H1a has a significance level less than 0.05 (*p*- value = 0.015, T-value = 14.46), therefore the H1a is accepted. A significance level is less than 0.05 in H1b (*p*-value = 0.31, T-value = 17.61), hence H1b is accepted. The significance level of H2 is less than 0.05 (*p*-value = 0.025, T-value = 18.23), therefore the H2 is accepted. H3 has a significance level that is less than 0.05(*p*-value = 0.033, T-value = 20.31), so the H1a is accepted. H4a has a significance level less than 0.05(*p*-value = 0.019, T-value = 16.90), hence the H4a is accepted. H4b has a significance level which is < 0.05 (*p*-value = 0.039, T-value = 14.96), therefore H4b is accepted.

Table 3 Scale of Pearson's correlation coefficient

Correlation correlation	Interpretation
0.8–1	Very high (positive/negative) correlation
0.60–0.79	High (positive/negative) correlation
0.40–0.59	Moderate (positive/negative) correlation
0.20–0.39	Low (positive/negative) correlation
0.1–0.19	Negligible (positive/negative) correlation

Table 4 Correlation matrix

	Accuracy	Capability	Personalized	Speed	Efficiency	Trend analysis	Overall performance	Life expectancy	User satisfaction
Accuracy	1	0.611	0.968	0.878	0.779	0.656	0.923	0.748	0.866
Capability	0.611	1	0.757	0.865	0.761	0.944	0.87	0.671	0.875
Personalized	0.968	0.757	1	0.752	0.87	0.756	0.818	0.791	0.656
Speed	0.878	0.865	0.752	1	0.828	0.978	0.939	0.841	0.929
Efficiency	0.779	0.761	0.87	0.828	1	0.798	0.721	0.944	0.652
Trend analysis	0.656	0.944	0.756	0.978	0.798	1	0.874	0.815	0.808
Overall performance	0.923	0.87	0.818	0.939	0.721	0.874	1	0.761	0.816
Life expectancy	0.748	0.671	0.791	0.841	0.944	0.815	0.761	1	0.765
User satisfaction	0.866	0.875	0.656	0.929	0.652	0.808	0.816	0.765	1

Table 5 Hypotheses testing

Hypotheses	Significance level	Test statistics	Decision
Hypothesis 1a	0.015	14.46	Acceptable
Hypothesis 1b	0.031	17.61	Acceptable
Hypothesis 2	0.025	18.23	Acceptable
Hypothesis 3	0.033	20.31	Acceptable
Hypothesis 4a	0.019	16.90	Acceptable
Hypothesis 4b	0.039	14.96	Acceptable

4 Results

The findings and conclusions of the present study are reported in this section. The data collected from the questionnaire obtained for the study used artificial intelligence-enabled predictive analytics to improve the fitness and performance of athletes. The dataset used in this study consisted of data collected through a questionnaire. The questionnaire was designed to gather information related to the fitness and performance of athletes. The proposed hypotheses (H1a, H1b, H2, H3, H4a, and H4b) and the test results are described in the following subsection and shown in Table 5.

4.1 Hypotheses and Result

The present research formulated the hypothesis according to the evaluation of the scope of the study. Table 6 shows the formulated hypothesis statements and their results.

The study result shows that the proposed H1a is statistically significant. Therefore, the proposed H1a "the deployment of the predictive algorithm depends significantly on how well sports forecasts are made" is accepted. The suggested H1b is statistically significant. So the suggested H1b "Many types of companies can benefit from the capacity to make more precise forecasts thanks to big data and artificial intelligence" is accepted. The analysis indicates that the proposed H2 is statically significant. Hence, the formulated H2 "The big data and artificial intelligence-based sports prediction systems can offer a customized solution" is accepted.

The proposed H3 is statistically significant. So the H3 “The effectiveness of the predictive model is largely influenced by the speed of execution" is accepted. The suggested H4a is statically significant. Therefore, the formulated H4a "The user experience and overall effectiveness of a prediction system determine its life expectancy” is accepted. The proposed H4b is statically significant. Therefore the proposed H4b "A reliable prediction system would evaluate the present pattern and adjust performance as necessary" is accepted.

5 Discussion

The training process of athletes is a complex combination of various factors which are essential to their development process and training process. Big data and AI prediction are useful for the development of sports industries. This involves providing players with more training to measure their health, thereby improving their performance, engagement,

Table 6 Hypotheses and results

Hypotheses	Statements	Results
Hypothesis 1a	The accuracy of sports prediction plays a vital role in implementation of predictive models	Significant
Hypothesis 1b	Big data and artificial intelligence has the capability to make more accurate predictions among all kinds of industries	Significant
Hypothesis 2	A personalized service can be provided by the big data and artificial intelligence based sports prediction systems	Significant
Hypothesis 3	Speed of execution is a major factor that determines the efficiency of the predictive model	Significant
Hypothesis 4a	Life expectancy of a prediction system relies on the user satisfaction and overall performance	Significant
Hypothesis 4b	An efficient prediction system would analyze the current trend and improve the performance accordingly	Significant

personalized skills, speed, etc. in the game. In this study, the focus was on the development of a sports predictive analytics system that integrates artificial intelligence and big data. The research delves into the utilization of artificial intelligence and big data in the sports domain, providing a comprehensive explanation of the functionality behind sports prediction systems. Data were collected using the questionnaire method from 159 individuals from various fields in sports. In the field of sports, AI is used to improve the capability and health of players. It helps in designing stratagems and strategies for a team and expanding its forcefulness [64].

Professional developers have made sports to the next competition level by coaching uniquely. Modern exercises are becoming more specialized for athletes as people understand better about sports practices and it can improve their performance. Proper training requires the athlete to carry out complete process exercises to achieve individual competitive training. Earlier in the field of sports, players' abilities were measured using visual observation-based training methods. Now the skills of the players are analyzed using computer technology [1]. AI can measure performance in training environments and competitive sports in less time. Predictive analytics with AI and big data helps improve the health and fitness of athletes and it also helps reduce injuries to players during sports [55].

Hypotheses were formulated and tested to investigate the aim of this study. Data were collected and measured to see if the predictive models measured accurately when implemented in sports prediction. It also investigated whether the speed of implementation is a factor in predicting the performance of the forecasting model and whether the lifetime of the forecasting system depends on beneficiary satisfaction and efficiency and whether an efficient forecasting system is working well in the current situation. This study revealed the strengths of prediction in sports. The results of this research provided detailed insights into the significance of big data and AI in the sports sector, highlighting their relevance across various industries. This study suggests that big data and AI prediction can be very useful in the field of sports to measure players' performance, improve their skills, monitor health, and avoid general injuries in sports.

6 Conclusion

The research examined the progress of an artificial intelligence and big data-driven sports predictive analytics system. It delved into the significance of big data and artificial intelligence in the sports industry, as well as the training sessions and health monitoring of previous predictive models. The study's findings emphasized the crucial role of accurate sports predictions in successfully implementing predictive models. The analysis demonstrated that among various industries, big data and artificial intelligence possess the potential to yield the most precise forecasts. The result indicated a personalized service can be provided by big data and artificial intelligence-based sports prediction systems. The research indicated Speed of execution is a major factor that determines the efficiency of the predictive model. The study analyzed the Life expectancy of a prediction system relying on user satisfaction and overall performance. The result indicates that an efficient prediction system would analyze the current trend and improve the performance accordingly. The study suggests AI and Big data prediction are used to improve an immeasurable role in winning competitions in exercise ability, fitness data, guidance stats, and analytics to help coach and athlete teaching sessions with personalized game strategies.

6.1 Limitations

This research has some limitations such as the researchers examine only to develop a sports predictive analytics system based on AI and big data, also presented the use of AI and big data in sports. Also the study did not analyze the disadvantage of the adverse impact on privacy rights in sports fields, and storage of big data using conventional storage may be too expensive. Big data analytics is against privacy principles. This paper needs to focus on changes in the basic sensing system and improving its performance and some of the technological disruptions caused by the use of big data and AI.

6.2 Future Scope

The information generated by this study can reduce the negative impact on privacy rights in the sports industry. Big data analysis can change the anti-privacy principles. Fix the changes in the basic sensing system early on and improve without technical disruptions caused by the use of big data and AI. Big data may increase players' interest in the game by approximately supplying data-sharing capabilities and other features.

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Code Availability Not applicable.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Human and Animal Rights This article does not contain any studies with human or animal subjects performed by any of the authors.

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Consent to Participate Not applicable.

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