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Article

# Research on the biomechanical characteristics of basketball player injuries and their application in sports rehabilitation

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**Abstract:** Basketball is a dynamic sport, characterized by fast moves, powerful hops, and constant changes in direction, which contributes to its great intensity and excitement. However, these same features elevate athletes to a risk of various types, which include the most common ones such as ligament tears, knee problems, and ankle sprains. The knowledge of the risk factors associated with particular movement patterns and environmental conditions is made possible by knowledge of the biomechanical qualities of these injuries is crucial if one has to develop effective preventive and rehabilitation strategies. The purpose of the study is to establish the biomechanical characteristics of basketball player injuries and their application in sports rehabilitation. The study proposed a novel Tunicate Swarm Optimized Flexible Extreme Boosting (TSO-FXGBoost) to predict the injuries of basketball players and their sports rehabilitation. Player's motion data capture sessions utilize cameras and sensors to record their biomechanics during basketball activities. A Gaussian filter was employed to process the data to eliminate the noise present in the biomechanical data. Principal component analysis (PCA) served as a dimensionality reduction approach to extract relevant features from the pre-processed data. The results demonstrate that certain biomechanical features have a strong correlation with the occurrence of injuries, which indicates great potential in the strategies of prevention of injuries. In a comparative analysis, the suggested approach performs various assessment metrics such as accuracy (98%), recall (96.2%), precision (98.49%), and $F1$ score (97.8%). The suggested approach and rehabilitation strategies can be customized to each player's unique biomechanical profile, improving rehabilitation times and lowering the risk of re-injury.

**Keywords:** basketball player injuries; rehabilitation; biomechanical; Tunicate Swarm Optimized Flexible Extreme Boosting (TSO-FXGBoost)

## 1. Introduction

Basketball is a sport that requires many movements in an explosive manner, requires agility, and requires a considerable amount of strength from the players. As a result of these demands on the body, players tend to get several injuries. Acute injuries, such as a sprain of the ankle, tearing of ligaments, and muscle strains are common to basketball players owing to the nature of the game, which is played at a fast pace [1]. Lower limb injuries arise from simple tasks such as twisting, jumping, and landing awkwardly. Basketball players often get ankle sprains, which are the type of injuries sustained when a player lands uncomfortably after jumping or steps on another player's foot [2]. Although these are common, more complicated injuries, such as tears of the anterior cruciate ligament that have longer recuperation periods, are not so frequent. However, they have the potential to occur, especially in environments that are competitive and this has high stakes.

Athletes, especially professional and highly active non-professional basketball players, often undergo chronic overuse injuries [3]. With time, exerting motions like sprinting, jumping, and twisting creates contusions and stresses on the muscles, tendons, and joints. Patellar tendinitis, or “jumper’s knee”, is one of the most respirable conditions caused by exhausting perspectives with a constant vertical component. This condition could affect a player’s ability to perform at their optimum and cause long-term distress to the player [4]. Other conditions, such as shoulder and back injuries, aside from knee injuries, are caused as a result of shooting, passing, and maintaining balance while in contact with opponents.

The employment of pertinent injury prevention measures, such as biomechanical assessments, strengthening, and stretching activities, is critical for the reduction of risk associated with both chronic and acute injuries [5]. Up to the point of full recovery, where an athlete can be termed as completely healed, stretch and strength rehabilitation protocols are critical within the healing process, as they ensure that the athlete goes back to the court fully healed with very low chances of sustaining injuries again [6]. Individualized training and recovery plans responding to each athlete’s specific physiological requirements are becoming more and more important as sports medicine and biomechanical analysis progress, to maximize performance and lower the chance of injury recurrence [7].

Basketball practice is always risky when it comes to injuries. The main causes of this scrambling, are crashes, heightened muscle tension, and physiological strain that occur during competitions. Damage to human organs or tissue brought by an external impact is referred to as an injury [8]. An injury can occur from repeated impacts on a specific muscle group or from a single, powerful, or inconsequential hit. There are numerous developments in basketball currently designed to improve players’ injury prevention and overall physical preparation for players [9]. Basketball players develop their endurance, strengthen their muscles and ligaments, and develop mechanisms to avoid injuries during tournaments through general physical training.

It is an intricate, challenging, and risky sport. As athletes strive to maximize their efficiency during training and competition, their injuries are showing a downward trend [10]. Numerous pieces of data indicate that sports-related injuries are on the rise and becoming a big problem for athletes. Technical mistakes, low intensity, extended periods, large repetition counts, and sudden movements can cause injuries to athletes [11]. The probability of an athlete suffering a sports injury increases with the length of time, they have been physically active and the severity of the injury. Professional athlete injuries have a significant effect on the sports business since they affect players’ mental health and a team’s ability to compete [12]. Basketball player injuries frequently lead to restrictions in mobility and effectiveness, reducing their ability to run, leap, and change direction successfully. Common ailments like knee problems and ankle sprains can need lengthy recovery times, which shorten a player’s career in general. The study suggested a brand-new method called Tunicate Swarm Optimized Flexible Extreme Boosting (TSO-FXGBoost) to forecast basketball players’ injuries and their sports rehabilitation.

### Key contribution

- Data on basketball player injury in sports rehabilitation was collected.
- The raw biomechanical data was filtered using a Gaussian filter to remove noise, guaranteeing high-quality inputs for further analysis and enhancing the accuracy of damage predictions.
- Principal component analysis (PCA) was applied to identify critical characteristics from the preprocessed data, lowering dimensionality while keeping essential information for forecasting injury risks in basketball players.
- The Tunicate Swarm Optimized Flexible Extreme Boosting (TSO-FXGBoost) approach is presented to improve basketball injury prediction accuracy and customize rehabilitation plans according to player biomechanics.

These categories could be used to group the remaining research components: Section 2 discusses the related work, Section 3 addresses the methods, Section 4 presents the experiment's results, Section 5 offers a discussion, and Section 6 concludes the study.

## 2. Related works

Recurrent neural networks (RNNs) and big data analytics were used in the study, to examine players' previous experiences with sports rehabilitation and forecast their prognosis [13]. The dataset contains information on athlete profiles, injuries, courses of therapy, and results. By rehabilitative procedures, the RNN architecture recognized temporal connections in sequential data. A variety of indicators was used to assess the model's performance.

Basketball players constantly engage in physical activities, which could contribute to injuries. Basketball motion tracking capture was a problem in machine vision systems that were covered in the study [14]. A deep learning-based multi-perspective human motion trajectories capture method framework was created to predict the location distribution of joint points. To provide a 3D posture assessment, the approach modified the three-dimensional spatial distribution of joint points.

As proposed in the research for tracking and preventing sports injuries in basketball, a motion capture system employing a Convolutional neural network (CNN) sensor was recommended [15]. The system collected dynamic data from the athletes, which included heart rate, energy expenditure, acceleration, and stride frequency among others. The system extended as well to improve intensity and safety in basketball games, encouraged training and tactical changes and comprehensive, scientific data was useful to athletes and coaches.

The primary focus of the research was on using wearables and analytics to assess injury risk factors in athletes [16]. High mechanical stress and high body mass were included as potential risk factors for injury. To ensure the desired development of the musculoskeletal system, the specialists recommended an increase in mechanical loads in exercise programs, but not abruptly. The study highlighted the importance of the training systems and their mechanical loads, concerning injury prevention.

Through mobility, exercise, and treatment, people recovering from injuries could benefit from sports injury rehabilitation, on the specialist field. Research used artificial intelligence to provide a customized sports injury rehabilitation assessment system [17]. Exercise movement image data and convolutional neural networks were utilized to propose an advanced Penguin Search Optimized Efficient Random Forest (APSO-ERF) for sports injury rehabilitation. When it comes to customized sports injury rehabilitation, the approach works better than the standard algorithms.

To predict injuries in sports professionals, the research investigated the application of big data analytics (BDA) with support vector machines (SVMs) [18]. While BDA assists in managing player fitness and resource distribution, SVMs are capable of managing intricate data linkages and effectively classifying information. An SVM model was developed by projecting the input information into a high-dimensional space to choose the optimal hyperplane. To categorize fresh data points as injury or non-injury, support vectors were utilized for prediction.

Due to the high number of player retirements resulting from injuries, basketball in China struggles to remain competitive [19]. Artificial neural network methods for sports injury risk early warning were being used to minimize sports harm. The algorithms were appropriate for early warning since they had demonstrated strong performance in the categorization and prediction of complex systems. An optimization analysis indicated that the technique was better at predicting both quality and problems.

An enhanced recurrent neural network (RNN) model for sports rehabilitation was provided in the investigation, with a focus on attention processes and sequential data processing [20]. The method ensured compliance with temporal structures of data by gathering real-time data from several sources employing wearable IoT devices. After the model was redesigned and trained on various datasets, the prediction accuracy improved by 15%, and rehabilitation efficiency increased by 20%.

Study focused on the application of support vector machines (SVM) to diagnose injuries in athletes, who engage in sports like badminton, table tennis, and tennis [21]. Considering an accuracy of 96.63%, the research created an automated technique to differentiate between normal and injured positions. It proved that an SVM-based method for injury diagnosis in racket sports was feasible, which was a major step towards computer vision problems in sports.

The SVM model was used in the research, to investigate a real-time injury monitoring system [22]. Joint detection was used by the system to extract joint motion patterns, while video detection was used to record human motion. Once the data became standardized, singular value decomposition was used to reduce dimensionality. Classifying the processed data was done using an SVM classifier. The SVM model performed better than popular models.

The purpose of the study was to forecast non-invasive lower body injuries that result from professional football competitions' over- or under-training [23]. It makes use of models for generating decisions that were based on information gathered from matches and training. Three techniques for producing decisions were used, the machine learning baseline XGBoost algorithm, fuzzy rule-based, and rule-based approaches. The most encouraging outcomes were produced by the XGBoost algorithm, which made it possible to accurately estimate the risk of damage depending on player-specific external load characteristics.

## 3. Methodology

Basketball player injury in sports rehabilitation datasets were used. To eliminate noise from the biomechanical data, a Gaussian filter was used during preprocessing. Using extracted features and dimensionality removal from preprocessed data, principal component analysis (PCA) is used. TSO-FXGBoost is to predict basketball players' injury and their rehabilitation. **Figure 1** shows the overall flow.

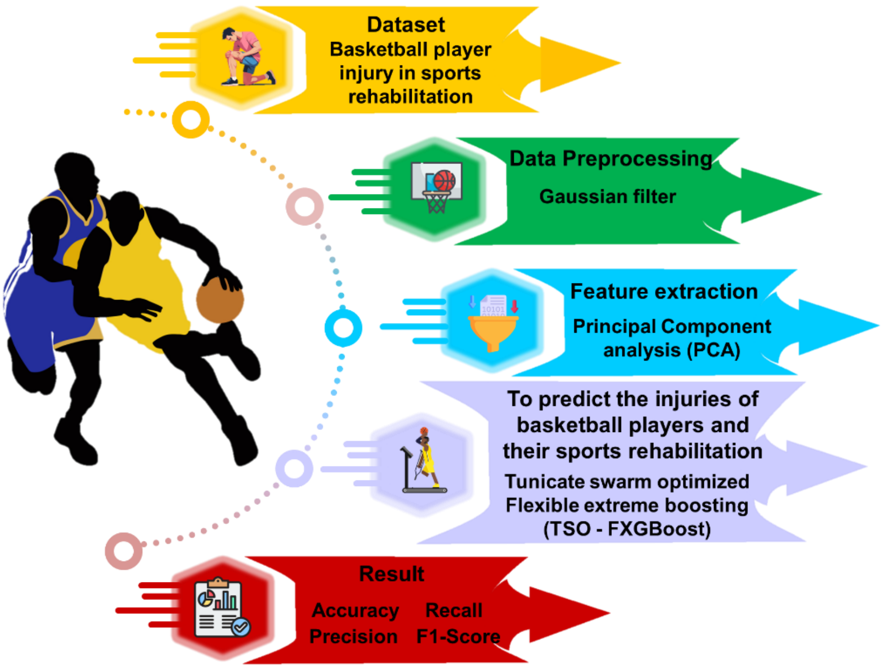


**Figure 1.** Overall flow of suggested TSO-FXGBoost methodology.

### 3.1. Dataset

This dataset records basketball players' biomechanical characteristics, injury specifics, and rehabilitation results to comprehend how movement patterns affect the probability of injuries and how individualized rehabilitation could speed up the healing and lower the incidence of recurrence. It contains information on player demographics, different injury kinds (such as hamstring strains, anterior cruciate ligament (ACL) tears, and ankle sprains), biomechanical parameters (such as knee angles, jump height, and speed), and specifics on rehabilitation (such as program type and efficiency). The dataset has applications in injury prediction, rehabilitation strategy optimization, and performance monitoring to guarantee full recovery in high-impact sports such as basketball. The data provides specific information on rehabilitation, which includes the type of rehabilitation and its effectiveness. This data is efficient for predicting injury and steps can be taken to prevent an injury before it happens. The possible correlation between specific biomechanical characteristics and certain types of injuries may provide visible indications about one or other injury risks. The basketball player's biomechanical characteristics sample data is displayed in **Table 1** [24].

**Table 1.** Sample data of basketball players' biomechanical characteristics.

| Player profile | Player ID | | |
|---|---|---|---|
| | **1** | **2** | **3** |
| Age | 24 | 32 | 19 |
| Height (cm) | 195 | 183 | 208 |
| Weight (kg) | 108 | 87 | 104 |
| Position | Center | Forward | Forward |
| Injury type | ACL tear | Ankle sprain | Hamstring strain |
| Injury severity | Severe | Mild | Moderate |
| Rehabilitation program | Physiotherapy | Physiotherapy | Physiotherapy |
| Rehabilitation time (weeks) | 7 | 8 | 7 |

### 3.2. Data pre-processing using Gaussian filter

Smoothing raw data, such as biomechanical measures or sensor data, to decrease noise and emphasize significant patterns is an essential phase in data preparation employing a Gaussian filter for basketball injury and rehabilitation prediction. By averaging data points that are weighted by their closeness, the Gaussian filter enhances signal clarity and assists in identifying trends. The Gaussian filter is a type of linear smoothing filter in which the weights are determined by analyzing the parameters of the Gaussian function. The resultant Equation (1) can be used to define the Gaussian filter in the nonstop space.

$$g(n,m) = \left(\frac{1}{\sqrt{2\pi\sigma}} f^{-\frac{n^2}{y\sigma^2}}\right) \times \left(\frac{1}{\sqrt{2\pi\sigma}} f^{-\frac{n^2}{y\sigma^2}}\right) \tag{1}$$

A Gaussian filter with one dimension has an impulsive response in Equation (2).

$$h(w) = \sqrt{\frac{b}{\pi}} f^{-bw^2} \tag{2}$$

The standard deviation can be used as a parameter in this Equation (3).

$$h(w) = \frac{1}{\sqrt{2\pi} \cdot \sigma} f^{-\frac{w^2}{2\sigma^2}} \tag{3}$$

### 3.3. Feature extraction using PCA

Basketball players could employ principal component analysis (PCA), a dimensionality reduction method, for injury prediction and recovery. PCA assists in identifying the underlying causes that contribute to injuries by identifying the most important aspects (such as movement patterns, joint angles, and muscle activity) from complicated biomechanical data. Based on these fundamental elements, specific rehabilitation plans could be developed and injury risk can be forecast. A data-driven modeling approach called PCA separates a larger group of correlated variables into a lesser number of new, non-correlated variables while preserving a large portion of the original data.

Consider $W$ is the input, with a sequence of $m$-dimensional values represented by every column. Consider that each function in the set of variables has an average of zero $(F(W) = 0)$. An original data matrix can be supplied as follows when there are $n$ samples and $m$ variables in Equation (4).

$$W = [w_1, w_2, \dots, w_m]^S = \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \cdots & \vdots \\ w_{m1} & \cdots & w_{mn} \end{pmatrix} \quad (4)$$

The PCA allows for the transformation of data and efficiency parameter input into a new event space while maintaining most of the original data.

The input data collections are shifted to a new subspace by identifying the directions with the maximum variance that has identical dimensions as the original space, if not less.

To move $W$ to a new space $T$, the orthonormal transformation $Y$ can be applied as follows in Equation (5).

$$S = YW \quad (5)$$

The $W$-matrix components are combined linearly to create the orthonormal vector that constitutes the ultimate score $S$-matrix, which represents the relationships between the samples. The matrix of $S$ covariance is in Equation (6).

$$D_S = YD_YY^S \quad (6)$$

The eigenvalue equation could be used to generate the loading matrix $Y$, which is written as follows in Equation (7).

$$(D_S - \lambda I)f_j = 0 \quad (7)$$

The covariance pairwise among several input variables is stored in the covariance matrix.

The decomposition of the eigenvectors and eigenvalues of the covariance matrix is shown in Equation (7). The corresponding eigenvectors form new orthogonal axes called "principal components", while the associated eigenvalues determine the scale of the component. In most cases, the first principal component will represent the greatest amount of variance, or information, followed by the second principal component representing the second highest amount of variance, and this pattern will continue until all the components have been listed in order of their eigenvalues and eigenvectors performance. It should be noted that the input variables may have some correlation because the eigenvectors constitute the principal components that have been decomposed and are orthogonal to each other, the principal components themselves are not correlated with each other.

### 3.4. TSO-FXGBoost

To anticipate basketball players' injuries and enhance their recovery strategies, Tunicate Swarm Optimized Flexible Extreme Boosting (TSO-FXGBoost) is a sophisticated machine learning model that combines two effective algorithms. FXGBoost is a dependable version of XGBoost that is adept at handling complex non-linear relationships within the data. It is particularly effective in predicting results, according to various factors, such as player biomechanics, injury history, and in-game performance. TSO is a technique used for optimizing model parameters. It is inspired by how tunicates behave in their natural habitat. TSO has been embedded in the FXGBoost to improve the forecasting efficiency. Employing these hybrid techniques, injury forecasting can be altered for different aspects, specifically player load, motion dynamics, and external aspects, such as the environment for training. Factors of TSO-FXGBoost can predict the patterns that cause damage in the possibility of basketball injuries and sports rehabilitation, allowing both the coaches and athletes to avoid any further damage. This model may provide personalized rehabilitation approaches according to the type of injury sustained and the biomechanical features of the injured athlete, thereby facilitating improvement and reducing the recovery period. Algorithm 1 displays TSO-FXGBoost.

**Algorithm 1** TSO-FXGBoost

```
function TSO_FXGBoost(data, parameters):
initialize parameters and tunicate swarm
for iteration from 1 to max_iterations:
for each tunicate in swarm:
model = FXGBoost(data, tunicate)
      fitness = evaluate_model(model, data)
      update_tunicate_position(tunicate, fitness)
    best_tunicate = select_best_tunicate(swarm)
    if stopping_criteria_met(best_tunicate):
      break
  final_model = FXGBoost(data, best_tunicate)
  return final_model
function FXGBoost(data, parameters):
  model = initialize_model(parameters)
  for epoch from 1 to num_epochs:
    predictions = model.predict(data)
    gradients, hessians = calculate_gradients(data, predictions)
    model.update(gradients, hessians)
  return model
function evaluate_model(model, data):
  predictions = model.predict(data)
  return calculate_performance_metric(data, predictions)
function initialize_tunicate_swarm(size):
  return [create_random_tunicate() for i in range(size)]
function update_tunicate_position(tunicate, fitness):
  tunicate.position = alpha × (best_fitness − fitness)
function select_best_tunicate(swarm):
  return max(swarm, key = evaluate_model)
function stopping_criteria_met(best_tunicate):
  return improvement < threshold
```

### 3.4.1. FXGBoost

A flexible XGBoost model can be employed to forest basketball player injuries and guide sports rehabilitation by integrating various characteristics such as player biomechanics, injury history, workload, and game performance measures. XGBoost's capacity to handle structured data and capture non-linear associations makes it effective in analyzing injury patterns. To provide an accurate forecast, a flexible version of the XGBoost algorithm is provided in Equation (8).

$$\hat{h}_j = E_2(C_j) = \sum_{l_2=1}^{L_2} el_2(C_j),\ \ el_2 \in \phi \tag{8}$$

where $\phi = \{e(C) = \omega_{T(C)}\}$ $e(C)\hat{h}_j$, consists of a group of decision trees. $\hat{h}_j$ is the $i^{th}$ prediction of the gain, and each tree $e(C)$ correlates to a structural variable $t$ and leaf weights $\omega$. The subsequent total loss equation is minimized to train the system.

$$K = \sum_{j=1}^{m_t} k(\hat{h}_j, h_j) + \sum_{l_2=1}^{L_2} \Omega(el_2) \tag{9}$$

where,

$$\Omega(el_2) = \gamma S + \varepsilon\ \|\omega\|^2 \tag{10}$$

In Equation (9), the loss function $h_j$ stands for the difference between the expected gain $\hat{h}_j$ and the realistic gain $h_j$. The decision trees' total number of leaves is $S$. The consequence period is represented by $\Omega$. The tuning parameters $\gamma$ and $\varepsilon$ regulate the decision trees' complexity.

$$k(\hat{h}_j, h_j) = (\hat{h}_j - h_j)^2 \tag{11}$$

The loss function is done iteratively. Equation (12) can be expressed as follows for the $t^{th}$ iteration of the $i^{th}$ sample:

$$K^s = \sum_{j=1}^{m_t} k(\ \hat{h}_j^{(s-1)} + e_s(C_j), h_j) + \Omega(e_s) \tag{12}$$

The model is greatly improved by the addition of feet using the XGBoost algorithm. Utilizing a second-order approximation, the target is optimized in Equations (13)–(15).

$$K^s \simeq \sum_{j=1}^{m_t} \left[k\left(\hat{h}_j^{(s-1)}, h_j\right) + c_j e_s(C_j) + \frac{1}{2} g_j e_s^2(C_j)\right] + \Omega(e_s) \tag{13}$$

$$c_j = \hat{\partial}_{h_j}^{(s-1)}\ k\left(\hat{h}_j^{(s-1)}, h_j\right) = 2 \times \left(\hat{h}_j^{(s-1)} - h_j\right) \tag{14}$$

$$g_j = \partial_{\hat{h}_j^{(s-1)}}\ {}^2 l\left(\hat{h}_j^{(s-1)}, h_j\right) = 2 \tag{15}$$

where the first-order and second-order gradients of$k\left(\hat{h}_j^{(s-1)},\ h_j\right)$, are represented by $c_j$ and $g_j$, respectively.

**3.4.2. TSO**

The Tunicate Swarm Optimization (TSO) method is a novel optimization method grounded in the internal interactions of the tunicate and its societal values. TSO is useful in the case of basketball players, their injuries, and their rehabilitation, as it can be employed to improve machine learning models. In this instance, TSO may modify the model parameters so that the prediction is improved for the biomechanical loads, performance parameters, and injury history of an athlete. TSO is a straightforward meta-heuristic optimizer inspired by the feeding and navigational skills of marine tunicates as well as jet propulsion technologies. These tunicates are millimeter-sized animals. Tunicate can locate aquatic food sources. However, the food source is not indicated in the provided search area (SA). When using the power of jets, a tunicate must adhere to three fundamental requirements, it must avoid colliding with other participants in the SA, choose the appropriate route to the optimal SA, and approach the top search agents as closely as possible. The potential solutions, or tunicates, for the TSO, require the ideal food source or logical value. Throughout this procedure, the optimal tunicates are retained and improved upon with each iteration, and they adjust their positions accordingly. As observed by the following Equation (16), TSO begins with a population of tunicates that are created at random based on the design variables' acceptable limits.

$$\vec{S}_o = \vec{S}_o^{min} + rand \times \left(\vec{S}_o^{max} - \vec{S}_o^{min}\right) \tag{16}$$

where $\vec{S}_o$ is considered as the location of every tunicate and rand is drawn from a uniform distribution in the range of $[0, 1]$. The lower and upper limits on the design variables are represented as $\vec{S}_o^{min}$ and $\vec{S}_o^{max}$. The tunicates change their positions during the iterations according to the subsequent Equation (17).

$$\vec{S}_o(w+1) = \frac{\vec{S}_o(w) + \vec{S}_o(\vec{w})}{2 + d_1} \tag{17}$$

In this case, $d_1$ stands for any value between $0 \; and \; 1$ inclusively, while $\vec{S}_o(w)$ is the modified location of the tunicate about the coordinates of the feed source illustrated in Equation (18).

$$\vec{S}_o(w) = \begin{cases} TE + B \times \left|TE - rand \times \vec{S}_o\right|, if \; rand \geq 0.5 \\ TE - B \times \left|TE - rand \times \vec{S}_o\right|, if \; rand < 0.5 \end{cases} \tag{18}$$

where $B$ is a randomized vector to avoid the appropriate position of tunicates for a population indicates the food supply, and $TE$ prevents tunicates from colliding with one another. This vector is described as follows in Equation (19).

$$B = \frac{d_2 + d_3 - 2d_1}{US_{min} + d_1(US_{max} - US_{min})} \tag{19}$$

Where $d_1, d_2$, and $d_3$ are random integers in the interval $[0, 1]$, $US_{min}$ and $US_{max}$, which are regarded as $1$ and $4$, respectively, represent the least and maximum speeds that encourage social communication.

## 4. Results

Python 3.10.1 is used to implement the suggested method on a Windows 10 laptop with an Intel i7 core CPU and 8GB of RAM. It used Tensor Flow/Keras or Scikit-Learn to train the proposed model using the training set. The suggested technique is TSO-FXGBoost is compared to the existing methods of dual-feature fusion neural networks (DFFNN) and deep Learning-assisted Systems (DLS) [25,26].

### 4.1. Injury type vs. average rehabilitation time (weeks)

The amount of time needed to recover from typical sports-related injuries is shown in **Figure 2**, which demonstrates average rehabilitation timeframes for various injury types. Ankle sprains are among the fastest-recovering injuries, usually requiring 4 weeks of therapy. ACL tears require a longer recovery time of about eight weeks due to the intricacy and seriousness of this injury. In between, hamstring strains require an average of six weeks for recovery. The illustrated depiction makes it easier to understand how various injuries require varied recovery durations, which is important information for athletes and medical professionals to develop effective rehabilitation programs.

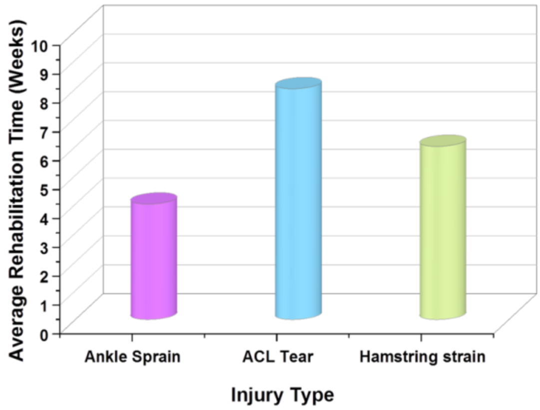


**Figure 2.** Output of average rehabilitation time.

### 4.2. Accuracy

The accuracy of a model or system in predicting the probability of an injury in basketball players is determined by its ability to consider multiple parameters, such as player biomechanics, training loads, and past injury history. Accuracy in sports rehabilitation also refers to how well rehabilitation plans perform in restoring players to where they were performing before their injuries.

**Figure 3** and **Table 2** show accuracy performance. The proposed method TSO-FXGBoost achieves 98% and the existing methods DFFNN and DLS achieve 97% and 86%. The proposed method achieves better performance when compared to the existing methods in terms of predicting the injuries of basketball players and their sports rehabilitation.

**Table 2.** Values for accuracy, recall, *F*1 score, and precision.

| Methods | Accuracy (%) | Precision (%) | Recall (%) | *F*1-Score (%) |
|---|---|---|---|---|
| DFFNN [25] | 97 | 98.4 | 95.7 | 97 |
| DLS [26] | 86 | 88 | 89 | 84 |
| TSO-FXGBoost [Proposed] | 98 | 98.49 | 96.2 | 97.8 |

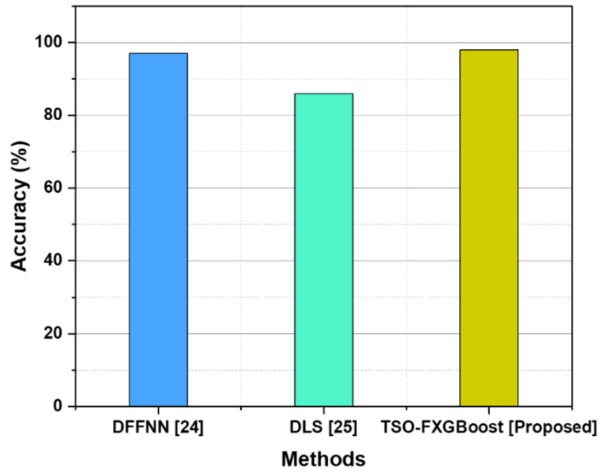


**Figure 3.** Accuracy performance of the suggested TSO-FXGBoost approach.

## 4.3. Precision

Precision is the ability to accurately and constantly predict future injuries employing a variety of data sources, including player biomechanics, previous injury patterns, and physical fitness. With the support of this approach, coaches and trainers can initiate precise preventative processes in place by recognizing risk features and susceptible areas using advanced statistics and modeling methods.

Precision performance is displayed in **Table 2** and **Figure 4**. The conventional approaches DFFNN and DLS achieve 98.40%, and 88%, respectively, whereas the suggested strategy TSO-FXGBoost has 98.49%. When it comes to basketball players' injuries and sports rehabilitation, the suggested strategy performed better than traditional strategies.

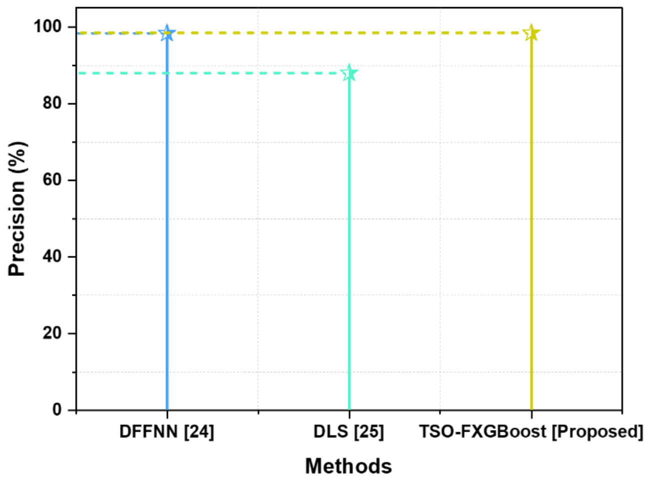


**Figure 4.** Precision performance of the suggested TSO-FXGBoost approach.

## 4.4. Recall

Recall is the ability of a model or system to correctly identify the presence of injuries among players about basketball players in particular who sustained such injuries. For evaluating the effectiveness of the injury, prediction models in this case, recall is particularly important because false negative cases indicate that there are players with injuries that are not detected.

**Table 2** and **Figure 5** display the result of the recall. TSO-FXGBoost, the suggested strategy, achieves 96.2%, whereas DFFNN and DLS, conventional approaches, achieve 95.70% and 89%. In terms of forecasting basketball players' injuries and their sports rehabilitation, the suggested approach accomplished better than the traditional methods.

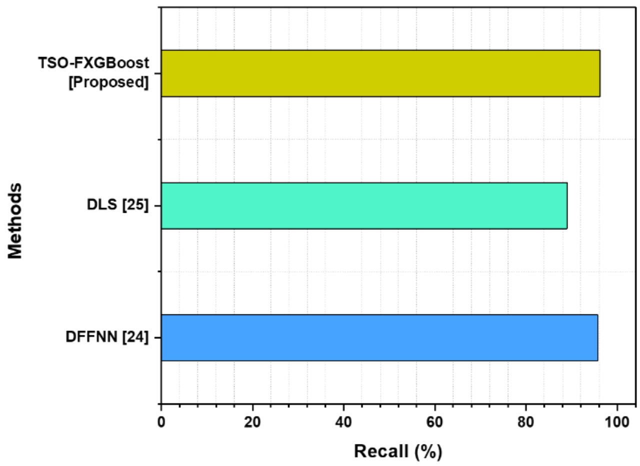


**Figure 5.** Output of the recall performance.

## 4.5. *F*1 score

The *F*1 score is a crucial metric for analyzing how well the predictive model functions. It offers a balanced metric that takes into consideration, both false negatives and false positives. It is the harmonic mean of precision and recall. In this instance, recall signifies the proportion of correctly forecasted injuries, out of all actual injuries, whereas precision displays the percentage of accurately forecasted injuries out of all predicted injuries.

*F*1 score results are presented in **Table 2** and **Figure 6**. Compared to the existing methods, DFFNN and DLS, which achieve *F*1 scores of 97% and 84%, respectively, the proposed approach, TSO-FXGBoost, achieves an *F*1 score of 97.8%. The suggested method outperforms the existing methods in terms of forecasting basketball players' injuries and facilitating their sports recovery.

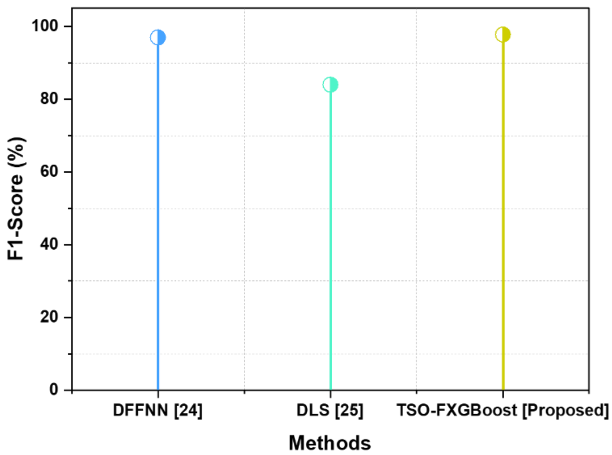


**Figure 6.** Output of the *F*1 score performance.

## 5. Discussion

The existing methods are DFFNN and DLS. Basketball player injury predictions made with the use of DLS algorithms could be skewed or lacking in information due to issues with data availability and quality. For the training and validation of the models, they also need a significant amount of computational power and knowledge. Furthermore, these algorithms lack sufficient transparency, making it difficult to understand the reasoning behind their forecasts, which is crucial for medical decisions in the rehabilitation process. Challenges of predicting basketball injury rehabilitation with dual-feature fusion neural networks as predicted for basketball injuries and their rehabilitation, which include the difficulty in effectively integrating heterogeneous data types from multiple domains (e.g., biomechanical with physiological features), the potential of overfitting that arises due to complex model architectures, and naturally the challenge associated with collecting high-quality labeled datasets from practice that encompasses detailed player performance information alongside injury-mechanisms. Multiplex feature integration may make the DFFNNs more specialized to the training data, which will reduce their ability to generalize toward new data. Similarly, the coaches and health staff may not understand what causes of injuries are influencing predictions because the DFFNN design is too complicated, which makes it not easily accessible. It is very efficient in practical applications only when complete, high-quality data are available, otherwise, incomplete or biased data may yield biased forecasts. Basketball players' injuries might also be limited by DLS due to their dependence on large datasets for training. DLS may produce wrong forecasts if the given dataset is small or does not include a variety of player states or injury types. In addition, DLS can be computational, especially for large-scale implementation and training, and may not be viable to organizations or teams. Basketball players' injury forecast is enhanced by TSO-FXGBoost, which manages intricate data designs well and increases accuracy by selecting a feature that is optimized. Personalized treatment strategies are made possible by this process's flexibility in responding to different sorts of injuries and rehabilitation results. Additionally, real-time understandings are made possible by its computing effectiveness, which enables rapid player health management activities.

## 6. Conclusion

Basketball is a fast-paced, high-intensity sport that is known for its strong jumps, quick movements, and frequent direction changes. This research aims to determine the biomechanical features of injuries sustained by basketball players and how these features could be utilized in sports rehabilitation. The research suggested an entirely novel approach called Tunicate Swarm Optimized Flexible Extreme Boosting (TSO-FXGBoost) to forecast basketball players' ailments and assist in their return to sports. Basketball player injury in sports rehabilitation dataset was gathered. To eliminate noise from the biomechanical data, a Gaussian filter was used during pre-processing. PCA is performed using extracted features and dimensionality reduction from pre-processed data. The proposed method is compared to the existing methods in terms of accuracy (98%), recall (96.2%), precision (98.49%), and $F1$ score (97.8%). The proposed method achieves better performance. Personalized biomechanics' intricacy and the dearth of extensive, long-term data on particular injury patterns are among its drawbacks. The limitations include the evaluation procedures differing and assessment criteria is not clearly defined, training and playing conditions may vary players differ in terms of physique and mechanics, sample size tend to be small, biomechanical data is not easily translated into rehabilitation plans for different types of injuries. The potential for the future is in the development of individualized rehabilitation regimens for real-time injury avoidance and recovery using wearable technologies and AI-driven models.

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## References

1. Aksović, N., Bjelica, B., Milanović, F., Milanovic, L. and Jovanović, N., 2021. Development of explosive power in basketball players. Turkish Journal of Kinesiology, 7(1), pp.44-52.
2. Taylor, J.B., Hegedus, E.J. and Ford, K.R., 2020. Biomechanics of Lower Extremity Movements and Injury in Basketball. Basketball Sports Medicine and Science, pp.37-51.
3. Okoroha, K.R., Haunschild, E.D., Gilat, R. and Cole, B., 2020. Management of ACL injuries in basketball. Basketball Sports Medicine and Science, pp.351-362.
4. Zhang, H., 2023. Analysis of College Basketball Injuries: Implications for Healthcare and Patient Well-being. Journal of Commercial Biotechnology, 28(2).
5. Arora, C., Singh, P. and Varghese, V., 2021. Biomechanics of core musculature on upper extremity performance in basketball players. Journal of Bodywork and Movement Therapies, 27, pp.127-133.
6. Kim, K.N., Msc, P.T. and Lee, B.H., The Effect of the Active Release Technique on Balance and Functional Movement in Youth Basketball Players.
7. Hanief, Y.N. and Widiawati, P., 2021. Characteristics of injuries in adolescent basketball athletes. Revista Pesquisaem Fisioterapia, 11(4), pp.711-721.
8. Wenjie, E., Yu, Q. and Guo, H., 2022. Sports medicine image modeling for injury prevention in basketball training. Contrast Media & Molecular Imaging, 2022.
9. Räisänen, A.M., Owoeye, O.B., Befus, K., van den Berg, C., Pasanen, K. and Emery, C.A., 2021. Warm-ups and coaches' perceptions: searching for clues to improve injury prevention in youth basketball. Frontiers in sports and active living, 3, p.619291.
10. Short, S.M., MacDonald, C.W. and Strack, D., 2021. Hip and groin injury prevention in elite athletes and team sport–Current challenges and opportunities. International Journal of sports physical therapy, 16(1), p.270.
11. Wong, J., 2020. An Investigation of Athlete Workload Monitoring and Injury in Professional Men's Basketball (Doctoral dissertation, Auckland University of Technology).
12. Koyama, T., Rikukawa, A., Nagano, Y., Sasaki, S., Ichikawa, H. and Hirose, N., 2022. Acceleration profile of high-intensity movements in basketball games. The Journal of Strength & Conditioning Research, 36(6), pp.1715-1719.
13. Cui, Y., 2024. An Efficient Approach to Sports Rehabilitation and Outcome Prediction Using RNN-LSTM. Mobile Networks and Applications, pp.1-16.
14. Ang, Z., 2023. Application of IoT technology based on neural networks in basketball training motion capture and injury prevention. Preventive Medicine, 175, p.107660.

15. Chen, Z. and Zhang, G., 2023. CNN sensor-based motion capture system application in basketball training and injury prevention. Preventive Medicine, 174, p.107644.
16. Zadeh, A., Taylor, D., Bertsos, M., Tillman, T., Nosoudi, N. and Bruce, S., 2021. Predicting sports injuries with wearable technology and data analysis. Information Systems Frontiers, 23, pp.1023-1037.
17. Zhan, C., 2024. Application of artificial intelligence in the development of personalized sports injury rehabilitation plan. Molecular & Cellular Biomechanics, 21(1), pp.326-326.
18. Li, W., 2024. A Big Data Approach to Forecast Injuries in Professional Sports Using Support Vector Machine. Mobile Networks and Applications, pp.1-17.
19. Cui, Z., Li, X., Guo, J. and Lu, Y., 2023. Sports injury early warning of basketball players based on RBF neural network algorithm. Journal of Intelligent & Fuzzy Systems, 45(3), pp.4291-4300.
20. Yao, H., 2024. An IoT-Based Injury Prediction and Sports Rehabilitation for Martial Art Students in Colleges Using RNN Model. Mobile Networks and Applications, pp.1-18.
21. Surasak, T., Praking, P. and Kitchat, K., 2023, October. Leveraging Support Vector Machine for Sports Injury Classification. In 2023 15th International Conference on Information Technology and Electrical Engineering (ICITEE) (pp. 234-238). IEEE.
22. Ren, L., Wang, Y. and Li, K., 2024. Real-time sports injury monitoring system based on the deep learning algorithm. BMC Medical Imaging, 24(1), p.122.
23. Piłka, T., Grzelak, B., Sadurska, A., Górecki, T. and Dyczkowski, K., 2023. Predicting injuries in football based on data collected from GPS-based wearable sensors. Sensors, 23(3), p.1227.
24. Ziya. Basketball player injury in sports rehabilitation. Available online: https://www.kaggle.com/datasets/ziya07/basketball-player-injury-in-sports-rehabilitation/data (accessed on 1 October 2024).
25. Meng, L. and Qiao, E., 2023. Analysis and design of dual-feature fusion neural network for sports injury estimation model. Neural Computing and Applications, 35(20), pp.14627-14639.
26. Wu, X., Zhou, J., Zheng, M., Chen, S., Wang, D., Anajemba, J., Zhang, G., Abdelhaq, M., Alsaqour, R. and Uddin, M., 2022. Cloud-based deep learning-assisted system for diagnosis of sports injuries. Journal of Cloud Computing, 11(1), p.82.