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Molecular & Cellular Biomechanics 2025, 22(2), 426.
https://doi.org/10.62617/mcb426

Article

Research on the prevention strategies of sports injuries in physical education teaching through sports biomechanics analysis

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CITATION

Duan W. Research on the prevention strategies of sports injuries in physical education teaching through sports biomechanics analysis. Molecular & Cellular Biomechanics. 2025; 22(2):426. https://doi.org/10.62617/mcb426

ARTICLE INFO

Received: 27 September 2024
Accepted: 12 October 2024
Available online: 10 February 2025

Abstract: Sports activities induce significant changes in cell mechanics. Physical exercise prompts molecular adaptations in muscles, and analyzing the biomechanics of specific sports is crucial. Sports injuries, commonly occurring during exercise, often stem from overuse, crashes, or excessive forces. The physical and psychological rigors of sports and intense competitions heighten the risk of damage. For instance, hamstring strain injury is prevalent among football players. Understanding the biomechanics underlying such injuries is essential. This research focuses on gathering biomechanical data from physical education exercises, including joint angles, forces, velocities, and muscle activations. By preprocessing this data through cleaning and normalization, we aim to decipher the molecular and cellular level changes. Maximal hamstring flexibility and muscular tightness, identified as key factors, can provide insights into muscle cell mechanics and potential injury prevention. A novel Intelligent Flamingo Optimized Residual Network50 (IFO-ResNet50) is proposed. Through biomechanics analysis in physical education teaching, it targets the prevention of football muscle injuries. The method's effectiveness is evaluated in terms of accuracy (98.1%), recall (98.4%), F1-Score (98.2%), AUC (98.5%), and precision (98.7%) in comparison to existing algorithms. This research not only aids in identifying the physiological and biomechanical changes at the cell or molecular level due to sports but also offers practical strategies for physical education teachers. By reducing injury risks, it can enhance student safety and performance in school sports programs, thereby contributing to a more comprehensive understanding of the relationship between sports and cell mechanics.

Keywords: prevention of sports injuries; physical education teaching; cellular mechanotransduction; muscle adaptation; intelligent flamingo optimized residual network 50(IFO-ResNet50)

1. Introduction

Sports injuries are a mutual incidence throughout physical doings, mostly in organized atmospheres like Physical Education (PE) plans. Such injuries can arise from various issues [1], including over-employment, sudden impact, or exerting force outside the body's physical competencies [2]. These injuries can range from mild strains to severe, incapacitating conditions, potentially affecting an individual's long-term physical health [3]. Unity of the greatest mutual injuries in sports, especially among football athletes, is the hamstring strain, which can significantly impact presentation and lead to protracted periods of retrieval [4]. Sports-related injuries in PE classrooms not only interfere with learning but also put students' overall health in danger. Students' varied degrees of health in addition to the workouts made by individuals can raise the risk of injury [5]. A particular level of physiological muscle is essential for optimal health, and skeletal muscle is essential for athletic performance. Skeletal muscle reactions to exercise training are partly responsible for the protective benefits of exercise towards non-communicable illnesses including heart failure and type 2 diabetes [6]. While there is a wealth of food that is high in energy these days, the requirement for active lifestyles has decreased in many civilizations. Insufficient utilization of skeletal muscle due to lifestyle choices is a significant and consistent risk factor for a number of chronic illnesses [7]. Chronic illnesses linked to overeating and/or inactivity are become more common in contemporary culture [8]. As a result, avoiding illnesses or injuries is a part of the job description for PE teachers in addition to instruction. Avoiding these risks requires a comprehension of the biomechanical elements that lead to injuries during sports [9]. Sports biomechanics examines the structure and motion of physical activities to shed light on the many stresses and motions that increase the risk of injury. Biomechanical evaluation assists in determining injury hazards by measuring important characteristics like joint angles, muscle strength, and patterns of motion [10]. With this knowledge, PE instructors may design workout regimens that reduce the risk of damage and put safeguards into place. By guaranteeing that students can engage completely and safely in sports, excellent injury prevention techniques not only increase the safety of students but also enhance athletic performance. A data-driven strategy for treating the underlying causes of sports injuries is offered by integrating biomechanical into PE, which serves as a priceless tool for teachers to foster a safe and efficient classroom [11]. Sports biomechanics evaluation avoids acute injury by recognizing trends that can result in chronic ailments like repetitive strain injuries (RSIs), which develop over time from persistent misuse of muscles or joints [12]. This is especially important for football players since their hamstrings are severely strained during routine tasks like kicking and running [13]. Teachers can take early action by recognizing these trends and modifying training plans or methods to reduce strain on susceptible muscles. A deeper awareness of how students' bodies react to physical stress is made possible by adding bio mechanicals into athletic settings, where the goal is both adaptive and instructional [14]. Younger athletes who might not yet completely comprehend the limitations of their bodies can benefit most from this. With this information, teachers can offer more individualized instruction that will guarantee that children develop flexibility and power in a balanced way, lowering their chance of injury [15].

Objective of the research: Improve injury prevention strategies for football by using IFO-ResNet50 in the analysis of biomechanics data on sports. Identifying the critical factors that lead to hamstring strains among others, equips physical education teachers with data-informed insights and thus makes their students safe enough to participate in any sports activities and improve their performance, eventually making school athletics safer. The following key contributions be

1) The dataset makes a substantial contribution to the comprehension of football damage trends, which facilitates the creation of prediction models that improve player security and guide focused preventative tactics.
2) The min-max normalization approach eliminates bias from changing feature scales by ensuring that every feature in the information being collected has been scaled to a consistent range, improving machine learning in general models' accuracy as well as performance.
3) The strength of Intelligent Flamingo Optimized Residual Network 50 (IFO-ResNet50) is its capacity to combine neural networks with sophisticated

optimization strategies for improved football damage prediction. It greatly enhances preventive tactics by precisely recognizing mechanical aspects, thereby boosting athlete efficiency as well as security in physical education settings.

Research was divided into five parts such as Part 2 presents the related work, the methodology is established in Part 3, the result is displayed in Part 4, Evaluation metrics are described in Part 5 and the conclusion is illustrated in Part 6.

2. Related work

Trasolini et al. [16] introduced sports involving throwing that were quite popular, but they can cause musculoskeletal injuries, particularly to the elbow and shoulder. Path mechanic characteristics that make throwers more prone to injury are identified through biomechanical investigations. Elbow and shoulder acceleration, elbow rotation, kinetic chain operation, and lower-extremity mechanics were examples of key performance indicators. Marker-based video recording of motion is one of the biomechanical analysis techniques used today; however, newer technologies like machine learning and marker less motion capture have the potential to improve comprehension even further. Zadeh et al. [17] focused on the use of wearable technologies and analytics to identify injury risk factors in athletes. It originated that high BMI and high automatic loads can lead to injury, suggesting that incremental mechanical load increases during practice season can prevent injuries. The research also highlighted the importance of imposing enough automatic masses in exercise programs for good muscle expansion. The results suggest that wearable technology can help identify and target players at increased risk for injury. Lloyd et al. [18] investigated the application of biomechanics to the diagnosis and treatment of orthopedic tissue harm and deterioration. The construction of training plans to preserve or restore tissue health was covered, with an emphasis on the functioning mechanical environment encountered in both every day and rehabilitative activities. The significance of customized neuromusculoskeletal modeling, wearable sensor integration, and machine learning (ML) in training programs was also emphasized in the research. Alsaeed et al. [19] analyzed 261 players over the age of 18 who were polled for a research conducted in the Basra Governorate, southern Iraq, to identify barriers to football training programs and the application of biomechanical and analytical tools. The research's findings pointed to a deficiency in sports sciences, and suggestions for improvement included creating development programs, learning biomechanics and kinetic analysis, and setting up facilities suitable for various age groups. Huifeng et al. [20] examined knee flexion movement and knee joint injuries in sprinters using a 3-dimensional replication organization prototypical of the human lap combined. The findings indicated that injuries to the meniscus and medial collateral ligament, which account for 24%, 7%, and 22.4% of knee joint injuries, respectively, were more prevalent. According to the research, knee joint injuries may be decreased and sprinter knee joint nursing can be enhanced by applying a foot strength curve recognition approach. Ba [21] offered a deep learning system constructed around MRI image processing that was proposed for medical athletics recovery. The cerebral cortex's capacity to analyze motions, the breathing and cardiovascular systems' functionality, and the excitability of the brain's nervous system were all enhanced by preparation exercises. The technology incorporated a deep learning model to improve and recognize images, demonstrating strong efficacy in mitigating sports-related injuries and optimizing physical mobility. Yeadon [22] suggested sports movement computer simulation modeling and motion analysis technologies have advanced significantly during the last 50 years. The recognition of the significance of physiological variation in sporting skills has resulted in a rise in the amount of research and subjects involved. Models for computer simulations have been both basic and complicated, with parameters that were both general and unique to each individual. Future research might concentrate on motor control elements in sports technique analysis, individual-specific parameters for models, and marker less capture of motion. Yan [23] examined the biomechanics of martial arts evolution in China, with a particular emphasis on Wushu. It examined doctorate dissertations and core publications from 2011 to 2015 using a bibliometric approach. The goal of the research was to comprehend the most recent advancements in martial arts routine biomechanical research. The findings demonstrate neuronal organization model outperforms basic Bayesian processes and approaches in the works in terms of test organization accuracy, recall, and *F* value. The objective of the goal [24] provided sensors that are worn are at present widely used to evaluate athletes' performance and human mobility technological improvements. Key performance indicators and comprehensive data, including kinematics, kinetic, and electromyographic data, were provided by these sensors. The best sensors for sport biomechanics applications were electromyography, which is force sensors, and inertial sensors. Fonseca [25] assessed that electromyography and force measurement devices were despite useful, even if inertial measurements were the most common. Scientists, athletes, and coaches can all benefit from this summary of the state-of-the-art technologies for measuring sports performance. Li and Li [26] explored the complicated phenomena of sports injuries that are influenced by several variables; therefore, an analysis of this phenomenon. High-order variables that characterize an athlete's unpredictable actions and forecast future occurrences, such as injuries, were the main emphasis of a complex systems approach. Kozin et al. [27] evaluated principles of complexity and the ramifications of acknowledging sports injuries as complex phenomena, which were covered in this article. To help sports professionals predict the incidence of injuries, it proposed four phases for a synergetic method based on autonomy and a phase change to sports injuries.

Using intelligent partial least squares (PLS) software, the research based on primary data analysis to identify these studies produced relevant findings, such as the confidence interval, the significant analysis between them, and descriptive statistical analysis [28]. To lessen injuries, it was necessary to comprehend the etiology of the many components and mechanisms. If biological variables might influence damage, then injury prevention could be enhanced.

The three movements that are tested are running, running, and static. The algorithm simulation was also conducted in research [29]. The findings demonstrate that the Back-propagation (BP) neural network classifier has the hidden layer node of 11 has the most recognition impact for running and running action. It examined the causes of sports injuries, suggested preventative methods, and suggested using wearable technology to further lower the incidence of sports injuries.

To predicting the likelihood of sports injuries is crucial for assessing the body's stability during physical activity. To address the problems of false alarms and missed alerts brought on by depending too much on local spatial attribute data, it developed an identification method based on feature sequence classification in conjunction with Bayesian filtering (BF). Deep neural networks (DNNs) and semi-supervised clustering theory serve as the foundation for the recognition method [30].

To delve deeper into the variables affecting young athletes' engagement in sports, this research integrates the theories of reinforcement, associative learning, and self-determination. To comprehend the elements, characteristics, and variances that affect young athletes' engagement in sports, experimental analysis was performed. In addition, it looked at the connections between various variables and young athletes' involvement in sports and created a structural equation model that could be applied to promote young athletes' engagement in sports. Lastly, it added three research variables perceived fun, situation, and trust to the Unified Theory of Acceptance and Use of Technology (UTAUT) [31] model, which has a stronger theoretical foundation. The understanding of the adaptations brought about by exercise is always changing as an outcome of ongoing quest to determine ways to recommend exercise to optimize performance and health consequences. Additionally, emphasizing substantial unrequited concerns about how humans adjust to training, Hughes et al. [32] could concentrate on current and emerging outcomes regarding variations to strength and endurance training. A complex interaction between several signaling pathways connected to downstream transcription and translation regulators mediates the notably diverse training responses elicited by aerobic and resistance exercise, which constitute extremities on the exercise continuum. In Egan and Zierath's study [33], go over the molecular processes and metabolic reactions that support skeletal muscle adaptation to intense physical activity and exercise training. The chemical, cellular, and mechanical mechanisms behind muscle damage and the ability of muscle to renew and heal itself are discussed in Tidball's study [34]. To illustrate the parallels and discrepancies between the damage and repair processes that take place in abruptly and chronically damaged muscles, the procedure of muscle injury, repair, and regeneration that takes place in muscular dystrophy is given as an instance of chronic muscle injury. It is believed that a number of types of muscular dystrophy and the age-related reduction in muscle function are caused by the loss of essential defense systems against injury or the inability to heal damaged muscle. The FEBS Journal features articles in Michele's study [35] that examine or discuss important routes for muscle regeneration and repair in reaction to injuries, as well as the roles those routes play in skeletal muscle wellness and disease. **Table 1** presents the overview of related work.

Table 1. Overview of related work.

Author Name	Year	Dataset	Objective	Proposed Methods	Result
Trasolini et al.	2022	Throwing Athlete Biomechanics.	Identify path mechanic factors in injury or performance issues.	3D motion capture, kinetic chain analysis, shoulder and elbow torque measurements.	Enhanced injury prediction, prevention, and rehabilitation.
Zadeh et al.	2021	Army ROTC Cadets (54 participants).	Mitigate injury risk in athletes using wearable technologies and analytics.	Zephyr Bio Harness Wearable technology for data collection.	Identified high BMI and mechanical loads as injury risk factors; highlighted the need for gradual load increase in training to prevent injuries.
Lloyd	2021	Biomechanics in Musculoskeletal Injury.	Identify mechanistic causes of tissue injury and develop training programs for tissue health.	Personalized neuromusculoskeletal modeling with real-time motion capture, medical imaging, and biofeedback technologies.	Improved tissue health through personalized, real-time biomechanical feedback and wearable sensors.
Alsaeed et al.	2021	261 football players in Basra.	Identify obstacles in football training and software use.	Questionnaire for football experts.	Found lack of sports science use; recommended training in biomechanics and better infrastructure.
Huifeng et al.	2021	3D knee joint simulation research.	Analyze knee flexion and injuries in sprinters.	3D image registration and knee joint motion analysis.	Medial collateral ligament and meniscus injuries are most common; the foot strength curve method effectively reduces injuries in sprinters.

Problem statement

Football players in physical education programs frequently get sports injuries, particularly, which are frequently the consequence of overuse and excessive force. Because there is a lack of a thorough grasp of the intricate complexities of these injuries, current preventative measures are inadequate. The lack of focused treatments makes it more difficult for teachers to shield pupils from harm, underscoring the requirement for creative fixes. To close these gaps, our research will use biomechanics to pinpoint important risk variables and create practical preventative measures. The present research uses the IFO-ResNet50 to evaluate large amounts of mechanical information to identify important injury predictors, such as strength and stiffness in the muscles of the hamstrings. This method not only improves the precision of preventative techniques but also gives physical education instructors practical knowledge that can be applied to drastically lower the risk of injuries. In the end, this research assists athletic teams in enhancing student safety and football efficiency.

3. Methodology

Initially, biomechanical information on joint angles, stresses, velocities, and muscle activations during football activities is gathered through physical education exercises. To maintain consistency, the data is preprocessed, which includes data cleansing and standardization. Subsequently, the processed data is analyzed using the IFO-ResNet50 to determine significant indicators such as hamstring strength of muscles and rigidity. **Figure 1** presents the methodology of the research.

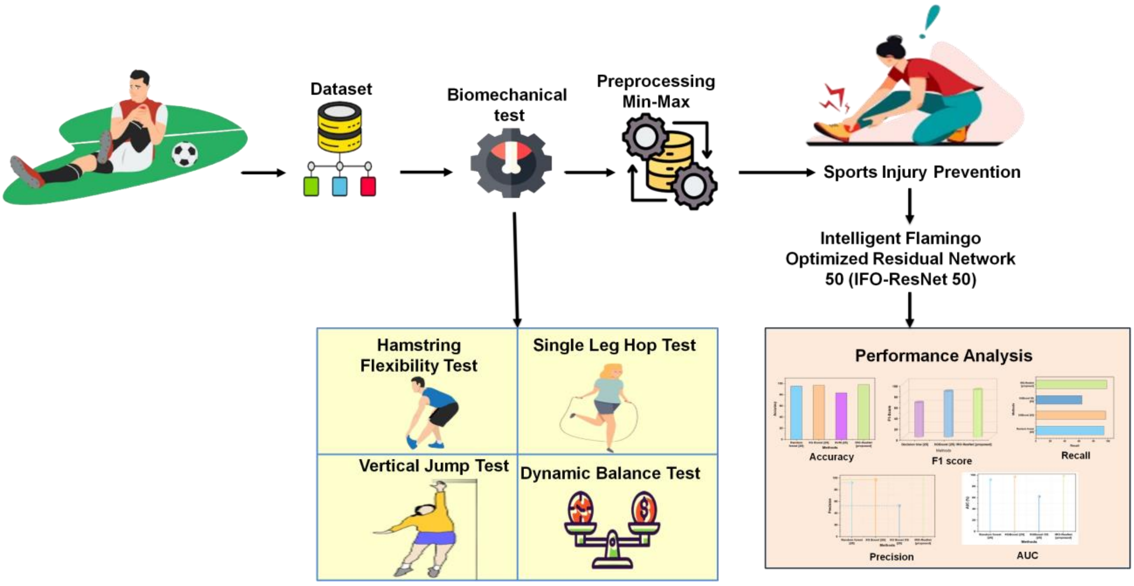

Figure 1. Methodology of the research.

3.1. Dataset

A football injury dataset gathered from Kaggle's (https://www.kaggle.com/datasets/kolambekalpesh/football-player-injury-data)data from 1320 football players was evaluated to build the proposed dataset, focusing on those who played in the British Premier League from the 2016/17 to the 2020/21 seasons. Key features included start year, season days injured, total days injured, season minutes played, season games played, height (in cm), weight (in kg), pace, FIFA rating, work rate(numeric), significant injury in the previous season and body mass index (BMI). The data was sourced from three main datasets: player attributes from FIFA (2016–2021), injury history from transformer, and player game time records. The data was combined and analyzed at a player-year level to ensure accuracy and relevance. Prohibiting criteria included wounds sustained within the last 3 months.

Biomechanical test for recovery

Hamstring Flexibility Test: This test measures the suppleness of the hamstring muscles, which is crucial for stopping strains. A common technique is the sit-and-reach test, where players reach forward while seated to amount to hamstring distance.

Single Leg Hop Test: This test assesses lower limb strength and stability by measuring the distance a player can hop on one leg. It helps to classify potential faintness or inequities, which can contribute to injury risk.

Vertical Jump Test: This test measures explosive leg power, crucial for performance in football. The height of the jump can designate the asset and training of the player's lower body, which can correlate with injury defenselessness.

Dynamic Balance Test: Using tools like the Y-Balance Test, assesses a player's aptitude to maintain stability while attainment in several instructions. Good balance is indispensable for stopping falls and injuries during dynamic actions in football.

3.2. Pre-processing using min-max normalization

A technique used to rescale data to a specific range, typically [0, 1]. This technique is mostly suitable in preparing biomechanical data for analysis because it ensures that every characteristic contributes evenly to the overall design, avoiding characteristics with wider ranges from dominating evaluated using Equation (1) for min-max normalization.

$$x' = \frac{x - x_{min}}{x_{max-}x_{min}} \tag{1}$$

Here x is the unique value, x_{min} is the feature's lowest value, and x_{max} is the characteristic's highest value. After utilizing this transformation, the normalized value x' falls within the defined range. This process is essential for biomechanical data, such as joint angles or forces, as it enhances the performance of machine learning algorithms by ensuring consistency across diverse features. Subsequently, min-max normalization helps in refining model accuracy and interpretability in injury prevention strategies in football.

3.3. Prevention strategies of sports injuries using intelligent flamingo optimized residual network50 (IFO-ResNet50)

The deep learning abilities of ResNet50 combined with the optimization strength of the IFO procedure; this approach ensures effective injury prediction. ResNet50 extracts biomechanical features, leveraging its ability to handle deep networks without performance degradation. The IFO algorithm optimizes the network by improving the initialization process through cubic chaotic mapping, leading to better solution distribution. This hybrid model provides improved accuracy, faster convergence, and more reliable predictions for injury prevention strategies in football, and Algorithm 1 shows the IFO-ResNet50.

3.3.1. Residual network50 (ResNet50)

Strong neural network architectures called Residual Networks (ResNet50) are essential to deep learning models, especially when it comes to applications like athletics biomechanical analysis and avoiding injuries. In this work, biomechanical data is analyzed and football-related injury predictions are made using ResNet50. The primary benefit is its capacity to train the network at considerably deeper depths without encountering the vanishing gradient problem, which frequently impairs the performance of traditional deep networks. Recursive learning was used to do this, where each layer is taught an acquired purpose that slightly orients the input instead of a fully new function. By keeping a mean of zero and a normal strangeness of one, batch normalization, a crucial component of ResNet50, is used to equalize activation. Because the gradient is stabilized, faster convergence and more effective computing are possible, which enhances the instruction process. In terms of football biological mechanics, this improves the model's capacity to identify important injury predictors, hence raising the precision of player preventive tactics used in athletic environments are evaluated using Equations (2)–(4).

$$\mu A \leftarrow \frac{1}{n}\sum_{j=1}^{n} wj \tag{2}$$

$$\sigma_A^2 \leftarrow \frac{1}{n}\sum_{j=1}^{n} (wj - \mu A)^2 \tag{3}$$

$$\widehat{wj} \leftarrow \frac{wj - \mu A}{\sqrt{\sigma_A^2 + \epsilon}} \tag{4}$$

whereas $n =$ pixels and $\mu A =$ average value, σA = standard deviation, w = zero-centered $\epsilon =$ extra value, typically 10^{-8}. Initially, a 255 × 255-pixel picture is convolved using a kernel size of 7 × 7 and a stride of 2. A feature map is produced by this convolution, and it is then normalized using batch normalization. Because training methods might result in values that fluctuate over time, this strategy equalizes the range of input values to assist prevent covariance shifts. Normalizing batches involves many steps, including establishing the miniature batch imply that mini-batch variation, normalizing, and scaling shift. After that, non-linearity is added to the feature extraction procedure by using the activation function of ReLU. Further convolution layers are applied once the output has been down-sampled at the max pooling layer. **Figure 2** illustrates the ResNet50 architecture through the network, conv-blocks, and identity blocks. According to the first theory, because Residual Network 50 can handle deeper networks more efficiently than conventional CNN, it has a better design.

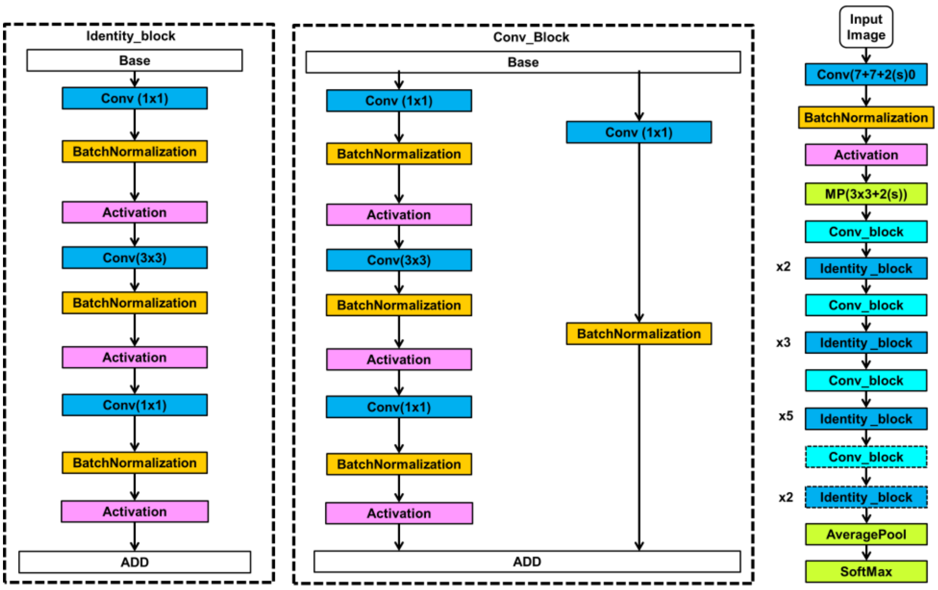

Figure 2. The ResNet50 architecture.

3.3.2. Intelligent flamingo optimization (IFO)

Optimized Residual Network 50 the Intelligent Flamingo Optimized Residual Network 50 addresses overfitting from improved initialization of a population and adaptive learning strategies. This reduces convergence times for optimized techniques towards efficiently improving performance while preserving interpretability in sports biomechanics applications. The random initialization of the initial population is a significant problem in IFO as it may lead to an unequal distribution of people throughout the proposed space. This unequal distribution frequently results in reduced accuracy of the solutions, impeding the algorithm's ability to choose the best course of action for preventing injuries. To get around this restriction, using cubic chaotic mappings is suggested. Using the intrinsic unpredictability and boundedness of the theory of chaos, this method generates an initial population that is more evenly distributed. It is ensured that the flamingos, which stand for possible solutions, are evenly dispersed over the examination interplanetary by using chaotic sequences.

The initialization process Crowd for Cubic Chao: The starting location of players is produced by accidental initialization when IFO is optimized for football injury prevention. This may result in a population that is distributed unevenly and less accurate solutions. Our improvement comes from the use of cubic chaos mapping, which gives everyone in the area of search an even distribution. Through the utilization of chaos theory's features, this technique enhances variety and facilitates a more efficient exploration of the solution space for injury prevention measures.

$$\gamma = \{z_1, z_2, \ldots z_c\} \tag{5}$$

where z_jj $\in [-1, 1], 1 \leq$ ij $\leq$ c

$$z_{m+1} = 4z_{m^3} - 3z_m \tag{6}$$

where $-1 \leq z_m \leq 1$ and $z_m \neq 0, m = 1,2,..,c$

$$w_{jc} = K_c + (1 - z_{jc}) \times \frac{V_c - K_c}{2} \tag{7}$$

V_cIs the higher certain, where w_{jc} is the c-dimensional location of the jth separate flamingo in the exploration space, and K_cIs the inferior certain of the c dimensional exploration space z_{jc}Is the d-dimensional coordinate of the jth individual got from Equations (5)–(7).

Information Feedback Model: The information feedback model improves solution quality by incorporating data from previous iterations. It generates new individuals through weighted summation from past generations. The model operates in two modes: random and fixed.

$$w_j^{s+1} = \alpha w_i^s + \beta z_j^{s+1} \tag{8}$$

$$\alpha = \frac{e_j^{s+1}}{e_j^{s+1} + e_i^s}, \beta = \frac{e_i^s}{e_j^{s+1} + e_i^s} \tag{9}$$

In this context, this is the location of the i-th from the previous group, z_j^{s+1} is the intermediate individual generated by the IFO, and e denotes fitness values evaluated using Equations (8)–(10). Each choice has distinct advantages: the fixed approach enhances convergence speed, while the random approach facilitates exploration.

$$\sigma = \left| \frac{e_j^{s+1} - e_j^s}{e'max - e'min} \right| \tag{10}$$

Here e_j^{s+1} is the fitness of the *j*-th the current generation. If σ is below a predetermined threshold (e.g., 10^{-4}) the model transitions to a random feedback mode to improve exploration capabilities.

The process of selection and Randomized Opposition-Based Training Approach: An ability to escape local optima, a random opposition-based learning strategy is incorporated.

$$\widetilde{w}_i = k_i + v_i - rand \times w_i, i = 1,2,..,m \tag{11}$$

This strategy adds a stochastic element to opposition-based learning, improving the algorithm's capability to explore new potential solutions. Additionally, elite flamingos are selected based on fitness values to maintain population diversity and accelerate convergence. The new position of elite individuals is determined in Equations (11) and (12).

$$w_j^{s+1} = \begin{cases} w_j^{new}, if\, e_j^{new} < e_j^{old} \\ w_j^{old}, if\, e_j^{new} > e_j^{old} \end{cases} \tag{12}$$

These enhancements to the IFO provide a robust framework for optimizing strategies aimed at preventing injuries in football, improving both convergence speed and exploration capabilities to better identify effective predictors of sports injuries.

Step 1: Set the quantity of the initial traveling F throughout each iteration as the migration proportion of the first migrating flamingos (0.1), consistent with FSA principles.

Step 2: Utilize cubic disordered mapping to initialize the flamingo population locations, ensuring a more uniform distribution for effective search.

Step 3: For the *i*-th iteration, divide the population into two migration phases, determining the number of flamingos migrating in the first phase.

Step 4: Assess adaptation values for each flamingo based on their effectiveness in predicting injury risk, ranking the populace to identify the greatest and altered persons.

Step 5: Execute migration updates for the selected individuals using Equation (6) and foraging updates for others using Equation (7). Evaluate the information for the commentary framework based on adaption values, using probabilistic backward training and aggressive choice for top performers.

Step 6: Process F those that exceed defined boundaries to maintain valid solution spaces, ensuring feasibility in injury prediction.

Step 7: If the extreme quantity of repetitions is touched, proceed to Stage 8; then, return to Stage 3 to continue optimization.

Step 8: Record an ideal injury prevention strategy and its corresponding worth, ready for implementation in training and gameplay settings.

Algorithm 1 IFO-ResNet50

1: Intitlally, ResNet50 model with biomechanical input data for football injury prevention.
2: Preprocess input images (255 × 255 pixels) using convolution, batch normalization using Equations (2)–(4), and ReLU activation.
3: Extract deep features using residual blocks (conv-blocks and identity-blocks).
4: Initialize IFO parameters (population size, iterations) and use cubic chaotic mapping for the initial population using Equations (5)–(7):
5: Map chaotic space to search space using Equation (7):
6: Evaluate the fitness of each flamingo using deep features from ResNet50 for injury prediction.
7: Rank flamingos based on fitness values and update positions using the Information Feedback Model Equations (8) and (9):
8: If convergence criteria are met (σ < threshold), apply the fitness ratio using Equation (10):
9: Apply Random Opposition-Based Learning strategy using Equation (11):
10: Update elite flamingo positions using Equation (12):
11: Repeat steps 6–10 until max iterations or σ threshold is reached.
12: Output optimal solution and the best predictors for injury prevention in football.

4. Evaluation metrics

Accuracy: The capacity of a model or algorithm to accurately forecast injury events based on biomechanical data and other pertinent variables. It represents the percentage of accurate forecasts with true positives and true negatives among every forecast that was made. The model successfully separates athletes’ danger in accidents evaluated in Equation (13).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

Precision: Regarding football injury prevention, precision is the percentage of actual positive injury predictions among all the optimistic forecasts generated by the model. It calculates the proportion of anticipated harm risks that were accurately detected. The risk of damage is decreased in Equation (14).

$$Precision = \frac{TP}{TP + FP} \tag{14}$$

Recall: Regarding football damage prevention, recall is the ratio of genuine affirmative injury forecasts to the real amount of injuries sustained. It gauges how well the model can pinpoint every pertinent harm risk in the population. This is necessary to improve average player security and put preventive measures into action on time are evaluated using Equation (15).

$$Recall = \frac{TP}{TP + FN} \tag{15}$$

$F-1$ *Score*: A statistic called the F1 score provides an equilibrium between recall and accuracy by combining both numbers. Since it represents the harmonic average of recall and accuracy, it is particularly helpful in injury prevention evaluation in Equation (16), where it is crucial to minimize mistakes while also detecting actual injury risks.

$$F - 1\,score = 2x\frac{precision.recall}{precision + recall} \tag{16}$$

AUC: Area measures how well a classification model performs in differentiating between injury risk categories under the receiver operating property curve. Higher *AUC* values are indicative of improved algorithm efficacy in accurately anticipating accidents in the setting of football avoiding injuries, Equation (17).

$$AUC = \int_0^1 \frac{FP}{TN + FN} \tag{17}$$

5. Performance analysis

The Python framework was used in conjunction with a Windows 13 operating system that was powered by an Intel® Core i9 CPU and equipped with 16.00 GB of RAM. This arrangement made it possible to retrieve the dataset for evaluating injury predictions virtually connected to football. The results reveal that the IFO-ResNet50 outperforms conventional techniques (XG boost [36]. Support vector machine (SVM) [36], Random Forest [36], decision tree [36] and XG Boost oversampling (XG Boost OS) [37]) in terms of accuracy and dependability. This development is essential for creating sports biomechanics injury prevention solutions that work, which will eventually improve player health and football performance administration. The correlation coefficient between the two factors is shown in **Figure 3** in each cell of this graphic, which depicts a correlation matrix for certain characteristics. Strong negative correlations (value 1) and strong positive correlations (value 1) are the range of values. Among the noteworthy correlations is the substantial positive correlation (0.94) between "season games played" and "season minutes played," indicating that athletes who participate in multiple games overall log more minutes. There is a moderate correlation between "total_days_injured" and "season_days_injured" (0.49). In contrast, "pace" and "height_cm" show a negative association (−0.48), suggesting that taller players tend to move more slowly. Additional attributes, including "weight_kg" and "BMI," have average associations with physical attributes like height and players.

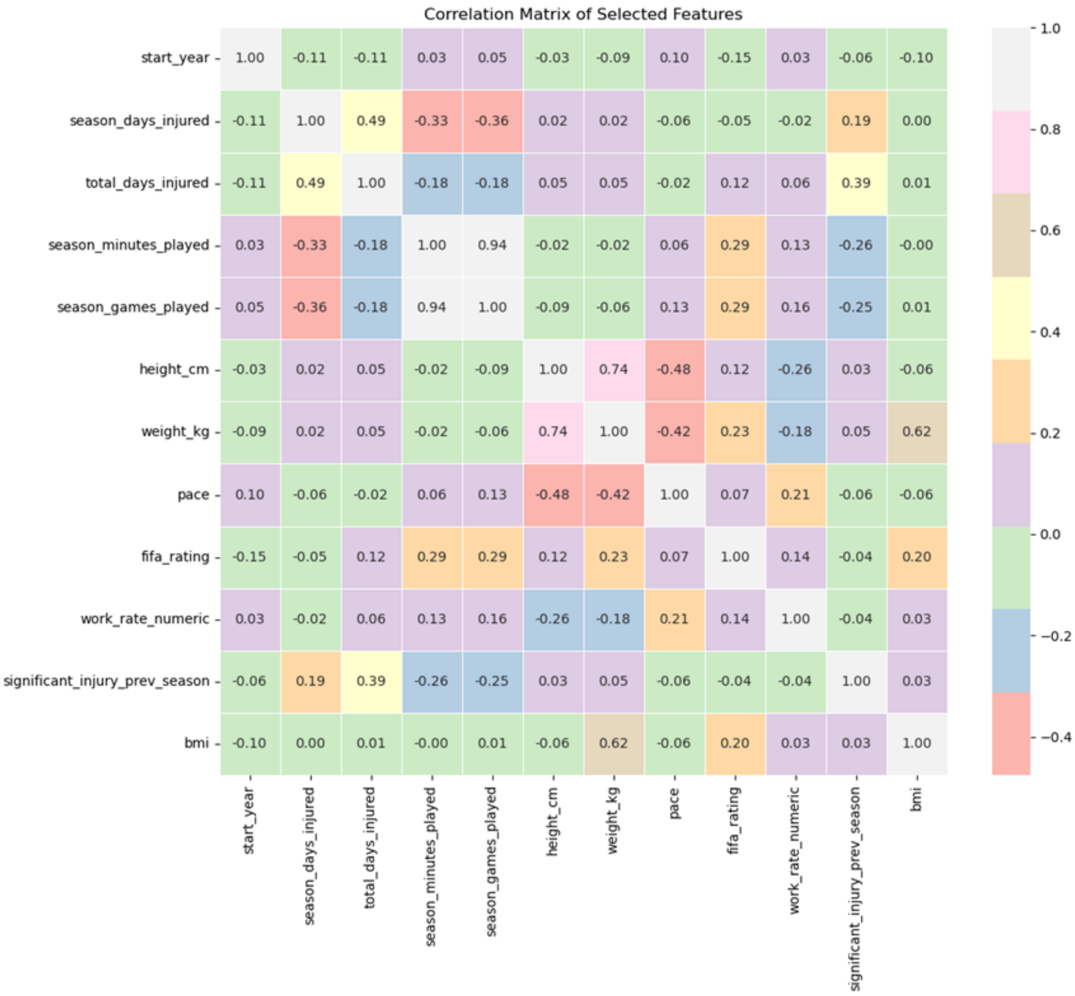

Figure 3. Correlation matrix.

Accuracy: **Figure 4** and **Table 2** shows the comparative analysis of existing and proposed approaches in accuracy. The suggested IFO-ResNet50 model achieves 98.1% accuracy, outperforming every existing approach. With the second-highest accuracy of 97%, this is a significant increase over of XG boost. SVM performance noticeably of inferior quality of accuracy at 83.5%, Random Forest archived 95.5% accuracy. These outcomes demonstrate how successful the IFO-ResNet50 model is compared to other well-known methods.

Table 2. Numerical values of accuracy.

Method	**Accuracy (%)**
Random Forest	95.5
XG Boost	97
SVM	83.5
IFO-ResNet50 [Proposed]	98.1

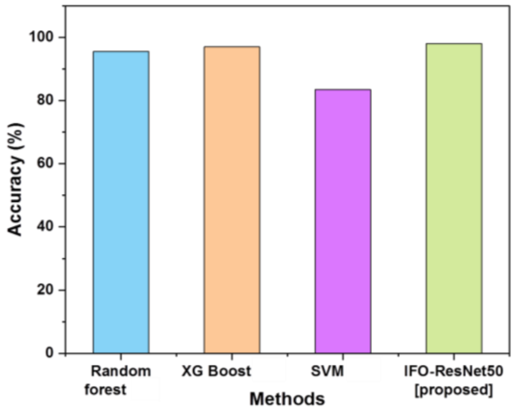

Figure 4. Comparison of accuracy.

Precision: **Table 3** and **Figure 5** present the precision values of various methods used for predicting football injuries. The suggested approach IFO-ResNet50 shows the highest level of precision (98.7%) efficacy in precisely categorizing the intended results. With a precision of 97%, XG Boost also demonstrates the performance. Random Forest achieved 92.2% precision. XG Boost OS demonstrates 53% precision, indicating that the oversampling strategy could have negatively affected the system's categorization accuracy.

Table 3. Numerical values of precision, recall, and AUC.

Method	Precision %	Recall %	AUC %
Random Forest	92.2	94.5	92
XG Boost	97	97	97
XG Boost OS	53	64	62
IFO-ResNet50 [Proposed]	98.7	98.4	98.5

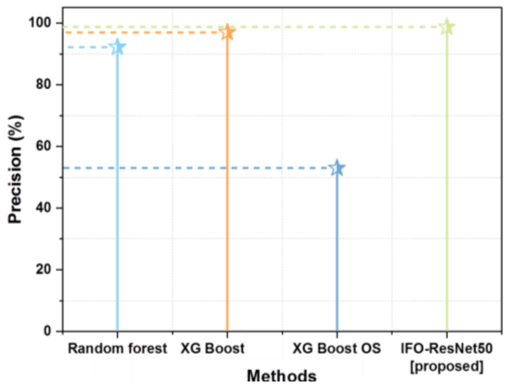

Figure 5. Outcome of precision.

Recall: **Figure 6** and **Table 3** shows the comparative analysis of the existing and proposed model in recall. The suggested IFO-ResNet50 method for higher performance in recall archived 98.4%. Random Forest demonstrated a recall of 94.5%, indicating falls to identify true positive cases. XG Boost performed a Recall of 97%, and XG Boost OS lagged at 64%.

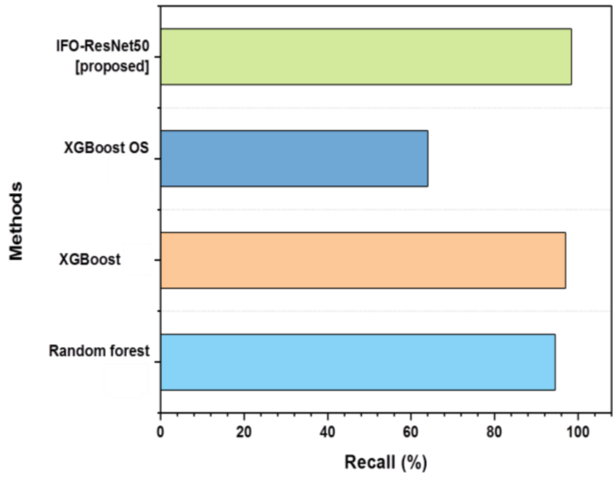

Figure 6. Bar chart of recall.

AUC: **Figure 7** and **Table 3** shows the AUC curve of the existing and proposed model. The 92% AUC of random forest demonstrated performance. XG Boost archived an AUC of 97% with XG Boost OS scoring just 62% performance. However, the recommended IFO-ResNet50 outperformed 98.5% of all other methods, showing its superior ability to distinguish is positive and negative instances in injury prediction.

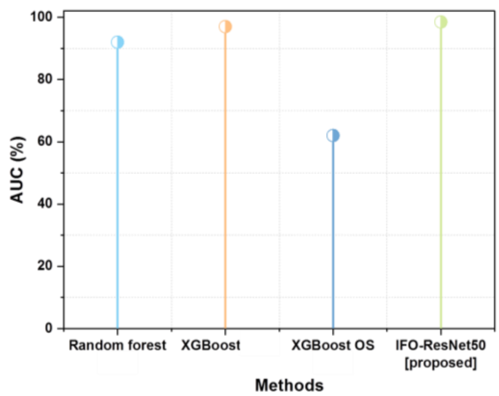

Figure 7. Graphical representation of AUC.

The F1 scores of many techniques for forecasting football injuries are shown in **Table 4** and **Figure 8**. The decision tree technique demonstrated 64%, and XG Boost [36] archived 85% of precision. The suggested IFO-ResNet50 obtained a significant F1 Score of 98.2%.

Table 4. Numerical values of F1 Score.

Method	F1 Score (%)
Decision Tree	64
XG Boost	85
IFO-ResNet50 [Proposed]	98.2

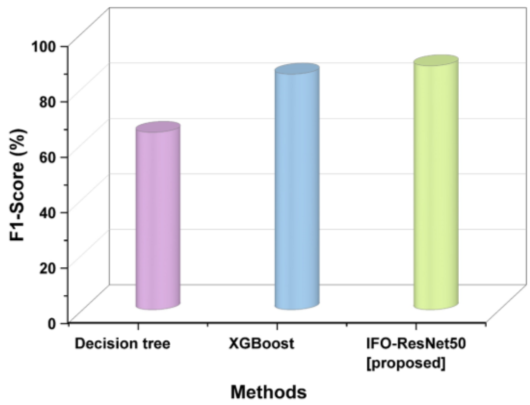

Figure 8. Comparison of F1 Score with existing and proposed techniques.

Discussion

Random forest a primary drawback is that an excessive number of trees may cause the algorithm to become unresponsive and unsuitable for real-time prediction. These algorithms often train quickly, but after training they produce predictions very slowly. Large data collections take more resources to store and process. Not only is XG Boost a powerful algorithm, but it also requires careful parameter setting. If not correctly regularized, the method may become too complicated and hence difficult to understand. Price rises outside of the range seen in the training data cannot be predicted by XGBoost. High computational costs are a drawback of SVMs, particularly when working with complicated and sizable datasets, to solve a quadratic optimization problem. This issue entails figuring out the kernel matrix and the Lagrange multipliers for each data point. We expressed the difficulties in managing resources and optimizing for high data volumes, which makes XG Boost OS difficult to employ in real-world scenarios. The decision trees have drawbacks in terms of variance, overfitting, and sensitivity to incomplete data. The performance and dependability of these systems may be enhanced for commercial applications by managing depth, utilizing ensemble approaches, and guaranteeing high-quality training data. However, regarding these questions, the IFO-ResNet50 improves the results mainly due to optimal feature extraction and better model stability. IFO-ResNet50 combines important aspects of the most recent optimization techniques with residual connections to prevent marginalization, allow interpretable interpretation, and achieve almost optimum performance in large datasets for machine learning research. Football-related muscle injuries are less common than in the IFO-ResNet50 model, which improves injury prediction accuracy through the use of sophisticated biomechanical data.

6. Conclusion

The physically demanding nature of football makes sports injuries particularly hamstring strains, a prevalent occurrence. Understanding biomechanics is crucial for developing injury prevention plans as well as ways to boost athletes' performance and safety. IFO-ResNet50 analysis of the biomechanical aspects of football may enhance injury prevention tactics. The model demonstrated its capacity to detect hamstring strains, without addressing potential injury concerns among students, with an exceptional accuracy of 98.1%, closely followed by an AUC at 98.5%, a recall to set at 98.4%, a precision at 98.7%, and an F1 score at 98.1%. To improve student safety and athletic performance, PE instructors would benefit from having this capacity to apply data-driven techniques. Its scalability and resilience need to be further verified on larger datasets and circumstances particular to sports. Some football injury scenarios may not be sufficiently represented by the specific datasets used in this research. Additional verification of IFO-ResNet50 in various sports contexts is required. Potential avenues for future research from this experiment might involve investigating high-performance machine-learning approaches to further increase the forecast's accuracy about football injuries. Wearable technology and the real-time integration of biomechanical data might offer this kind of player health intelligence. A comprehensive approach to athlete satisfaction would include expanding the model's application to more sports and psychological variables associated with injury risk.

Funding: The Research Project of Education Science in Shaanxi Province During the 14th Five-Year Plan: Research on Methods and Pathways of Ideological and Political Education Construction in Public Physical Education Courses at Colleges and Universities (NO. SGH22Y1871); Regular Project of Shaanxi Sports Bureau in 2023: Research on the Relationship between Chinese Sports and Chinese Classical Philosophy (NO. 2023571).

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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