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Molecular & Cellular Biomechanics 2024, 21(2), 384.
https://doi.org/10.62617/mcb.v21i2.384

Article

Intelligent rehabilitation assistant: Application of deep learning methods in sports injury recovery

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CITATION

Guan L. Intelligent rehabilitation assistant: Application of deep learning methods in sports injury recovery. Molecular & Cellular Biomechanics. 2024; 21(2): 384. https://doi.org/10.62617/mcb.v21i2.384

ARTICLE INFO

Received: 18 September 2024
Accepted: 26 September 2024
Available online: 6 November 2024

Abstract: In recent years, sports injury rehabilitation has developed into a specialized field that has forced the combination of an orthopedic surgeon, sports physiotherapist, and sports physician. Determining the appropriate time for an injured athlete to resume practice or competition is regarded as sports rehabilitation. Discovering the best solutions to avoid injuries, maximize recovery, and enhance performance is crucial for sports activities. The study introduced an intelligent rehabilitation assistant (IRA) that leverages advanced deep learning (DL) methods to enhance sports injury recovery. In this study, the IRA incorporates redefined prairie dog optimized bidirectional long-short-term memory (RPDO-Bi-LSTM) to enhance accuracy, predicting sports injury recovery. The study collected data on the state of rehabilitation, physiological parameters, and general health using wearable sensors and movement patterns. The data was preprocessed using a median filter to remove noise from sensor data. Region-based segmentation using segmented images from preprocessed data. Convolutional neural networks (CNN) using extracted features from obtained data. The IRA provides personalized recovery plans and real-time feedback. The framework consists of the components, suggested models to create quality scores for motions, measurements to quantify motion performance, and scoring of performance measurement elements into numerical quality scores. The proposed method is implemented using Python software. RPDO-Bi-LSTM presentation is evaluated by various metrics, such as accuracy 94.2% recall 98.2%, precision 96.5%, and specificity 95.2%, f1 score 95.6%, he planned technique attained good performance and improved the accuracy of sports injury recovery.

Keywords: intelligent rehabilitation assistant (IRA); sports injury recovery; redefined prairie dog optimized bidirectional long short-term memory (RPDO-BiLSTM)

1. Introduction

Athletic injury recovery plays a vital role in ensuring sportspersons can maintain optimal performance and overall well-being. Injuries, whether they are acute or chronic, can severely impact an athlete's physical abilities and emotional state, creating significant barriers to returning to their peak condition [1]. Traditionally, recovery has involved a structured combination of medical intervention, rehabilitation exercises, and physical therapy designed to rebuild strength, flexibility, and endurance [2]. Sports injury recovery is not just about bodily curative; it is a complete-process that comprises emotional and emotional support [3]. Being sidelined due to injury often has a significant mental toll on athletes, leading to stress, anxiety, or even depression. Recovery incorporates mental health support alongside physical therapy [4]. Elements like psychological flexibility training and psycho-social interferences have assumed critical roles as key contemporary strategies of reintegration. These practices assist the sport people to make sense of this pressure and maintain concentration on the recovery objectives [5]. Incorporation of mental and physical rehabilitation in the recovery programs ensures that a holistic recovery approach is taken to address the entire athlete [6]. The integration of such sophisticated technology with the focus on emotional and psychological support creates a more holistic approach to recovery [7]. The process not only assists athletes in recovering but also protects their wellbeing, hence facilitating a healthier and safer return to the field of play [8]. The progress made over recent decades has been dramatic, especially with the appearance of deep learning and AI in injury rehabilitation. The use of AI which is deep learning has made new opportunities in the working out of sports injury rehabilitation [9]. These technologies utilize large amounts of data; including biomechanics, movement patterns, and even the patient's injury history, to enable a tailor-made rehabilitation process [10]. In this case, therefore, AI outperforms conventional approaches that depend on fixed recovery procedures for the athletes. In doing so, it allows for a better prognosis of how long the recovery process will take, helps identify potential issues such as re-injury, and adapts the rehabilitation schedule based on actual progress [11]. Automated data analysis through deep learning algorithms can provide large and diverse patient datasets where accurate interpretations are completed within seconds, far surpassing human time and capacity. For instance, AI is capable of tracking an athlete's healing process after biomechanical shifts during a program involving rehabilitation exercises and modifying the program's intensity and method according to the performance data. This modified method allows rehabilitation to be more adaptive, catering to the unique physiological needs of each individual [12]. MRI is an essential diagnostic technique for sports' muscle injuries. It facilitates discerning the phases of healing that involve demolition, restoration, and reconstruction.

Organization of the Study: To develop an intelligent rehabilitation assistant (IRA) that utilizes advanced deep learning methods, specifically RPDO-Bi-LSTM, to enhance sports injury recovery by providing personalized recovery plans and real-time feedback for athletes.

Key contributions:

- The dataset enables 480 players' personalized rehabilitation by using wearable sensors and deep learning to monitor sports injuries, optimizing recovery protocols based on real-time injury severity and progression.
- The study used a median filter to remove noise from wearable sensor data, ensuring cleaner input for further analysis.
- Preprocessed data was segmented using region-based techniques to identify key areas for investigation, crucial for exact motion tracking.
- Feature extraction using Convolutional neural networks (CNN) remained employed to excerpt relevant structures from the segmented data, aiding in accurate performance evaluation.
- The RPDO-Bi-LSTM model approach for enhancing the accuracy of sports injury recovery prediction. This method integrates advanced deep learning methods with real-time personalized rehabilitation feedback, improving rehabilitation outcomes.

Organization of the study: Part 2 related work, the methodology is established in Part 3, the performance evaluation is displayed in Part 4 and the conclusion is illustrated in Part 5.

2. Related work

Rommers et al. [13] addressed the chances of an incident in young football players who are at the top level utilizing artificial intelligence (AI). In general, the system performs acute and overused injury distinction fairly accurately by relying on anthropometric measurements, motor skills, and athletic ability to predict injury. Ramkumar et al. [14] also described how knowledge of these risks might be useful in developing strategies for managing the threats of getting hurt. As possibilities in image interpretation, predicting accidents, assessing the patient’s outcome, and improving the client’s opportunities. Namiri et al. [15] proposed an AI package to revolutionize surgery and athletic medicine. It means that gaining receptiveness and market acceptance of the value proposition of AI-based solutions remains a distant goal. To understand how AI can benefit the healthcare of athletes and patients being treated for sports medicine; the professionals require knowledge of the benefits, drawbacks, and application of the technology. Gautam et al. [16] explored the datasets of the 14 leading volleyball players across the 2018 global season employed in the study under actual machine learning (ML). According to the training carried out by the markers and their general health, they were in a position to obtain groups of days that had a higher probability of resulting in an injury [17]. Assessed studies focused on daily check-ins, interactions between training intensity and wellbeing measures, and a specific approach to assist in finding out how overuse injuries develop and advance. Other elements were also postulated to be closely linked to overuse problems included the training load and well-being factors. Rapp et al. [18] proposed the two convolutional neural networks (CNNs) were applied, and their diagnostic performance in terms of grading of anterior cruciate ligament (ACL) injury was evaluated. Significantly, the sensitivity and specificity measured in both 2D and 3D CNNs support the potential of utilizing to aid non-experts when grading ACL injuries. Nwachukwu et al. [19] suggested a transfer-learning Long-term Recurrent Convolution Network (LRCN) for predicting knee joint angles and categorizing lesser limb actions. The average classification accuracy after training the model for predicting knee joint angles was 92% among participants without knee disease. 4% for knee arthroscopy with 98% for those with knee pathology. Yu et al. [20] suggested an Internet of Things (IoT) technology for tracking the health data of athletes using the medical devices that are worn and utilized to identify health markers and machine learning models. The system inertial information and deep learning show that cancer, heart disease, and tumors in the brain can be diagnosed successfully as well as predict lower extremity joint angle with more precision even without the use of magnetometer measurement. Richter et al. [21] found the reduced errors by retraining deep artificial neural networks on artificial gyroscope data, obtaining some improvements in the estimate of gait kinematics in real-world conditions. Regarding 2 years after hip arthroscopy, they employed the ML-based model of pre-treatment predictors. As a result, the training showed by Khalid et al.

[22] originated the indicators associated with the failure in the achievement of Minimal Clinically Important Difference (MCID) appearing as depression or anxiety, the duration of the illness, and body weight. In patients with acute stroke, when they first arrived with a Magnetic Resonance Imaging (MRI), a deep learning (DL) model was tested to assess their final infarct lesions. In their systemic study, Di Paolo et al. [23] found a median area under a DSC of 0.53, curve of 0.92 and a capacity fault of 10 ML achieved by the model. Using a wearable sensor device and a marker-based photonic scheme, the correctness was equivalent to or higher than the current clinical approach in populations that had minor or significant reperfusion measured the combined kinematics of 34 well sports persons to measure their reappearance to struggle and treatment next an anterior cruciate ligament (ACL) injury. Desai [24] offered sagittal level kinematics of the knee and hip, while the frontal and transverse plane kinematics. During complex gestures, the body-wide linked device demonstrated fair-to-excellent simultaneous cogency in evaluating specific combination parameters. Isern-Kebschull et al. [10] analyzing 310 magnetic resonance imaging (MRI) MRI scans of 128 athletes who had suffered muscle rips, the authors suggest a categorization scheme based on signal intensity and shape. Phases can overlap, and a small fusiform thickening of connective tissue characterizes the ultimate healed stage. A follow-up MRI should evaluate warning signals and any changes in muscular edema. Wille et al. [25] suggested hamstring strain injuries (HSI) are a prevalent problem with few predictive markers and a high recurrence rate. Risk reduction and expectation management can be aided by the evaluation of injury characteristics at the time of injury (TOI). The predictive utility of MRI for soft tissue injuries was a topic of contention, despite its use in injury management. Shiguang [26] investigated the use of fiber optic sensors and ML algorithms in a sports injury prevention and rehabilitation monitoring system. The sensors gather information on possible injuries while tracking the movement of players' joints and muscles. These data are analyzed by machine learning algorithms to find risk variables. Cui et al. [27] examined bodily healing and injury prevention, and the use of wearable technology in physical education instruction. They employ methods such as time series analysis, ML algorithms, and artificial neural networks to gather real-time data from students' exercise records in order to forecast the likelihood of physical recovery and damage.

3. Methodology

Initially, sports injury data is collected and pre-processed using median filters and region-based segmentation techniques to clean and organize the data. Feature extraction is performed using Convolutional Neural Networks (CNNs) to capture relevant patterns. The RPDO-Bi-LSTM model is applied to this processed data, combining RPDO-Bi-LSTM for enhanced prediction accuracy. This approach ensures effective monitoring and recovery management. **Figure 1** illustrates the proposed methodology.

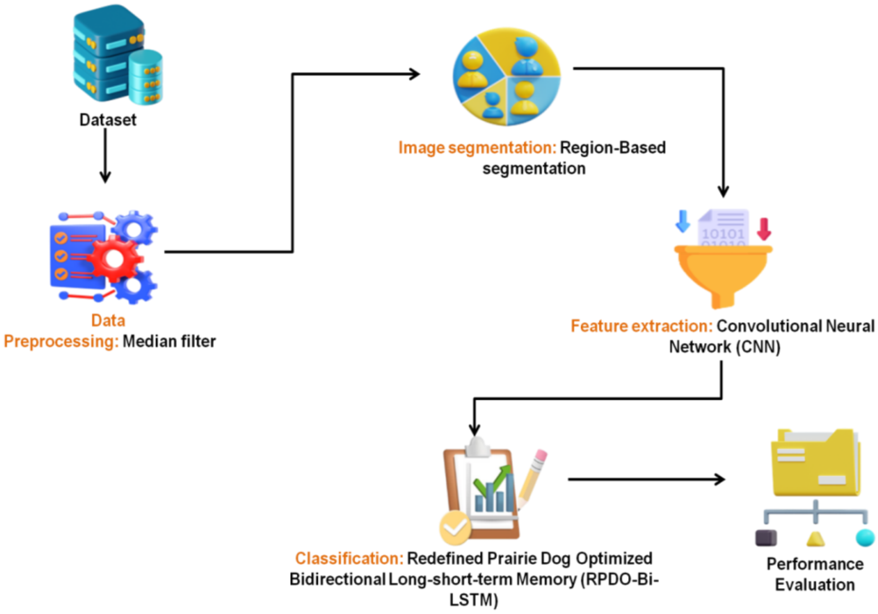

Figure 1. Methodology flow.

3.1. Dataset

The dataset was a collection of 480 sports players, gathered to monitor and analyze injuries during and after play sessions, as well as throughout rehabilitation. The sensors track injured areas and collect data on the severity and progression of injuries. Using deep learning methods, this data is analyzed to create personalized rehabilitation exercises aimed at healing specific injuries. The dataset features various wearable sensors, such as accelerometers, gyroscopes, and Electromyography (EMG) sensors, positioned on critical body parts like knees, ankles, elbows, and shoulders. Data was recorded during gameplay throughout the recovery process to optimize rehabilitation protocols. **Table 1** and **Figure 2** illustrate the dataset.

Table 1. Dataset.

Sensor Type	Wearable Device	Wearable Location	Frequency	Sample	Volunteers	Placement of the Sensor	Types of Activities	Exercise
Accelerometer	Smart Band	Wrist, Ankles	100 Hz	Raw Acceleration	100	Integrated into the band	Impact and movement analysis	Squats, Running, Jumping
Gyroscope	Smart Shoes	Feet	100 Hz	Rotational Data	100	Built into the soles of shoes	Rotational movement and stability	Running, Twisting Movements
EMG Sensor	EMG Arm Band	Forearms, Calves	1000 Hz	Muscle Activity	100	Wrapped around the forearms and calves	Muscle strain and performance	Strength Training, Resistance Exercises
Heart Rate Monitor	Smart Watch or Chest Strap	Chest, Wrist	1 Hz	Heart Rate Data	100	Around the chest or wrist	Cardiovascular response and recovery	Cardiovascular Exercises, Running
Inertial Measurement Unit (IMU)	Smart Glasses	Head	100 Hz	Motion Data	100	Mounted in the frame of glasses	Dynamic movement analysis	Agility Drills, Sprinting

3.2. Data preprocessing using median filter

Intelligent Rehabilitation Assistant for sports injury recovery, the median filter is employed as a non-linear filtering technique to improve image quality by removing noise, particularly salt-and-pepper noise, from medical images like MRI or X-rays. The filter works by computing the median of the pixel set within a defined $N \times M$ district, replacing each pixel with this median value. This method is robust against outliers and preserves critical high-frequency details without offering unrealistic pixel values, thus maintaining image sharpness and preventing edge blurring. As the window size increases, the noise elimination effect of the median filter recovers, enabling clearer visualization of injury expenses for more precise diagnosis and treatment planning. Evaluated in the Equation (1) $M \times M$ neighborhood.

$$e(w, z) = \text{median}_{(t,s)\in \text{Twz}}\{h(t, s)\} \tag{1}$$

where T_{wz} are the organizes of the image opening of size $M \times N$.

3.3. Region-based image segmentation

It plays a critical role by assemblage and patterning pixels corresponding to specific injury areas. This subdivision relies on principles such as value comparison, which includes gray value alterations and variance, and three-dimensional nearness, defined by Euclidean distance and region compactness. By accurately segmenting injury regions, this method enhances the effectiveness of deep learning models in identifying injury patterns and assessing tissue damage. Appropriate thresholding techniques are crucial for refining segmentation, and ensuring precise localization of injuries. This facilitates the creation of customized recovery protocols, optimizing rehabilitation outcomes and accelerating the recovery process for athletes. Presuming that image are gathered in pixel J and that equality is achieved Q, now let's split the image J into a set of n areas Qj, if Equations (2)–(4) clasps, then all pixels of slightly assumed region content the homogeneity established$U$. Also, any two-together areas cannot be compounded into a single area.

$$\bigcup_{j=1}^{m} Qj = \text{True} \tag{2}$$

$$\forall J, O(Qj) = \text{True} \tag{3}$$

$$O(Qj \bigcup Qi) = \text{False} \tag{4}$$

3.4. Feature extraction using convolutional neural network (CNN)

The Intelligent Rehabilitation Assistant for sports injury recovery, CNN to extract diverse topographies employs from medicinal images, such as echography scans recognized as the pioneering architecture for convolutional neural networks, generates multiple feature maps at each layer, allowing for a comprehensive capture of visual patterns compared to conventional methods. This characteristic makes it highly effective for segmenting and analyzing regions of interest in injury sites. While it is traditionally used for classification tasks, in the approach; it is solely utilized for feature extraction, capturing intricate details of the injury. For the classification stage, an ensemble learning framework integrates that surpasses ordinary neural networks with fully connected layers. This combination enhances the accuracy of detecting and characterizing sports injuries, ultimately leading to more personalized and operative rehabilitation strategies by precisely identifying injury types and monitoring recovery progress. First, a difficulty coating with six 5 × 5 screens and a stride of 1 is applied to an image by 32 × 32 × 1, producing an output matrix of 28 × 28 × 6. When the stride is set to 1 and no padding is used, the characteristic map shrinks from 32 × 32 × 28 × 28. Then, utilizing a characteristic assembling with a strainer thickness of two and a stride of two, the measurement is reduced by an influence of two, resulting in 14 × 14 × 6. Moreover, an additional convolution layer consisting of 16 of 5 × 5 strainers is employed, resulting in a production medium measuring 10 × 10 × 16. Subsequently, an additional assembling layer is employed, culminating in a final matrix measuring 5 × 5 × 16. Consequently, extracted sixteen 5 × 5 characteristic maps of the single image, and single characteristic map (5 × 5), together with **Figure 2**, demonstrate the CNN architecture.

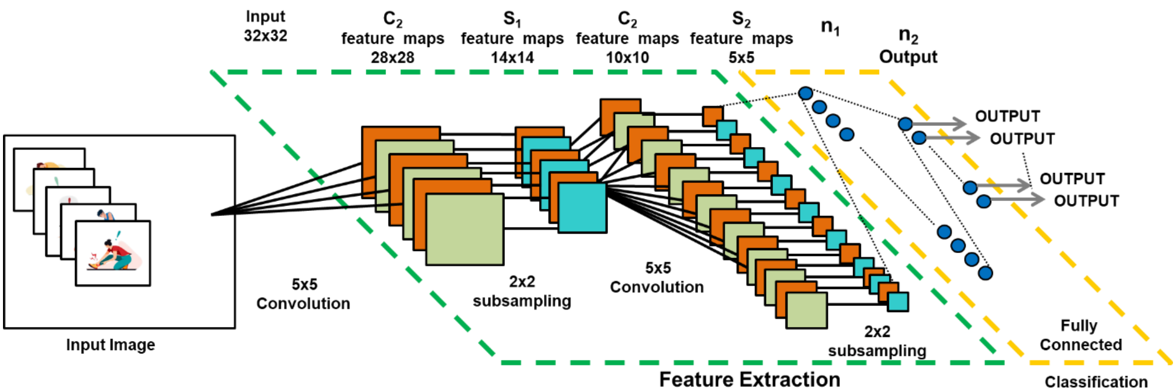

Figure 2. Convolutional neural network architecture.

3.5. Predicting sports injury recovery using redefined prairie dog optimized bidirectional long-short-term memory (RPDO-Bi-LSTM)

Intelligent Rehabilitation Assistant for sports injury recovery enhances performance by integrating Bi-LSTM networks with Redefined Prairie Dog Optimization (RPDO). Bi-LSTM processes medical data to capture temporal dependencies in recovery patterns. RPDO, inspired by prairie dog signaling, optimizes Bi-LSTM parameters to manage noise and computational demands. This hybrid approach delivers personalized recovery plans, monitors progress, and improves athlete outcomes by combining deep learning with bio-inspired optimization for accurate, efficient injury recovery forecasting. The optimization strategy lies in the exploration and manipulation of parameters through the optimization of signal strength. When applied in an injury recovery context, RPDO further optimizes the Bi-LSTM network parameters for accurately identifying.

Bidirectional long short-term memory

An intelligent rehabilitation assistant that is specifically built for sports injury rehabilitation. It is a crucial component of the system since it can handle sports data bilaterally. Unlike conservative LSTM networks, which process data in a forward way, the Bi-LSTM network captures hidden features and patterns that might be overlooked. This dual-directional processing allows the model to better understand the temporal dependencies in injury-related data, such as patient movement or muscle activity over time. By accurately identifying underlying patterns, Bi-LSTM enhances the precision of injury calculation and recovery monitoring, allowing more personalized rehabilitation strategies and improving the efficiency of therapeutic interventions for athletes. **Figure 3** illustrates the Bi-LSTM architecture.

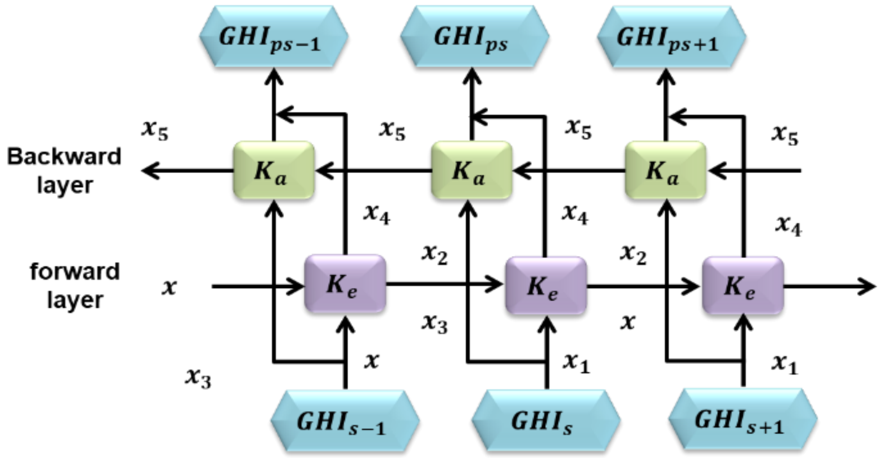

Figure 3. Bi-LSTM architecture.

The advancing concealed sheet $'K_e'$the regressive hidden layer $'K_a'$and output arrangement $'GHI_p(s)'$appraise the network. The network apprises iteratively in retrograde, i.e., from ‘s’ to ‘1’ and forward direction, i.e., ‘1’ to ‘s’. The updated parameters of the network can be uttered mathematically in Equations (5)–(7).

$$K_e = \sigma\left(x_1 \mathrm{GHI}_j(s) + x_2 K_{e-1} + a_{K_e}\right) \tag{5}$$

$$K_a = \sigma\left(x_3 \mathrm{GHI}_j(s) + x_5 K_{a-1} + a_{K_a}\right) \tag{6}$$

$$\mathrm{GHI}_p = x_4 K_e + x_6 K + a_{\mathrm{GHI}_p} \tag{7}$$

where, “K_e”, “K_a” & “GHIo(t)” are onward pass regressive pass, and final output layers respectively. ‘W’ is the weight constant and a_{K_e} , a_{K_e} & a_{GHI_p} are the prejudices.

3.6. Redefined prairie dog optimization (RPDO)

Optimization techniques like Prairie Dog Optimization (PDO) can boost Bi-LSTM performance by efficiently tuning hyperparameters, reducing computational costs, and preventing overfitting. RPDO relates to prairie dog foraging, which optimizes the convergence rate and accuracy confronting Bi-LSTM networks while working with real-time applications and noisy data. But in the domain of sports injury recovery, the idea of frequency wave coordination in communication of the prairie dogs can create new viewpoints towards better rehabilitation strategies through deep learning. In the same way that prairie dogs use different sounds to communicate about food or threats to the entire population, deep learning algorithms can be programmed to change the degree and style of restoration activities, given input from patients, and then the feedback signs produced by the system are much stronger and motivate the patient to stay in the same performance. If the system observes that the patient appears weak or overworking, "low intensity" feedback could quickly modify the exercises so as not to worsen strain or re-injury. Moreover, as prairie dogs change their behavior depending on the perceived threat, the intelligent rehabilitation assistant should be able to propose different care plans depending on the degree of an injury or the stage of recovery. By applying this frequency-based strategy, the optimization performance of the deep learning algorithm is enhanced which is important to more real wound retrieval and deterrence. This analogy bridges the gap between nature-inspired strategies and advanced deep learning techniques for enhancing rehabilitation outcomes.

The frequency wave strategy's sound factor, B, is characterized as changing at random in response to shifts in the locations of natural adversaries or food sources. The complete basic area is clear as area, while the separation between the prairie dog and food remains specified as c are using Equations (8)–(10).

$$B = 2 \times \text{rand} \tag{8}$$

$$c = \text{Pos} - \text{PD} \tag{9}$$

$$\text{area} = \left(\text{abs}\left(\text{Pos}^2 - \text{PD}_{j,i}^2\right)\right)^{0.2} \tag{10}$$

The audio wave length variation among 0 and 1 brought on through haphazard shifts in location food is denoted by the term "rand" in the calculations above. Food is found in Pos (natural enemies). The following is the precise frequency wave strategy updating evaluated in Equation (11).

$$\begin{gathered} w_{\text{new}} = PD_{j,i} - B \times c \times \text{Levy} \quad B < 1 \\ w_{\text{new}} = PD_{j,i} + q \times B \times \text{Area} \quad \text{else} \end{gathered} \tag{11}$$

where, between -1 and 1, P is a random integer w_{new} and is the prairie dog's new location.

3.6.1. Initialization of tent chaos

Intelligent Rehabilitation Assistant: Application of Bi-LSTM in sports injury recovery use of a tent chaotic initialization method can be beneficial for improving rehabilitation strategies. Similar to how the tent chaotic initialization in the RPDO algorithm ensures randomness and diversity in population delivery, applying this approach in rehabilitation could improve the adaptability and customization of recovery plans. By ensuring a more diverse and balanced initialization of treatment protocols, the algorithm can expand the search space for optimal recovery paths, allowing for more personalized and actual injury recovery solutions while maintaining flexibility and diversity in patient care and evaluated in Equation (12).

$$w_{j+1} = \begin{cases} \frac{w_j}{0.7} \; w_j < 0.7 \\ \frac{10}{3}\left(1 - w_j\right) \; w_j \geq 0.7 \end{cases} \tag{12}$$

3.6.2. Opposition-based learning approach using lenses

Conventional opposition-based learning generates the present answer in the opposite direction in an attempt to broaden the search space. The opposing solution is provided and fixed, which makes it difficult for the algorithm to locate a better location. Using simplistic inter planetary as a sample, the organizing axis $[va, ka]$ signifies the search variety, and the axis signifies the convex lens, which is based on the optical concept of convex lens imagination. In the event where $m$people exist and their height is G, then $W$is the reflection on the organized axis. The lens system$y$ refracts light to create the image.n', which has a height of $G'.W'$ represents the projection of n'on the organized axis. The opposing single W'produced.

$$\frac{(va + ka)/2 - W}{W' - (va + ka)/2} = \frac{G}{G} \tag{13}$$

$G/G' = l, l$ added l to Equation (13) and used it as the grading feature to understand the goal mechanism for the antagonist response W':

$$W' = \frac{va + ka}{2} + \frac{va + ka}{2l} - \frac{W}{l} \tag{14}$$

Equation (14) represents the conventional opposition-based learning approach when l = 1. The location of producing the antagonism explanation in the D-dimensional area is haphazard, the geographic searching possibility is progressively increased, and altering the scaling factor k's value has no effect on the population. Sports injury recovery and the foraging and burrowing behaviors of prairie dogs can provide an analogy for optimizing rehabilitation through deep learning. Just as prairie dogs must balance the need for nourishment with the constant threat of predators, patients in rehabilitation must navigate between pushing their physical limits and avoiding re-injury. Prairie dogs have evolved a sophisticated communication system using different audio signals to respond to threats, much like how an intelligent rehabilitation system could use real-time data to adjust the intensity of exercises. A "faster" signal, representing higher urgency, could prompt more cautious movements when the patient is at risk of overexertion or re-injury, whereas a "slower" signal could encourage the patient to continue if they are progressing well. By using chaotic initialization techniques, the rehabilitation system could ensure a diverse range of recovery strategies, improving patient outcomes. Opposition-based learning could expand the search space for optimal recovery methods, similar to how prairie dogs expand their search for food while staying alert to threats. The application of these audio signal factors in rehabilitation allows for more adaptive and personalized care, helping patients recover efficiently while avoiding setbacks, much like how prairie dogs balance survival and foraging, Algorithm 1 represents the modified Prairie Dog optimization and **Figure 3** displays the RPDO algorithm flowchart.

Algorithm 1 Redefine prairie dog optimization algorithm pseudo-code

Consuming the Equation (12) for the populace starting
Analyze suitability value
While $s \leq S$
Implement lens opposition-based knowledge approach over Equation (14)
Analyze the sound frequency issue B using Equation (8)
Calculate the distance c using Equation (9)
If $s < S/4$

$$OC_{j+1,i+1} = \text{HBest}_{j,i} \times qOC \times CT \times \text{Levy}(m) \tag{15}$$

Else if $S/4 \leq s < S/2$

$$OC_{j+1,i+1} = \text{HBest}_{j,i} \times OF \times \text{rand} \tag{16}$$

Else if $S/2 \leq s < (3 \times S)/4$

$$OC_{j+1,i+1} = \text{HBest}_{j,i} - fD\text{Best}_{j,i} \times \varepsilon - \text{DOC}_{j,i} \times \text{rand} \tag{17}$$

Else if $(3 \times S)/4 \leq s$

$$OC_{j+1,i+1} = \text{HBest}_{j,i} \times fD\text{Best}_{j,i} \times \rho - \text{DOC}_{j,i} \times \text{Levy}(m) \tag{18}$$

End
Analyze the range using Equation (10)
If $B < 1$

$$\begin{matrix} w_{new} = PD_{j,i} - B \times c \times \text{Levy} & B < 1 \\ w_{new} = PD_{j,i} + q \times B \times \text{Area} & \text{else} \end{matrix} \tag{19}$$

Else

$$\begin{matrix} w_{new} = PD_{j,i} - B \times c \times \text{Levy} & B < 1 \\ w_{new} = PD_{j,i} + q \times B \times \text{Area} & \text{else} \end{matrix} \tag{20}$$

End
$s = s + 1$
End

3.7. Redefined prairie dog optimized bidirectional long-short-term memory (RPDO-Bi-LSTM)

Intelligent Rehabilitation Assistant for sports injury recovery, the integration of Bi-LSTM networks with RPDO considerably improves the performance of the system. Medical data, like muscle activity or the progression of an injury, is fed into the Bi-LSTM network, which can traverse the data forward and backward to capture essential temporal dependencies to understand how individuals recover. The Bi-LSTM networks can be computationally inhomogeneous and sensitive to missing or noisy data in general. To cope with these challenges, RPDO is incorporated and used as an optimization tool. Considering the features of prairie dog's signaling, RPDO imitates the reaction to the changes in environment using the frequency-modulated signals. The optimization strategy lies in the exploration and manipulation of parameters through the optimization of signal strength. When applied in an injury recovery context, RPDO further optimizes the Bi-LSTM network parameters for accurately identifying and forecasting the current and potential injury patterns with few computational demands and overfitting. This hybrid approach ensures that the rehabilitation assistant can provide highly personalized recovery plans, monitor progress effectively, and improve outcomes for athletes by leveraging the strengths of deep learning and bio-inspired optimization methods. Algorithm 2 shows the RPDO-Bi-LSTM.

Algorithm 2 RPDO-Bi-LSTM

1. Initialize BiLSTM parameters Equations (21)–(23)
$K_e = \sigma\left(x_1 GHI_j(s) + x_2 K_{e-1} + a_{K_e}\right)$ (21)
$K_a = \sigma\left(x_3 GHI_j(s) + x_5 K_{a-1} + a_{K_a}\right)$ (22)
$GHI_p = x_4 K_e + x_6 K + a_{GHI_p}$ (23)
2. Set Population size M, search space dim, and iterations S
3. Apply Tent Chaos Initialization for Bi-LSTM hyperparameters
$w_{j+1} = \begin{cases} \frac{w_j}{0.7} w_j < 0.7 \\ \frac{10}{3}\left(1 - w_j\right) w_j \geq 0.7 \end{cases}$ (24)
For each patient (i = 1 to M)
a. Evaluate fitness (rehabilitation progress) using Bi-LSTM
Calculate audio signal factor $\mathrm{BB} = 2 \times \mathrm{rand}$ (25)
b. Calculate distance $\mathrm{c} = \mathrm{Pos} - \mathrm{PD}$ ... (9)
c. Update prairie dog positions using Equation (11)
d. If B < 1, Update using w_ new = PD − B × C × Levy
e. If recovery Progress improves, stores HB set and update fitness
4. Apply opposition-based learning via lens strategy using Equation (14)
5. Recalculate the area using Equation (20)
6. Update frequency wave strategy if necessary (Equation (11))
7. End loop if max iterations S reached or recovery archived

4. Evaluation metrics

Accuracy: The capacity of the system to accurately forecast or categorize rehabilitation outcomes, such as the state of an injury or the rate of recovery, based on patient data is referred to as sports injury recovery accuracy. High accuracy guarantees personalized recovery plans, efficient treatment suggestions, and trustworthy performance tracking throughout the rehabilitation process, as assessed by Equation (26).

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \quad (26)$$

Precision: Sports injury precision is the ability of the organization to correctly categorize cases that are truly positive for injury status or recovery without adding false positives. High accuracy ensures that suggested courses of action are focused and pertinent to the real-world circumstances of patients (Equation (27)).

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \quad (27)$$

Recall: The organizational capacity to categorize all recoveries or injuries that are truly positive, reducing the number of incorrect diagnoses. Reduced likelihood of injuries being unnoticed: a high recall guarantees the system accurately identifies all patients in need of assistance examined in Equation (28).

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} = \mathrm{FN}} \quad (28)$$

F-1 score: The exactness and recall of the F1-score stability point to a single measure that can be used to evaluate the system's performance in injury recovery prediction. When false positives and false negatives have different significances as determined by Equation (29), it is very valuable.

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Rcall}} \quad (29)$$

Specificity: The system's ability to precisely detect genuine negative instances, guaranteeing that statuses other than injury or non-recovery are appropriately identified. Elevated specificity diminishes false positives, augmenting the dependability of the system in differentiating between various ailments indicated in Equation (30).

$$\text{specifity} = \frac{TP}{TP + FN} \quad (30)$$

5. Performance analysis

Windows 13 and an Intel® Core i9 workplace with 8.00 GB of RAM were mutual with the Python framework to allow rapid admission to the data. Sports Injury Recovery is the approach achieved significant advancements through data preprocessing with a media filter, region-based segmentation, and CNN-based feature extraction. The integration of RPDO-Bi-LSTM further enhanced classical accuracy by optimizing hyperparameters and capturing complex patterns in injury data. The provided Receiver Operating Characteristic (ROC) arc validate representation the planned RPDO-Bi-LSTM model in sports injury retrieval calculation. An area below the curve (AUC) of 0.94 is seen after the true positive rate (sensitivity) is plotted against a negative rate. The representation's strong capability to distinguish between negative and positive instances, as well as its appealing injury organization accuracy, as shown by this in height AUC. **Figure 4** displays the result of ROV.

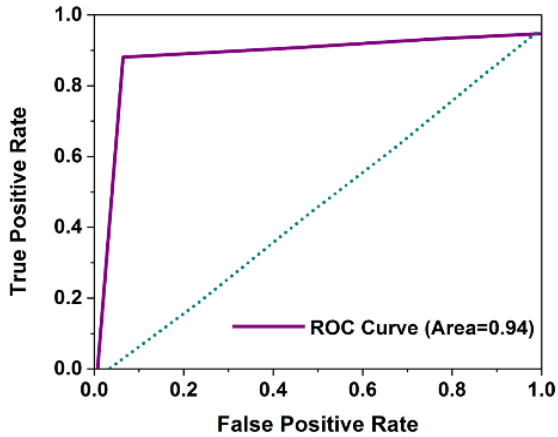

Figure 4. Result of ROC.

Accuracy: The numerical outcomes demonstrate that the proposed RPDO-Bi-LSTM method achieved an accuracy of 94.2 %, surpassing CNN-LSTM with 93.0 % and XGBoost with 90.0%. This development underlines the improved presentation of RPDO-Bi-LSTM in exactly predicting and handling sports injuries. **Table 2** indicates the performance analysis of the study. **Figure 5** graphical representations of model accuracy metrics.

Table 2. Performance analysis.

Methods	Accuracy	Precision	F-1 score	Recall	Specificity
XGBOOST [25]	90.0	92.0	94.7	97.6	-
CNN-LSTM [26]	93.0	95.0	92.0	-	93.0
RPDO-BiLSTM [Proposed]	94.2	96.5	95.6	98.2	94.2

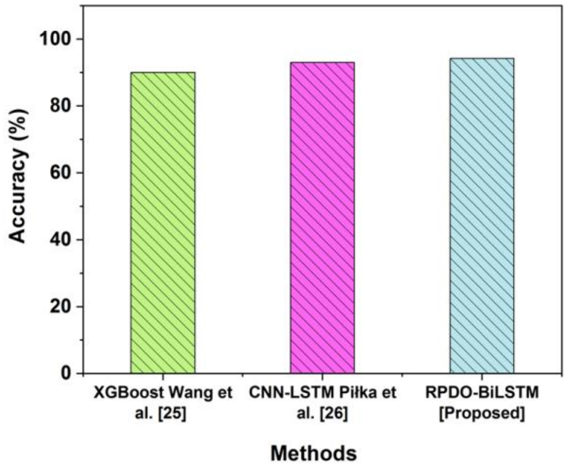

Figure 5. Graphical representation of model accuracy metrics.

Precision: The mathematical significance display that the coming RPDO-BiLSTM technique attained an accuracy of 96.5 %, outdoing CNN-LSTM with 95.0 % and XG Boost with 92.0 %. The precision of RPDO-BiLSTM in identifying relevant features for sports injury prediction, reducing false positives compared to another approach. **Figure 6** denotes the precision of sports injury.

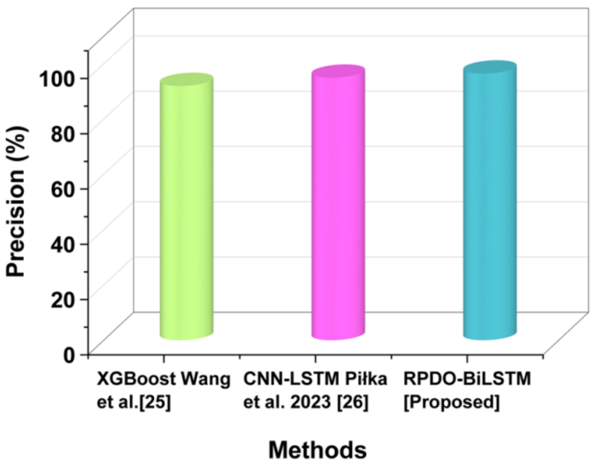

Figure 6. Outcomes of precision.

Recall: The RPDO-BiLSTM model presented a recall rate of 98.2% exceeding that of XG Boost, thus demonstrating its better ability in identifying sports injuries correctly. Such high recall level suggests that RPDO-BiLSTM is good at those true positive cases, i.e., it is able to identify a higher fraction of its actual target class of injuries. The superior performance is caused by the fact that the model has a bi-directional structure which is capable of understanding the complex temporal dynamics of the data. Moreover, the inclusion of RPDO optimization strategies also enables the above model to further enhance the detection performance. Below **Figure 7** provides a comparison graph of the values of recall depicting the benefits of RPDO-BiLSTM over XG Boost.

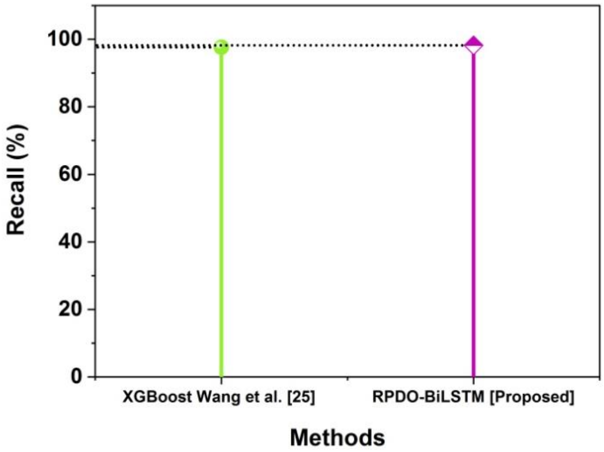

Figure 7. Comparison of recall.

F-1 Score: The F-1 score of the suggested RPDO-BiLSTM procedure was recorded at 95.6% which was higher than the F-1 score of CNN-LSTM which stood at 92.0% and XG Boost which stood at 94.7%. This finding points out the efficiency of RPDO-BiLSTM in detecting the sports injuries without compromising on the recall and precision levels. The high F-1 score achieved in the study demonstrates the model's ability to control both types of errors effectively. Such equilibrium is also important in a clinical environment because it is possible that injury status may have an effect on treatment decisions. These F-1 scores are depicted in **Figure 8** below that compares the models' performances visually.

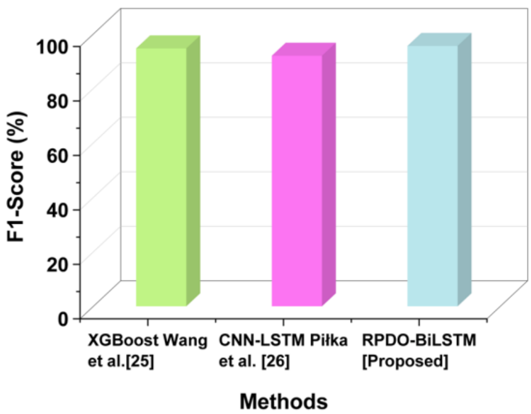

Figure 8. Bar chart of F-1 scores.

Specificity: The RPDO-Bi-LSTM method scored 94.2% in terms of specificity, which was much higher than that of the CNN-LSTM model that had a specificity of 93.0%. This shows once again that RPDO-Bi-LSTM can be applied more effectively to minimize the occurrence of false positives in determination of negative cases in detection of sports injuries. This is evident as the enhanced specificity results from the ability of the model to attend to both the past and the present temporal dynamics of the data. In addition to that, the prairie dog optimization method ascertains that the proper features are used for feature selection which ensures the classification is done using the best features. To sum up, these enhancements have the best impact when it comes to differentiating between the injured and non-injured athletes in **Figure 9**.

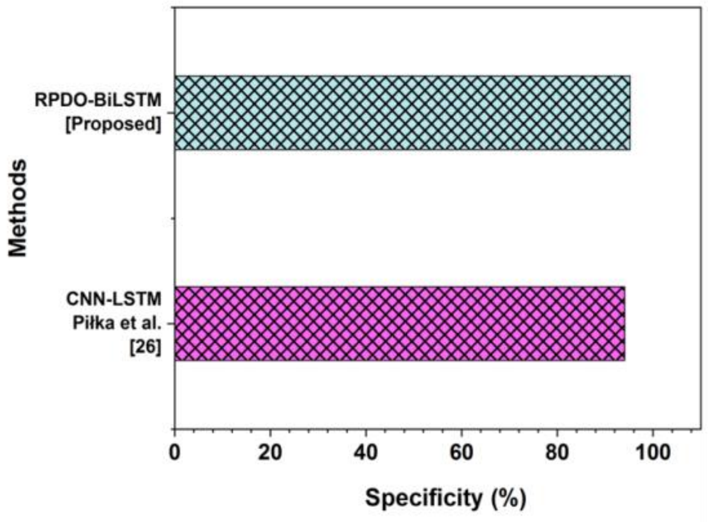

Figure 9. Graphical representation of specificity.

6. Conclusion

Intelligent Rehabilitation Assistant is a system that uses deep-learning decision-making mechanisms to analyze data and generate individual rehabilitation plans and strategies for people suffering from sports injuries to maximize the results of their recovery. With the help of RPDO, the hyperparameters were subject to nature-inspired optimization while deepening the Bi-LSTM, which enabled both forward and backward analyses of the data. This innovative approach yielded its best in terms of accuracy achieving 94.2%, F-1 score of 95.6%, Recall 98.2%, Precision 96.5% and specificity 94.2 %. Accordingly, the study’s findings demonstrate that RPDO-Bi-LSTM’s capabilities for sports injury prediction and management are more accurate and advanced than those of conventional techniques. Further research may target the improvement of the RPDO-BiLSTM model in the context of various and actual injury data by feeding the model with various datasets and real-time monitoring input data. Furthermore, exploring integration with wearable technology and extending its applicability to other forms of sports may also enhance performance and recovery from injuries as well.

Funding: (1) Inner Mongolia Autonomous Region Education Science Research 2023 “14th Five-Year Plan” project “Inner Mongolia Higher Vocational Colleges physical Education curriculum ideological and political elements into the teaching practice” project number: NGJGH2023199. (2) The key project of Inner Mongolia Vocational College of Commerce in 2023 “Governance System Research on Public

Physical Education Teaching Reform in Higher Vocational Colleges in the New Era based on students' physical health" project number: NSZY202303.

Ethical approval: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

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