Artificial intelligence in sports: Enhancing athlete performance and injury prevention

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ABSTRACT

The rapid development of modern technologies, particularly artificial intelligence (AI), has significantly influenced the sports industry by improving athlete performance and reducing injury risks. AI is now widely applied in areas such as performance evaluation, referee decision-making, fan engagement, and injury diagnosis. These advancements have enabled the creation of predictive models for player performance, injury prevention, and match analysis, as well as new algorithms for talent identification and performance assessment. Although AI offers substantial benefits, relying solely on data also carries risks, making informed judgment and proper training essential for coaches and athletes. This study proposes and evaluates a hybrid model that integrates deep learning methods (LSTM, DNN) with machine learning techniques (SVM, RF) to predict the probability of sports injuries. Using a manually collected real-world dataset from sports websites, the model achieved an accuracy of 81%. The findings provide valuable insights for injury prevention strategies and support more effective decision-making in the sports industry.

1. Introduction

The growth of technologies increases the likelihood of reducing these technologies with sports development; however, these have a direct impact on injuries, including individual athletes and the wider sports landscape. The impact of sports injuries on players and clubs, both psychologically and economically, cannot be overstated. However, the use of technology in sports in general has a positive impact on sports, as it improves sports performance and enables initial medical diagnosis, as well as analysis of matches and the amount of interaction with fans. The most prominent use of artificial intelligence (AI) was in diagnosing sports injuries and preventing them; in addition, the results of matches can be analyzed or predicted. This scientific research aims to explore the multiple applications of technology in the field of sports, focusing mainly on the role of artificial intelligence. This helps to study

how to use artificial intelligence to predict injuries to prevent them as much as possible, improve performance, and raise the level of the fan experience in general (Toffaha et al., 2023). The use of technology in sports science has evolved beyond traditional approaches in sports science. The merger led to improved sports performance, injury diagnosis, and match analysis. The power of AI to analyze complex data patterns and make predictions has transformed the sports industry into a new format where injuries are reduced or prevented. A large amount of sports data can be provided as input to an artificial intelligence model that can identify key factors that can give a prediction of the occurrence of sports injuries. This feature has great benefits for athletes, as it enables them to be careful and take all necessary precautions and methods to avoid injury or reduce the risk of injury (Musat et al., 2024).

In addition, the accuracy of AI in analyzing matches and predicting their results is considered more accurate than other methods. Artificial intelligence applications were used to analyze fans' information and predict the extent of their enjoyment and turnout, in addition to helping coaches make the appropriate decision. AI predictions mainly rely on data quality, real-time player statistics, and contextual variables that form

the basis of AI algorithms. Therefore, these algorithms have an impact on performance and excitement in sporting events. This combination of data-driven analysis and technological innovation not only increases athletes' plans at the professional level but also makes the fan experience more exciting (Frevel et al., 2022). Since sports research emphasizes that the relationship between technological innovation and sports excellence is largely relative, this research aims to integrate ideas from relevant research and empirical studies with the latest technological developments. This helps deepen understanding of the dynamic interaction between sports science and artificial intelligence. This scientific research seeks not only to contribute to enriching academic research but also to provide practical implications for sports practitioners and stakeholders navigating the evolving landscape of artificial intelligence in sports.

Injuries at all levels of athletic activity, from professional competitors to amateur enthusiasts, are a major problem. The spill-over effects of sports injuries are not confined to time lost from play due to direct physical injury, but include mental health, team functionality, and economic costs to the sports organization. What can be more valuable than predicting sports injury beforehand with intervention from damage? Today, in the sports industry, the widespread use of AI is a testament to the technological advancements it has witnessed. Across the industry, AI is helping transform the sports sector, improving training to make it more competitive and efficient, while analyzing and predicting athlete performance. AI powered Sports Science ushers in a whole new dimension of data-driven, science-informed individual strategies for injury risk assessment and injury management.

This research aims to predict the probability of sports injuries using intelligent algorithms. A hybrid model was developed that combines deep learning and machine learning techniques. Unlike previous studies that relied on limited datasets, the proposed model was tested on integrated, manually collected real-world data obtained from sports websites. The study compares several machine learning models and examines how feature selection and optimization techniques improve predictive performance. The results show that the proposed approach achieves high accuracy in predicting sports injuries. The findings can support the development of effective prevention strategies and assist decision-makers in reducing material costs and human losses in the sports field.

2. Background

AI has been widely used in many industries, including sports. Artificial Intelligence has radically changed the sports industry in many ways, increasing competitiveness and efficiency in training. There are many positive aspects of integrating AI into the sports industry. Including saving sports teams time and money while improving performance. For example, the costs related to analyzing the video footage needed by coaches can be reduced using artificial intelligence (Glebova et al., 2024). Athlete training programs can also be customized using AI based on their individual needs and performance (Reis et al., 2024). AI provides small teams with access to data and tools that large teams have and enables small teams to be more competitive with large teams (Thorsen et al., 2024). Although the applications of artificial intelligence are endless, applications in the field of sports are still in their early stages. With progress and the widespread integration of intelligence into the field of sports, new methods and solutions will be invented that can accelerate progress in the field of sports science. Therefore, examining the risk factors for injuries and their interactions is the best way to prevent sports injuries.

Sports injuries are a major problem in all types of sports. It is a problem that all athletes suffer from, whether professional or amateur. Injuries are not limited to any type of sport, as they are found in individual and team sports. The effects of a sports injury are not limited to losing part of playing time due to direct physical harm, but also extend to the state of psychological well-being, the level of team performance, and the financial impact on the sports organization. Given the profound effects of sports injuries, predicting them has become an urgent necessity to prevent them early by reducing their effects and damage. The incorporation of AI into sports science has been a major reason for this, as a new world of personalized, data- and experience-driven approaches to injury risk assessment and management has emerged. Traditional machine learning or deep learning algorithms can be used to identify sports injuries. In recent years, the use of advanced AI methods has emerged (Glebova et al., 2024) to investigate the complex factors that cause player injuries and improve the accuracy of injury prediction. The focus should not be solely on the injury prediction, but also on identifying injury risks and implementing strategies to mitigate the risks. Artificial intelligence is the simulation of the human brain in acting and solving problems. It is a broad concept that includes several branches. Machine learning (ML) methods are techniques that learn from data to be able to make decisions. ML methods include neural networks, support vector machines, or random forests. Research starts exploring methods to predict sport injuries (Bai et al., 2018). Analysis of sports injuries through factors is the way to prevent injury. Even though accurate prediction is still a challenge, improving accuracy is based on identifying correct variables to implement an organized system that prevents injury (Fonseca et al., 2020). For that reason, we need to explore how athletes, coaches, and doctors look at sports injuries. The perception of sport injury proven to be different between athletics and other sport stakeholders (Bolling et al., 2019). A real-time sports injury monitoring system developed using a support vector machine (SVM) shows higher accuracy than other

methods (Ren et al., 2024). However, the type and location of injuries make it difficult to monitor and prevent sports injuries effectively. The K-Nearest Neighbors (KNN) algorithm analyzes data collected from athletes' body movements and identifies patterns that may lead to injury, allowing preventive actions to be taken (Liu et al., 2014).

KNN is used along with k-means and SVM to develop a machine learning framework that detects player injury. The framework was tested on integrated data from 21 football players and showed good accuracy and ability to identify players at risk (Naglah et al., 2018). K-means clustering was employed to categorize runners with similar injuries into two distinct groups (Dingenen et al., 2020), highlighting that runners within each group could exhibit the same injury patterns. K-means is used to customize training for basketball players to avoid injuries and improve players' performance (Ibáñez et al., 2022). It was used to classify basketball players into two groups and analyze acceleration, deceleration, impact, and velocity thresholds among the players. The result shows significant differences between the two groups. Due to its simplicity and effectiveness, K-means can be applied to clustering problems. Support Vector Machines (SVMs) were used to predict sport injuries (Van Eetvelde et al., 2021). It was determined to be the most accurate method compared to other techniques, including logistic regression, multilayer perception, and random forest (Landset et al., 2017). SVM is still suitable for accurate prediction even though it shows less effectiveness in some research (Reis et al., 2024), and its performance becomes better when combined with other algorithms in a hybrid model. Decision trees (DT) are used in sports injury prediction (Rommers et al., 2020), but their performance varies based on the data and model structure. The performance of random forest in predicting sport injury is the same as DT; it varies from dataset to dataset.

Artificial neural networks (ANN) and Deep Neural Networks (DNN) are examples of deep learning techniques. They have been used to enhance the performance of predictive models in a variety of industries (Nozari et al., 2024), including the prediction of sports injuries. ML is a subfield of AI that enables systems to build knowledge and learn from provided data with no need for programming. In ML, learning is the capability of a machine to acquire knowledge from data, train the model, measure its performance, and then present predictions. An ANN is essentially a machine learning algorithm. A neural network is a network of interconnected individuals known as nodes, where each node performs a single computational process. If ANN architecture has more than one hidden layer, then it's called DNN. A mathematical model is used in these networks to process complex data (Tarawneh et al., 2022). DNNs include many hidden layers between their input and output. Both structured and unstructured data can be processed by these networks, as shown in Fig. 1. Like the human brain,

they feature a hierarchical architecture of neurons. The neurons transmit the signal to other neurons based on the information they receive. Numerous neurons form a layer, and each neuron executes an activation function. They provide a gateway for the signal to reach the next linked neuron. The input to the next neuron's output and then the last output layer are affected by the weight. Initial weights are randomly assigned, and they are improved when the network is trained iteratively, to be sure that the network prediction is correct.
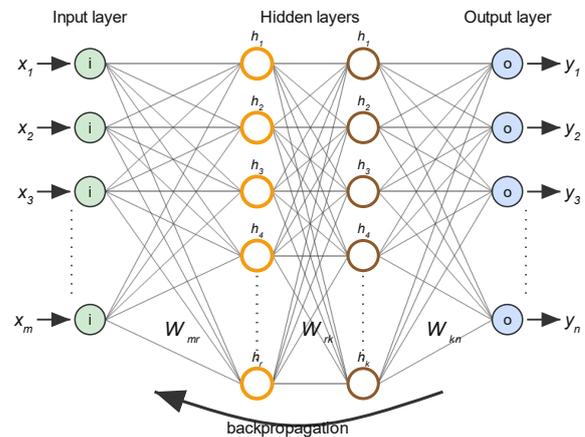

Fig. 1: Deep neural network architecture

A convolutional neural network (CNN) is used to monitor sports injuries and prevent them. It was used to analyze players' data collected from wearable sensors. CNN improves classification accuracy in comparison to other machine learning methods, including SVM, KNN, and DT (Kautz et al., 2017). It was used to analyze different games such as beach volleyball (Thorsen et al., 2024), soccer, and football (Ghazi et al., 2021). The focus in all works was to identify risk movement and avoid it to prevent injury. Long Short-Term Memory Neural Networks integrated with other methods to achieve higher accuracy in classifications (Meng and Qiao, 2023).

There is a recent comprehensive review of sports injury prediction using different ML techniques (Wang, 2024). The study concluded that machine learning methods, including KNN, K-means, SVM, decision trees, random forests, and deep learning, showed good accuracy in predicting sports injuries. Although there are some challenges, such as the structure of the data set, these techniques are important tools to learn more about sports injuries and try to avoid these injuries.

Based on the above literature, we can conclude that KNN has data size limitations but can enhance the accuracy of other algorithms. K-means is effective for feature extraction and data classification, making it ideal for early data processing. SVM is useful for predicting injuries and identifying risk factors. Decision trees offer acceptable classification accuracy. Most algorithm performances were tested on artificial datasets, so differences are expected when applied to real

datasets. Also, each study targets one injury type. Therefore, the use of machine learning to predict sports injury faces challenges, and comprehensive, organized structures that contain all important features do not exist. The use of AI lacks the power to predict future injury for players to help coaches, clubs, and other stakeholders make decisions. In this paper, we employ AI algorithms to predict the probability of sports injuries. Hybrid algorithms will be developed to offer valuable insights for injury prevention strategies and optimize decision-making processes in sports.

3. Methodology

Deep learning approaches have proven to be effective in handling large and complex data. The main aim of this article is to predict the future. The main aim of this study is to use the potential of deep learning methods to predict the probability of sports injuries, facilitating more accurate decision-making in matches or player selections. By integrating the power of AI and sport techniques, this improves the percentage of correct decisions regarding wins, player performance, and the team's benefits. The main stages of the models are shown in Fig. 2.

- Data Collection: The data has been collected from different sources, including known platforms such as Kaggle, data.gov, and UCI. However, not all information was available in these data stores. Therefore, additional necessary information has been added manually from various sports websites that provide such information about players. This stage was a challenge, as it is not easy to get all the information in one place, but the rich collection is more for reading world variability.
- Data Preprocessing: The collected data was preprocessed to make sure it fits the prediction model. Preprocessing includes addressing missing values by linear interpolation and normalization to make sure of equal contribution from all features in the model. The linear interpolation is a method that calculates missing values based on previous and next data, to avoid incompleteness in that data without losing its value. The normalization process is necessary to adjust the scale of the data to know range, putting all extracted features on the same scale, and ensuring that no single feature disappears from the model processing.
- Model Development: LSTM (Long Short-Term Memory) neural network model developed using TensorFlow and Keras libraries. This neural network model is the most suitable for processing and predicting the sequence of the data, making it more effective in injury prediction. The architecture of the model consists of 50 hidden units and one output unit. The LSTM network consists of 10 input layers for 10 features, followed by 3 hidden layers with 50 KSTM units, and one output layer that denotes injury or not

(0,1). The need to capture temporal dependences in sequential data enforces using an LSTM. Standard configuration used and adjusted by grid search where necessary for all ML models (RF, SVM, KNN, LR, GA). The hidden layers are learning complex patterns in the data and capturing significant temporal dependencies and relationships between features over time. The single output unit is the final prediction of injury. This architecture utilizes the input data effectively and provides accurate predictions of future sports injuries.

- Performance Evaluation: The performance of the model was evaluated using several key metrics: Mean Squared Error (MSE), Variance Accounted For (VAF), and Euclidean Distance (ED). The primary goal is to reduce the gap between the observed and predicted flow values. Multiple metrics are calculated in the evaluation process to get a comprehensive picture of the prediction result.
- Results Visualization: It is essential to visualize the model performance to assess its effectiveness, identify some key factors in the data, and ensure that the prediction is accurate. The results of the model were mapped to provide a clear picture of its performance. Heatmap highlighted the relation between features and identified important features that affect predictions. A scatter plot was used to show the classification results.

3.1. Dataset

Unlike previous studies that relied only on public datasets, this research integrates manually collected real-world data from official sports websites with publicly available datasets from Kaggle and the UCI Machine Learning Repository. Player information was manually obtained from international sports teams and official websites.

The dataset was enhanced with detailed player-level features, such as recovery time, match activity level, and the number of previous injuries. The collected data focus on football players and include 10 attributes related to player demographics, performance metrics, and injury history. These attributes are described in Table 1.

Table 1: Description of features in the dataset

| Feature	Description
Player ID	Unique identifier for each player
Age	Age of the player in years
Height	Height of the player in centimeters
Weight	Weight of the player in kilograms
Minutes played	Average number of minutes played per game
Distance covered	Average distance covered per game in kilometers
Sprints	Number of sprints per game
Previous injuries	The number of previous injuries each player has had
Recovery time	Average recovery time in days following an injury
Injury occurred	Indicates whether an injury occurred (true/false)
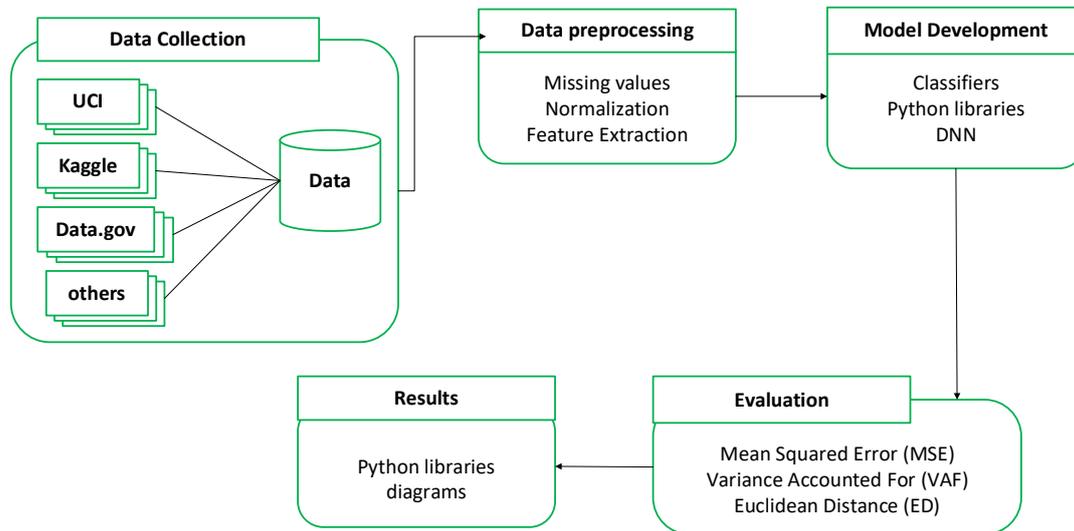
Fig. 2: Proposed model stages

3.2. Model development

The dataset is divided into training and testing sets: training (90%) and testing (10%). Several supervised machine learning models were employed to assess the prediction of sport injuries using different algorithms:

- Random forest (RF): A set of decision trees used to improve classification accuracy through majority voting.
- Support vector machines (SVM): An efficient algorithm for small and medium-sized datasets and best suited for binary classification tasks.
- K-nearest neighbors (KNN): A classifier that assigns class labels based on the most common class among the k nearest points.

RF classifiers distinguish between decision trees, SVMs are fit for small data sets, and columns of data sets classified using KNNs. The machine learning methods utilized were more like feature selection techniques. Each algorithm is applied to the dataset using consistent preprocessing and assessment metrics to guarantee fair comparison.

The prediction system is implemented using python library. DNN is implemented to capture hidden and complex relationships in the dataset. The DNN architecture contains four hidden layers of a deep neural network, with 12, 16, and 14 neurons. The architecture of four-layers algorithm gives better performance in predicting injuries. There were 10 input layers for 10 features selected from the data set. There is only one output layer that can infer it as an occurrence of injury. The developed model was trained using a binary cross-entropy loss function, and the Adam optimizer was used to improve model performance. Training was done using ten epochs, with accuracy and loss metrics used to track its performance.

The confusion matrix was utilized to evaluate the supervised machine learning algorithms, as it provides a simple accuracy assessment. Fig. 3 shows the correlation between all features, which indicates that the longer the playing time and the number of sprints per game, the greater the probability of being injured. Also, players who have had more prior injuries may suffer injuries in the future. Weight can affect the occurrence of injuries. On the other hand, we note the weak influence of age, height, distance traveled, and recovery time on the occurrence of injury. Other metrics were calculated to compare and evaluate all models, such as precision, recall, F1 score, and ROC-AUC.

4. Results

This research proposes an integrated machine learning approach based on deep neural networks (DNNs) for injury prediction. The study evaluates several machine learning models, such as logistic regression, naive Bayes, random forests, support vector machines (SVMs), k-nearest neighbors (KNNs), decision trees, and a basic deep neural network. The Scikit library in Python was used to implement ML models.

The performance of these algorithms was evaluated using five metrics: Accuracy, Precision, Recall, F1 score, and ROC-AUC. Table 2 shows a comparison between the machine learning models. The logistic regression, Naive Bayes, and genetic algorithm models outperformed the other models with the highest accuracy (0.65). We can consider them as the best model that can be used to predict injury. The baseline DNN has an accuracy of 62% before optimization, with potential for improvement.

Fig. 4 shows the distribution of players among three clusters based on the features that identify a pattern for injury. First Cluster (0) includes a group of young players who have low activity and a high previous injury rate. The second Cluster (1) includes older players who have played more and have a high rate of previous injuries. The last cluster (2). It consists of players with a high number of sprints and distances covered, with a lower weight on average and a moderate incidence of injury. This analysis helps design injury prevention strategies based on player profiles.
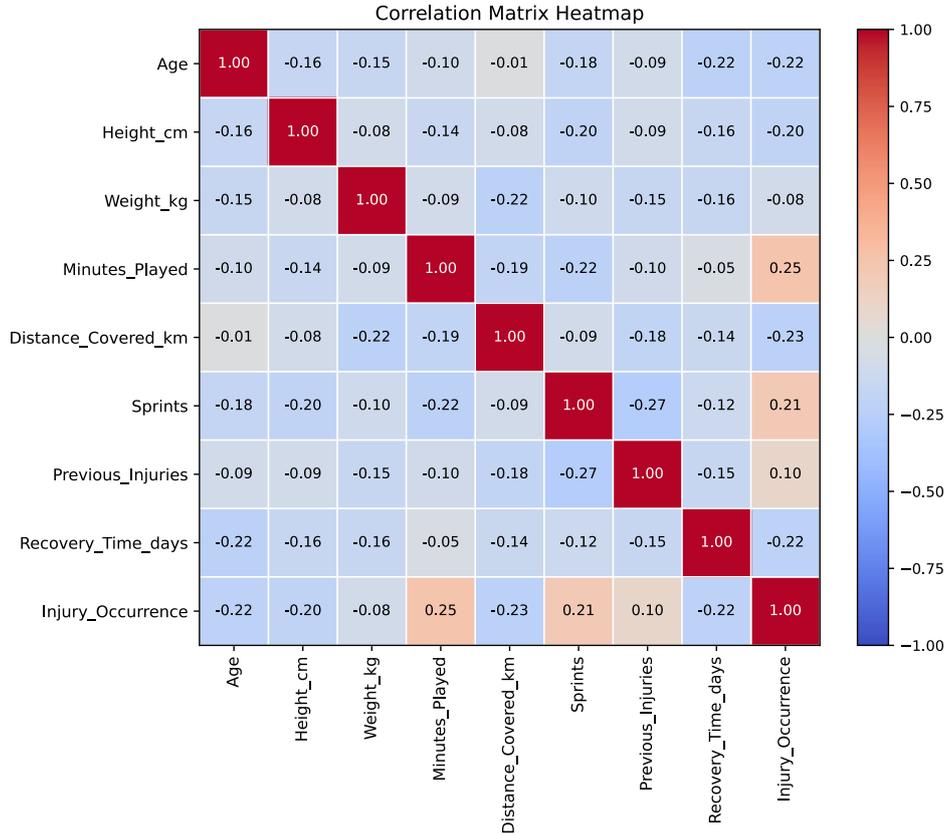
Fig. 3: Correlation between all features

Table 2: The comparison between the methods

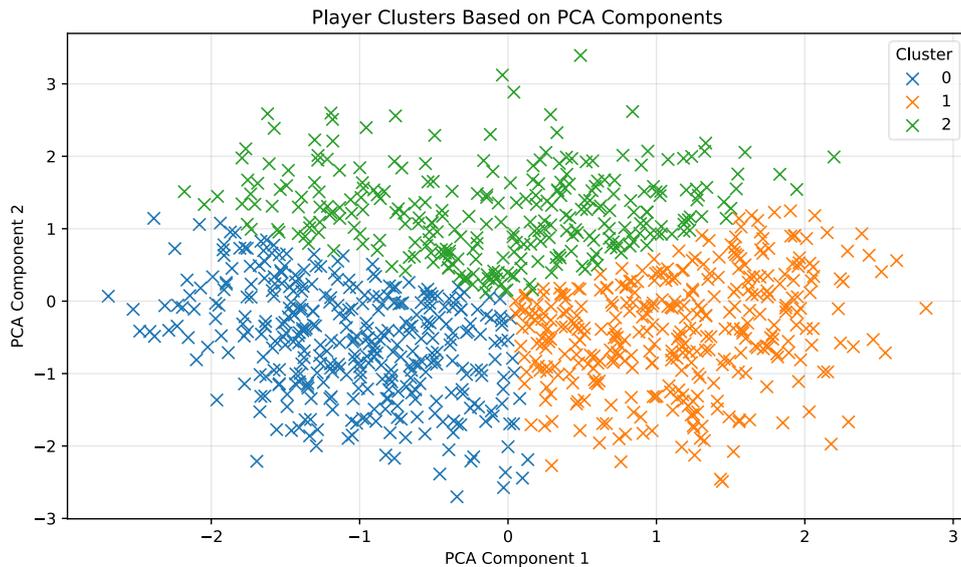| Model	Accuracy	Precision	Recall	F1 score	ROC-AUC
Logistic regression	0.65	0.67	0.63	0.65	0.65
Random forest	0.62	0.64	0.57	0.6	0.62
Support vector machine	0.63	0.63	0.65	0.64	0.63
K-nearest neighbors	0.57	0.58	0.59	0.58	0.57
Naïve bayes	0.65	0.67	0.63	0.65	0.65
Decision tree	0.54	0.55	0.57	0.56	0.54
Deep neural network	0.62	0.62	0.67	0.64	0.62
Genetic algorithm (PCA + LR)	0.65	0.66	0.65	0.65	0.65

Fig. 4: Player clusters based on PCA components

The DNN architecture is optimized to improve its performance. The final model includes three hidden layers, containing 5, 10, and 20 neurons, respectively. The input layer consists of ten features, while the output layer is a single neuron to represent a binary classification (0 or 1). The DNN was trained over 10 epochs on the dataset. Training accuracy is 62.29%, and testing accuracy is 66%. After studying the features and their impact, features with weak influences, such as age, height, distance traveled, and

recovery time, were removed, and a significant improvement was noted in the accuracy of the model, as the training accuracy increased to 81.5%, which proves that the model learns data patterns efficiently. The test accuracy improved 81%, and this improvement indicates the model's ability to discover invisible data. The model's performance is promising, achieving a high accuracy rate and suggesting that it effectively captures the underlying patterns of the dataset.

A comparison between the different models in terms of accuracy is presented in Table 3. It was noted that the deep neural network (DNN) achieved the highest accuracy of 81%, and the DNN outperformed other models, including logistic regression, random forest, support vector machine, Naïve Bayes, and genetic algorithm (PCA + LR), which has proven effective in capturing basic patterns in data.

Table 3: Comparison between models' accuracy

Model	Accuracy
Logistic regression	0.78
Random forest	0.72
Support vector machine	0.75
Naïve bayes	0.77
Deep neural network	0.81
Genetic algorithm (PCA + LR)	0.80

5. Conclusion

Sports have been revolutionized with artificial intelligence in sports. Improves athletic performance and prevents injuries. This research has shown that artificial intelligence can improve the accuracy of sports injury prediction. By using large amounts of data, AI can identify patterns and risk factors, providing a head start on injury prevention and improved decision-making. Traditional machine learning algorithms such as Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) can predict infections, and SVM is always more accurate. However, deep learning models, especially deep neural networks (DNNs), outperform all methods by capturing complex patterns in the data, as evidenced by the highest accuracy achieved by the DNN model. Furthermore, reducing the number of features by removing features with weak influences, such as age, height, distance traveled, and recovery time, as well as increasing the number of epochs during model training, improves the accuracy of both training and testing. This underlines the importance of feature selection and model optimization in improving prediction.

The use of artificial intelligence in sports is not limited to predicting injuries only. But it goes beyond evaluating performance, identifying talent, predicting match outcomes, and enhancing fan engagement. All of this highlights the benefits and potential of integrating AI into sports. As a result, a more dynamic and strategic sporting environment can be created. However, one must be careful not to rely too much on artificial intelligence and know the limits and risks associated with it. While AI provides valuable insights, the role of human judgment remains essential. Coaches, athletes, and sports professionals must be trained to interpret AI-driven insights effectively and make informed decisions.

The use of AI in sports has great potential for advancing athlete performance and injury prevention. The continuous evolution of AI technologies will likely yield even more sophisticated tools and methodologies, enhancing the sports industry. By embracing AI and incorporating it with human expertise, the sports industry can achieve new heights of excellence, safety, and commitment.

List of abbreviations

AI	Artificial intelligence
ANN	Artificial neural network
CNN	Convolutional neural network
DNN	Deep neural network
DNNs	Deep neural networks
DT	Decision tree
ED	Euclidean distance
GA	Genetic algorithm
ID	Identifier
KNN	K-nearest neighbors
LR	Logistic regression
LSTM	Long short-term memory
ML	Machine learning
MSE	Mean squared error
PCA	Principal component analysis
RF	Random forest
ROC-AUC	Receiver operating characteristic – area under the curve
SVM	Support vector machine
SVMs	Support vector machines
UCI	University of California, Irvine
VAF	Variance accounted for

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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