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Article

Application of artificial intelligence in the development of personalized sports injury rehabilitation plan

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Abstract: Sports injury rehabilitation is a kind of physical treatment used to address musculoskeletal system disorders, injuries, and discomfort in patients of all ages. Sports rehabilitation promotes health and fitness, aids in injury recovery, and lessens pain through movement, exercise, and physical therapy. During a sports injury, rehabilitation has developed into a specialized profession that has gradually brought together sports physicians, sports physiotherapists, and orthopedic surgeons. Finding the best ways to minimize recovery time, avoid injuries, and enhance performance is crucial for sports athletes. The aim of this research is to establish a personalized sports injury rehabilitation evaluation system enabled by artificial intelligence (AI). In this study, a novel advanced penguin search optimized efficient random forest (APSO-ERF) has been proposed for sports injury athletics exercise rehabilitation. This study used exercise movement image data to develop personalized sports injury rehabilitation. The data was preprocessed using a Wiener filter for noise reduction and image restoration. Convolutional neural networks (CNN) are used to extrapolate top-level characteristics from images. The proposed method is used to evaluate physical rehabilitation by assessing patient performance during the completion of prescribed sports injury rehabilitation exercises. The proposed method is compared to other traditional algorithms. With 97.80% accuracy, 96.01% sensitivity, 97.90% specificity, 98.88% precision, 96.11% recall, and 97.50% F1-score, the APSO-ERF approach beats conventional algorithms in tailored sports injury rehabilitation. The result illustrated that the proposed method achieved high performance in the accuracy of sports injury athletics exercise rehabilitation.

Keywords: personalized sports injury rehabilitation; exercise; athletes; advanced penguin search optimized efficient random forest (APSO-ERF)

1. Introduction

A state-of-the-art development in rehabilitative healthcare is personalized sports therapy, which offers individualized treatment regimens made to fit each patient's unique needs [1]. There are new chances to improve patient care and integrate resources in treatment when medical big data and AI are integrated into traditional medical models. This sector has grown significantly in many nations, saving money and lowering the risk of patient deterioration [2]. Sports performance is significantly impacted by injuries. In professional sports, critical player injuries can be the difference between a team's achievement and failure, costing millions in salaries and lost income [3]. To increase their physical capabilities, elite athletes in several sports must optimize their training volumes. However, there is a higher chance of overtraining and overuse problems if they do not involve enough rest. Most research in this field focuses on the frequency of injuries or lost time as a result of them [4]. A key component in the development of contemporary technology is AI, a multidisciplinary area that draws from computer science, theory of control, information theory, systems science, and philosophy [5]. Value-based healthcare integrates patient happiness and functional rehabilitation into orthopedic surgery by focusing on cost reduction and improving patient outcomes [6]. Massive athlete is made possible by technological improvements, which improve performance analysis, injury risk assessment, and scouting. Sports science is using machine learning (ML) models more and more to analyze difficult data [7]. AI is a crucial component of health data analytics, supporting prognosis, diagnosis, and tailored treatment plans. Traditional methods make use of population data to find statistical trends that highlight salient characteristics [8]. Physical exercise and a nutritious diet are essential for a healthy lifestyle since insufficient nutrition raises the risk of conditions like diabetes and obesity. Nutrition specialists can assist in achieving this; however, there are obstacles such as high expenses, restricted availability, and difficulties in offering professional services [9]. Wearables are tiny electronic gadgets that can communicate wirelessly. They provide early diagnosis, treatment, and vital sign monitoring [10]. **Figure 1** illustrates the athlete sports injuries rehabilitation.

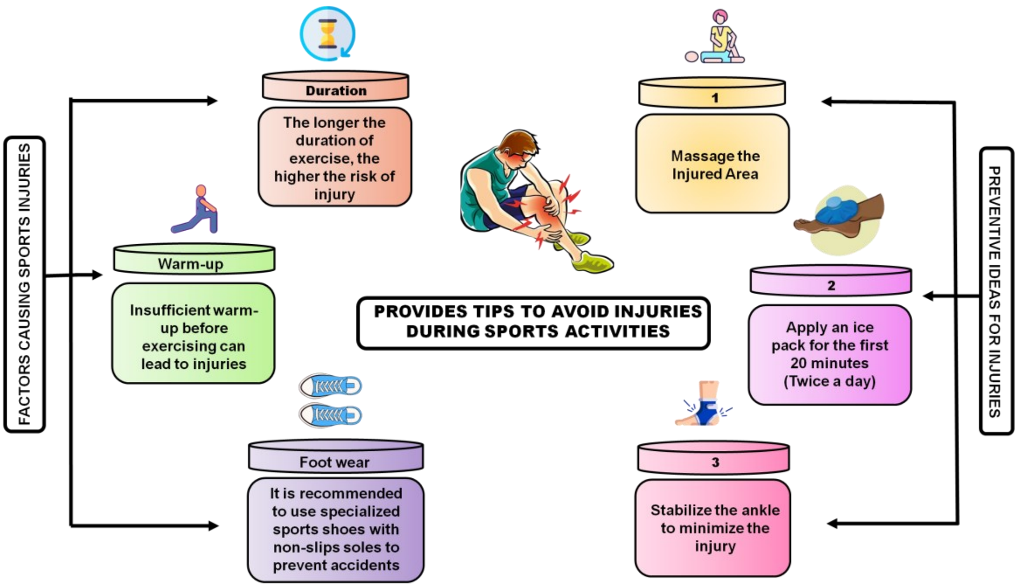

Figure 1. Athletes sports injuries prevention ideas.

Objective of the study: This study aims to create a customized assessment system for sports injury rehabilitation by utilizing an advanced Penguin Search Optimized Efficient Random Forest (APSO-ERF) methodology. The system uses AI to evaluate and optimize exercise performance based on image data to improve rehabilitation accuracy and efficacy.

Key contributions:

- APSO-ERF uses sophisticated image analysis to precisely customize rehabilitation strategies for sports injuries.
- AI-powered evaluations maximize the benefits of training while shortening athletes' recuperation periods.
- According to the study, APSO-ERF works better than conventional techniques, leading to better overall rehabilitation results.

The following phases constitute the overall paper: Phase 2 offers relevant works; Phase 3 offers tool and material selections; Phases 4 and 5 evaluate the outcome and give discussion; and Phase 6 ends with conclusions.

2. Related work

Katović et al. [11] found that computer technologies were integrated into kinesiology to analyze, diagnose, and evaluate individuals or groups. Pose estimation technology uses computer vision and neural networks to track human movement in real-time. According to Den Hartigh et al. [12], resilience was essential for athletes to recover from adversities, and a multidisciplinary study agenda was set out to comprehend the dynamic process. Resilience losses can be identified by new technology and data science applications. Montull et al. [13] highlighted the need for more study in the field by proposing to rethink athletes as complex adaptive systems (CAS), which provide better subjective monitoring capabilities than objective systems. Taimoor and Rehman [14] suggested AI/ML algorithms were used to turn the healthcare industry into personalized, Internet of Things (IoT) based services. Unfortunately, interrelated medical issues were frequently overlooked by present services, which have an impact on patients' long-term and sustainability of care. The goal of Healthcare 5.0 technology was to improve patient care by overcoming these shortcomings and achieving completely autonomous services. Jauhiainen et al. [15] used data from 314 juvenile basketball and floorball players to investigate the application of predictive ML techniques to detect sport injury risk variables. The findings demonstrated that some risk variables can be reliably identified even in the face of poor predictive ability. Zhao et al. [16] introduced a gamified fitness assistant system that used player modeling and individualized information to increase preference, motivation, and happiness for fitness activities. It showed the system's efficacy over 60 days. Thurzo et al. [17] assessed how patient behavior in a current clinical orthodontic application was affected by computerized tailored decision algorithms. The findings indicated a noteworthy enhancement in patient app interaction, discipline, and clinical aligner tracking except clinical non-tracking in males. Migliaccio et al. [18] stated that sports monitoring and analytics were revolutionized by wearable technology that tracks heart rate and sleep quality, despite several constraints related to cost, accuracy, validity, dependability, and interpretability. Burford et al. [19] used Large Language Models (LLMs) such as ChatGPT-4 and discovered a moderate degree of agreement between LLM and text string-search methods for evaluating clinical narratives and determining helmet wear status in incidents involving micro-mobility. Huihui [20] investigated the use of wireless sensor networks (WSN) and machine vision technologies for the real-time monitoring and analysis of the movement posture of yoga practitioners. It decreased sports injuries brought by bad postures by increasing the timeliness and precision of monitoring. Haick and Tang [21] improved patient care, individualized medication, and wearable sensing devices for evidence-based analysis and personalized monitoring can all be facilitated by the combination of AI with medical sensors based on nanotechnology in sophisticated clinical decision support systems. Navandar et al. [22] presented an IoT-based approach for monitoring and evaluating athletic success in sports in real time. In terms of recall, accuracy, F1-score, and specificity, it suggested the Adaptive Coral Reefs Optimized Xgboost (ACRO-XB) framework, which performs better than conventional techniques.

To enhance performance and lower the risk of injury, Zhihong [23] investigated the application of technology and customized therapy in sports rehabilitation. It emphasizes how crucial it is to support sportsmen and make investments in cutting-edge technologies, and it implies that this strategy can be advantageous to a number of industries. The effectiveness of OpenAI's GPT-4 model in prescribing exercise for five patient profiles with various health issues and fitness objectives was assessed by Dergaa et al. [24]. Experts discovered that while the model can produce safety-conscious systems, it frequently gave safety precedence over efficacy. While AI can make things more accessible, it cannot replace progressive, individualized, and condition-specific prescriptions. McBee et al. [25] assessed the benefits and drawbacks of utilizing chatbots in sports rehabilitation through the use of simulated panel discussions. PanelGPT is a model that mimics the conventions in the real life and it highlighted the advantages like individualized guidance and round-the-neck help but also pointed out drawbacks including constrained interaction options and data privacy concerns.

3. Methods and materials

This section outlines a six-step process, beginning with the data collection where the information was gathered and organized. It then moved to the automation, focusing on the automating tasks through systems or networks. Next is engineering and design, involving technical development and system monitoring. Integration follows, where components are connected to ensure seamless functionality. Quality assurance and testing is conducted to verify system accuracy and performance. Finally, analysis and reporting assesses outcomes, providing insights for informed decision-making or project completion. The Wiener filter built by the recommended method is applied to the deteriorated image to reduce noise and blur. Convolutional neural networks (CNN), which are made up of convolutional, pooling, and fully connected layers with rectified linear unit (ReLU) activation to avoid the vanishing gradient problem, are then used to extract features from images for sports injury rehabilitation. The rehabilitation procedure then employs the APSO-ERF algorithm for precise and optimal prediction. For improved solution search and robustness, the optimization procedure utilizes consideration of Gaussian exploration and penguin search behavior. **Figure 2** represents the proposed methodology.

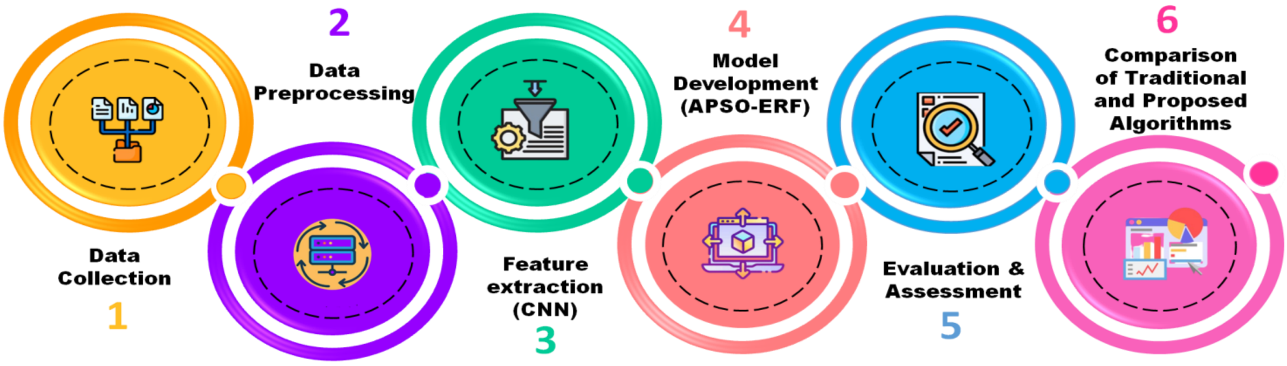

Figure 2. Proposed methodology.

3.1. Data collection

The datasets were collected from the open-source Kaggle: https://www.kaggle.com/datasets/mrsimple07/injury-prediction-dataset. The dataset that depicts synthetic dataset was created especially for injury prediction to meet the rising concern about player security and avoiding injuries in professional sports. Important characteristics including player demographics, training intensities, recuperation timeframes, and past injury histories are captured in synthetic dataset. A realistic depiction of player health and injury data was the study's main goal. To create associations between these attributes and the probability of further injuries to faithfully replicate real-world situations.

3.2. Preprocessing using a wiener filter

A traditional method of lowering the mean square error, the Wiener filter is an ideal low pass and non-linear filter that employs least squares [1,4]. Wiener filters are strong because they simultaneously remove or decrease noise and blur from an image, which makes them most useful in applications like AI-enabled sports injury rehabilitation evaluation systems. The blurry and noisy image is initially processed through the Wiener filter by constructing it, according to the suggested manner. The following Equation (1), is used to create the Wiener filter:

$$X(v,u) = \frac{G^*(v,u)}{|G(v,u)|^2 + \frac{1}{SNR(v,u)}} \tag{1}$$

Suppose, $\frac{1}{SNR} = L$

where, the complex conjugate of the degradation function is denoted by G^*, and the degradation function itself is represented by G. The Wiener filter with the aforesaid design is then applied to the deteriorated images.

3.3. Feature extraction using CNN

A neural network designed to handle multi-dimensional data, such as images and time series data, is called a CNN. Weight computation and feature extraction from the assessment system for sports injuries are included in the training phase. CNN is used to train and evaluate models, as well as extract characteristics for individualized sports injury rehabilitation. Convolutional, pooling, and fully connected layers were the three layers that CNN employed to derive traits from the images of the sports injury rehabilitation. The dense layers are created by thickening both the convolutional and max pooling layers. Personalized sports injury rehabilitation CNN layers provided by the Python Keras application programming interface (API) of the Tensor flow library were used to create the sequential model after it was input into the dense layer. It took into consideration the following layers for the CNN model.

A layer of pooling: The layer of convolution provides images of pooling to the AI max pooling layer, which controls window size, operation, kernel size, and stride length. By employing AI strategies for sub-sampling processes using maximum pooling and average pooling, this layer helps to downscale the input image, lessening the number of image variables and the computationally demanding nature of the CNN model. The size 2 × 2 layer for pooling adjusts the dimensionality of each feature map using the 'MAX' function. A pair of hyper-parameter values, such as filter (E) and walk (T), are needed for the pooling layer. If the input image is $X1\times G1 \times C1$, the layer of pooling produces an outcome of size $X2 \times G2 \times C2$, as depicted in the Equations (2)–(4).

$$X2 = \left(\frac{X1E}{T}\right) + 1 \tag{2}$$

$$G2 = ((G1E)/T) + 1 \tag{3}$$

$$C2 = L \tag{4}$$

where L is the total number of filters utilized, T is the stride size, and E is the filter size. It is important to note that only used for each Conv2D layer, there is one Max pool 2D layer.

Initiation: CNN makes use of a variety of activation functions, including $tanh$, sigmoid, SoftMax, and ReLU. To perform constitutional image classification using the ReLU activation function. ReLU is the function that is employed, since it avoids and corrects the diminishing gradient problem. When it comes to personalized sports injury rehabilitation of evaluation systems enabled by AI, ReLU-based neural network models outperform models that use other activation functions, like hyperbolic tangent or sigmoid activation functions. They are also easier to train.

Pool size selection: A 3 × 3 filter size is used for feature extraction, taking into account the distinctive properties of the identified injured image.

Flatten layer: It modifies the input before sending it to the fully networked categorization layer. As a result, the completely connected layer can quickly handle the attribute map that has been constructed. The input images are transferred to the fully linked layer after convolutional, pooling, and flattening layers. Data that is two-dimensional is transformed into single-dimensional data by the AI-enabled individualized sports injury rehabilitation evaluation system. The collection of flattened images is categorized using the fully connected layer.

Optimizer and decreased overfitting: It utilizes the Adam optimizer for the CNN model since it is more effective for big datasets and parameters, is simple to build, memory-efficient, and takes less work. Furthermore, a dropout probability of 0.2, 0.25, and 0.3 for individualized sports injury rehabilitation is employed before fully connected layers to lessen the overfitting of the training datasets.

3.4. Advanced penguin search optimized efficient random forest (APSO-ERF) for sports injury athletics exercise rehabilitation

To improve sports injury rehabilitation, the APSO-ERF combines penguin search optimization with a simplified random forest method. Through effective analysis and prediction of rehabilitation results, APSO-ERF enhances individualized treatment plans and improves athlete recovery regimens. This method makes use of cutting-edge ML algorithms to deliver accurate and useful insights for exercise rehabilitation.

3.4.1. Efficient random forest (ERF)

The ERF classifier method, which uses several decision trees, is one of two components of the improved random forest methodology. ERF generates the branches of the tree by dividing the input into smaller sections. The result is a tree with leaf nodes and decision nodes at each level. Numerous branches inside the decision node display the relevance of each decided component, while the leaf node preserves the significance of the outcome based on the individual's possible circumstances. The risk that a single decision tree would not be able to accurately forecast the value attribute has been eliminated by using several classifier decision trees. To get the outcome, the ERF links the output from several trees. Equations (5)–(7) were used to express the functions in margins for the ERF, approximation error, and confidence estimations. In the example, the values represent an ensemble of classifiers, while the vectors include the input data. That is the precise way that the margin is expressed in the AI-enabled individualized sports injury rehabilitation evaluation system.

$$NH(A,B) = zu_l J(g_l(A) = B) - \max_{i \neq B} zu_l J(g_l(A) = i) \tag{5}$$

$J(g_l)$ is the symbol for the indicator function. The inaccuracy in generalization is represented by these values.

$$OF *= O_{A,B}\big(NF(A,B)\big) < 0 \tag{6}$$

the A, B dimension is used to explain the possibilities. Since, $g_l(A) = G(A, \mathrm{P}_l)$ every group of trees in an RF contains more classifiers. Equation (7) is determined by the probability $OF*$ based on the forest layout and effective equation of large numbers.

$$O_{A,B}(O_{\mathrm{P}}(g(A,\mathrm{P}) = B) - \max_{i \neq B} O_{\mathrm{P}}(g(A,\mathrm{P}) = i) < 0) \tag{7}$$

After sports injury rehabilitation, the weighted algorithm offers an updated method to enhance the model. One of the best methods in ML is this one. Here is the Equation (8) that explains the correction method.

$$g(a) = \mathrm{sign}\left(\sum_{s=1}^{S} \alpha_s g_s(A)\right) \tag{8}$$

Assuming that for every $s = 1, \ldots, s, (A_1, B_1), \ldots, (A_N, B_N)$, for $A_i \in a, B_i \in b = \{-1, +1\}$. Start at $C_1(j) = \frac{1}{N}$. Following insufficient workouts, WRF makes use of the distributions (C_s). In this case, Y_s is the normalization variable. Equation (9) looks to be the outcome.

$$C_{s+1(i)} = \frac{C_s(i)}{Y_s} \times \left\{ F^{-\alpha s} if\, g_s(A_j) = B_j F^{\alpha s} if\, g_s(A_j) \neq B_j = \frac{C_t(j) exp\left(-\alpha t B_j g_s(A_j)\right)}{Y_s} \right\} \tag{9}$$

The ERF approach prevents a considerable increase in the total variance of the model, resulting in accurate predictions. Where C is a chosen value inside the interval [0, 2], and Y is the random integer. The most recent iteration of the optimization process is indicated by b, where $Iter_{\max}$ represents the greatest iteration that can be attained. The novel approach known as the ERF sports injury rehabilitation is crucial for managing public health assessments. It properly determines the places with landslide potential by utilizing ERF prediction capabilities and ERS optimization skills. It is a productive, creative method for preparation and landslide mitigation that also lowers the health risk and allows for quick response. Furthermore, the AI-enabled individualized sports injury rehabilitation assessment system improves.

3.4.2. Advanced penguin search optimization (APSO)

There are several approaches to characterize the optimization technique that is based on penguin hunting behavior. While all approaches agree to maximize their goal functions, such as the quantity of energy retrieved from the energy invested, it is suggested to streamline the optimization function by allowing the penguins' search strategy to be guided by the guidelines that are explained below. This strategy can work especially well for AI-enabled individualized sports injury rehabilitation assessment systems. The exploration operator has not been taken into account in this method, as was previously mentioned in the earlier version. Because of the algorithm's appropriate performance and considerably greater simplicity, the developers can use it for this problem. Nonetheless, for complex situations, the algorithm's effectiveness greatly depends on the stochastic search of the decision space in Evolutionary algorithms (EAs). Given how penguins live in the wild, it is therefore feasible that, while traveling toward a certain location, they discover a better area for hunting; as a result, they can abruptly and erratically alter their intended route. The aforementioned movement might be characterized as exploration and considered an unforeseen movement in the algorithm. The technique based on Equation (10) was expanded in the current work to include a Gaussian exploration function. The findings of the original algorithm, in addition to its updated form, are shown in the following section. This includes a customized sports injury rehabilitation evaluation system.

$$\mathrm{Sol}_{\mathrm{new}}^{j,i} = \mathrm{Sol}_{\mathrm{old}}^{j,i} + \sigma \times \mathrm{rand}n \tag{10}$$

There are several normal distributions with mean equal to zero and standard deviation equal to one, and $\mathrm{Sol}_{\mathrm{new}}^{j,i}$ the j^{th} modified decision variable related to i^{th} solution, $\mathrm{Sol}_{\mathrm{old}}^{j,i} = thei^{th}$ decision variable before modification related to ith solution, and σ Gaussian exploration parameter. Certain answers in Equation (10) are changed entirely at random. Algorithm 1 shows a hybrid pseudocode for APSO-ERF.

The suggested hybrid APSO-ERF algorithm is intended to provide a customized system for evaluating sports injury rehabilitation. The ERF model begins using default settings, whereas APSO originates with a random solution. APSO creates the new solution by using the iterative optimization, which involves altering the best solution currently in place, assessing its fitness and updating the best solution whenever an improvement is noticed. The parameters of the ERF model are then configured after this procedure is repeated until the best solution is identified. At the center of the rehabilitation assessment system is the optimally adjusted ERF model, which provides tailored suggestions based on training data.

Algorithm 1 Hybrid APSO-ERF

```
Initialize ERF model with default parameters
Initialize a random solution for APSO
Set best_solution = random_solution
Set best_fitness = Evaluate fitness of best_solution
For each iteration in APSO:
    Generate new_solution by modifying best_solution randomly
    Calculate new_fitness = Evaluate fitness of new_solution
   If new_fitness is better than best_fitness:
        Set best_solution = new_solution
        Set best_fitness = new_fitness
   Else:
        Keep best_solution unchanged
Set ERF model parameters using best_solution
Train the ERF model on training data using best_solution
Return the trained ERF model as the personalized sports injury rehabilitation evaluation system
```

4. Results

The recommended solution was applied to a desktop PC running Windows 10 with a 4 GB CUDA-supporting GPU, and a 64-bit Intel Core i7 CPU from the 18th generation. The framework was built using TensorFlow and Python 3.5, with Keras acting as the backend. Compared standard techniques like support vector machine (SVM), 3D Convolutional Neural Networks (3D-CNN), Residual Neural Network (ResNet), and dual-feature fusion neural network (DFFNN) [26]. Algorithms were used to build a customized AI-powered sports injury rehabilitation assessment system to improve the accuracy of the results covered in this part. Using APSO-ERF to produce customized sports injury rehabilitation outcomes has yielded positive results. The study evaluated and compared the proposed technique with many other ways that are currently in use using a variety of metrics, including precision, recall, accuracy, F1-score, sensitivity, and specificity. Based on this characteristic, the outcomes demonstrated that the recommended technique worked better than other traditional approaches.

4.1. Accuracy

The accuracy of a sports injury rehabilitation system that can be modified guarantees precise injury diagnosis, personalized treatment recommendations, and effective progress tracking. This enables tailored treatments and accurate predictive modeling, which enhance overall recovery outcomes and suit individual needs. The accuracy percentages of several methods for a particular task are displayed in **Table 1** and **Figure 3**. With the highest accuracy of 97.80%, the APSO-ERF approach proposed in this study beats other methods such as ResNet, DFFNN, 3D-CNN, and SVM.

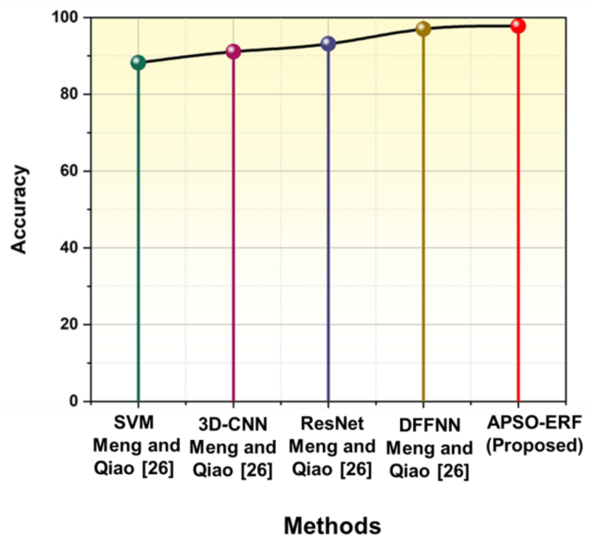

Figure 3. Results of accuracy.

Table 1. Results of accuracy.

Techniques	Accuracy (%)
SVM [26]	88.02
3D-CNN [26]	91.08
ResNet [26]	93.12
DFFNN [26]	97.00
APSO-ERF (Proposed)	97.80

4.2. Sensitivity

The sensitivity of several models for sports injury recovery is displayed in the table. Sensitivity quantifies the percentage of real positives that the model properly detected. **Table 2** and **Figure 4** present that when compared to SVM (87.32%), 3D-CNN (92.42%), ResNet (95.43%), and DFFNN (95.70%), the suggested APSO-ERF technique achieves the maximum sensitivity at 96.01%, suggesting greater performance in identifying injuries. The sensitivity of each model indicates how well it can identify damage instances.

Table 2. Outcomes of sensitivity.

Techniques	Sensitivity (%)
SVM [26]	87.32
3D-CNN [26]	92.42
ResNet [26]	95.43
DFFNN [26]	95.70
APSO-ERF (Proposed)	96.01

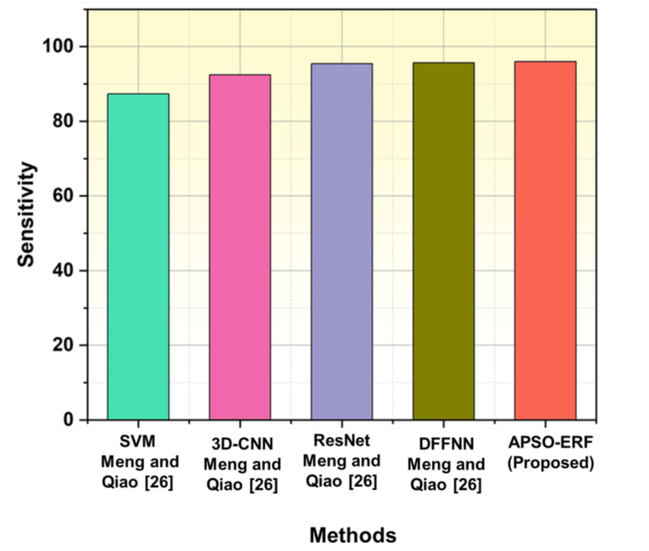

Figure 4. Results of sensitivity.

4.3. Specificity

A model's specificity indicates how effectively it avoids producing false positives by measuring the percentage of genuine negatives that the model detects. The specificity for SVM is 86.37%, indicating a moderate level of accuracy in preventing false positives. With a specificity of 89.20%, the 3D-CNN model exhibits increased accuracy. With a specificity of 93.75%, ResNet performs well in detecting instances without injuries, while the DFFNN model performs well with 97.54% specificity. The suggested APSO-ERF model has the best specificity at 97.90%, suggesting higher accuracy in identifying non-injury situations. **Table 3** and **Figure 5** represent the outcomes of the specificity.

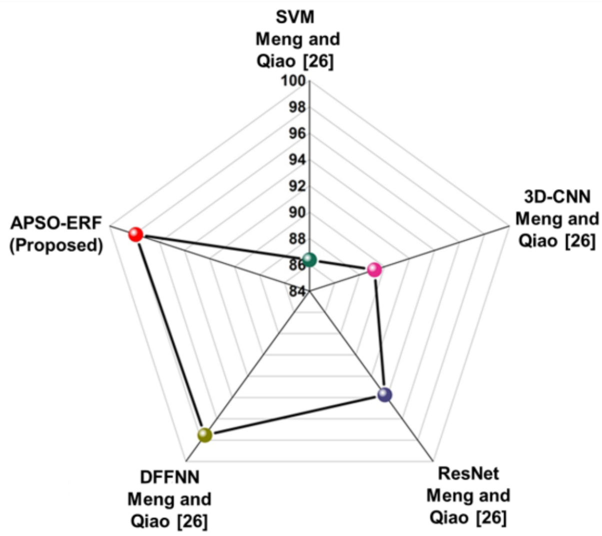

Figure 5. Results of specificity.

Table 3. Outcomes of specificity.

Techniques	Specificity (%)
SVM [26]	86.37
3D-CNN [26]	89.20
ResNet [26]	93.75
DFFNN [26]	97.54
APSO-ERF (Proposed)	97.90

4.4. Precision

The precision of a model is measured by how well it can distinguish pertinent cases from the ones that it has classified as relevant. A better precision in the context of sports injury rehabilitation suggests that the model is more successful in giving precise evaluations and treatment suggestions. In comparison to existing approaches such as SVM (88.68%), 3D-CNN (90.70%), ResNet (93.86%), and DFFNN (98.40%), the suggested APSO-ERF method achieves a precision of 98.88%, demonstrating its better capacity to provide accurate and dependable injury evaluations. By doing this, the possibility of inaccurate evaluations is decreased and it is ensured that the recommendations made are both pertinent and effective. **Table 4** and **Figure 6** represent the outcomes of the precision in below.

Table 4. Results of precision.

Techniques	Precision (%)
SVM [26]	88.68
3D-CNN [26]	90.70
ResNet [26]	93.86
DFFNN [26]	98.40
APSO-ERF (Proposed)	98.88

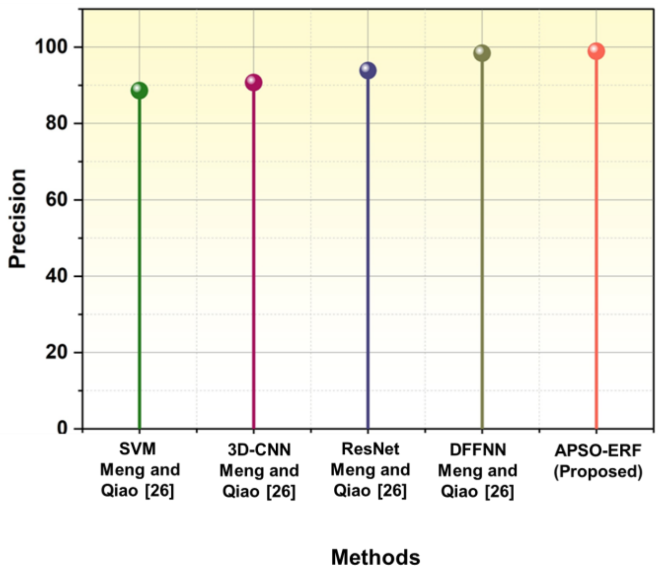

Figure 6. Results of precision.

4.5. Recall

The recall efficacy of many sports injury rehabilitation techniques is displayed in **Table 5** and **Figure 7** below. The percentage of real positives that the model accurately detected is measured by recall. Recall percentages for SVM were 87.32%, 3D-CNN was 92.42%, ResNet was 95.43%, and DFFNN was 95.70%. With a recall of 96.11%, the suggested APSO-ERF approach had the highest recall, demonstrating its greater capacity to recognize sports injury situations.

Table 5. Results of recall.

Techniques	Recall (%)
SVM [26]	87.32
3D-CNN [26]	92.42
ResNet [26]	95.43
DFFNN [26]	95.70
APSO-ERF (Proposed)	96.11

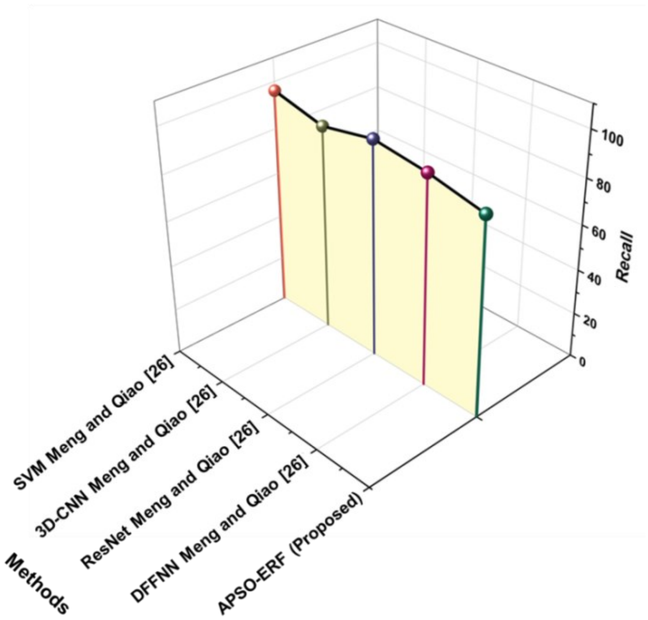

Figure 7. Results of recall.

4.6. F1-score

The F1 score is essential for evaluating accuracy and recall and creating personalized sports injury rehabilitation regimens. A high F1-score denotes competence in correctly predicting and assessing rehabilitation outcomes. Compared to other methods with SVM (88%), 3D-CNN (91.0%), Resnet (93%) and DFFNN (97%). The APSO-ERF model performs better with an F1-score of 97.5%. In the evaluation of tailored sports injury rehabilitation, the DFFNN and APSO-ERF exhibit superior performance. The following **Table 6** and **Figure 8** depict the results of the F1-score.

Table 6. Results of F1-score.

Techniques	F1-score (%)
SVM [26]	88
3D-CNN [26]	91.0
ResNet [26]	93
DFFNN [26]	97
APSO-ERF (Proposed)	97.50

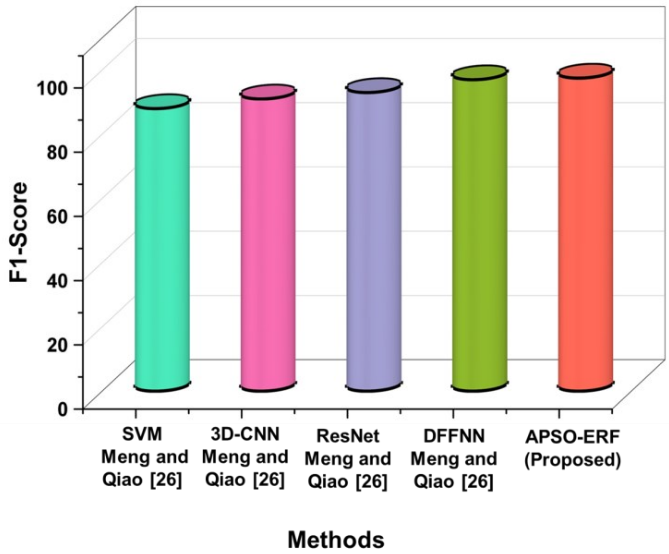

Figure 8. Results of F1-score.

The APSO-ERF method provides strong injury identification and customized therapy, with exceptional performance in accuracy (97.80%), precision (98.88%), and specificity (97.90%). By decreasing false positives and improving decision reliability, APSO-ERF approach enhances the efficiency recovery management, which performs better than the DFFNN. Although DFFNN might provide better learning and feature extraction, APSO-ERF's optimization guarantees speedier processing and flexibility. In general, APSO-ERF offers a more equitable trade-off between computational efficiency and performance indicators for the rehabilitation of sports injuries.

5. Discussion

Large datasets in customized sports injury rehabilitation are less suited for the SVM method because of its subpar performance in noisy or overlapping target classes. Furthermore, it performs poorly when analyzing complicated injury data when there are more characteristics than training examples. Due to the significant computational cost associated with using 3D convolution, one of the main drawbacks of 3D CNNs in the development of customized sports injury rehabilitation systems is this. Their high resource need renders them impractical for widespread application in medical image computing. As such, there is yet little usage of them in customized injury rehabilitation. ResNet can classify images with high accuracy, but because gradients might vanish in very deep networks, it cannot be suitable for individualized sports injury rehabilitation. This issue can hinder gradient descent and increase the complexity of network training as the number of layers increases. When DFFNN causes input images to lose part of their spatial resolution and detail, the processes of feature extraction and integration can become more challenging. This approach increases computational costs and complicates the process of identifying and selecting the most critical components of customized sports injury treatment. The APSO-ERF technique eliminates the shortcomings of SVM and handles the high computational costs of 3D CNNs with optimal resource utilization by efficiently managing noisy and complex data. It improves feature extraction and uses advanced optimization techniques to mitigate ResNet's gradient vanishing issues while maintaining spatial resolution and reducing processing costs. The scalable and precise performance of this technology enhances personalized sports injury rehabilitation. AI's capacity to evaluate enormous datasets from a variety of athletes and injuries makes it possible to continuously improve rehabilitation regimens and customize interventions to each person's particular reaction. This dynamic technique adjusts in real-time to changes in an athlete's condition, which not only speeds up recovery but also lowers the chance of recurrence. AI improves the efficacy of sports injury rehabilitation by tailoring recovery plans to the unique injury patterns and progression of each athlete, hence increasing treatment precision. AI-driven insights allow for more rapid modifications to treatment plans, which shorten recovery times and enhance results. AI is also able to forecast the likelihood of injuries, which helps to maintain long-term sports fitness by averting future injuries.

6. Conclusion

The novel APSO-ERF approach significantly accelerates the healing from sports injuries by using AI and image data. CNN integration for feature extraction and Wiener filter preprocessing results in a very accurate evaluation and customization of rehabilitation exercises. Outperforming traditional algorithms on all parameters, the APSO-ERF technique achieves 97.80% accuracy, 96.01% sensitivity, 97.90% specificity, 98.88% precision, 96.11% recall, and 97.50% F1-score. This demonstrates its higher performance in customized sports injury rehabilitation when compared to SVM, 3D-CNN, ResNet, and DFFNN. Its exceptional memory and precision reduce false positives and negatives, guaranteeing accurate injury treatment and detection. These findings highlight how AI has the ability to completely transform the rehabilitation of sports injuries by providing more efficient and customized care. Athletes can recuperate and perform at a higher level because of the APSO-ERF technique's superior accuracy and efficiency when compared to traditional algorithms. This advancement not only shortens recovery times but also offers a personalized rehabilitation experience, which makes it a major improvement in the management of sports injuries. The results attest to APSO-ERF's effectiveness in enhancing rehabilitation results.

Limitation and future scope: The computational complexity of the APSO-ERF is one of its limitations for big datasets; this can mean significant resource requirements. Subsequent investigations can concentrate on refining the method to minimize computing expenses and augmenting its expandability. Furthermore, investigating hybrid models that combine APSO-ERF with additional ML methods can enhance performance and be applicable in a variety of sports injury scenarios.

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References

1. Qazi A, Iqbal A. ExerAIde: AI-assisted Multimodal Diagnosis for Enhanced Sports Performance and Personalised Rehabilitation. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2024. pp. 3430-3438.
2. Li Y, Li X. The Artificial Intelligence System for the Generation of Sports Education Guidance Model and Physical Fitness Evaluation Under Deep Learning. Frontiers in Public Health. 2022; 10. doi: 10.3389/fpubh.2022.917053
3. Kakavas G, Malliaropoulos N, Pruna R, et al. Artificial intelligence: a tool for sports trauma prediction. Injury. 2020; 51: S63-S65. doi: 10.1016/ j.injury.2019.08.033
4. de Leeuw AW, van der Zwaard S, van Baar R, et al. Personalized machine learning approach to injury monitoring in elite volleyball players. European Journal of Sport Science. 2022; 22(4):511-520. doi: 10.1080/17461391.2021. 1887369
5. Yang R, Yuan Q, Zhang W, et al. Application of Artificial Intelligence in rehabilitation science: A scientometric investigation Utilizing Citespace. SLAS Technology. 2024; 29(4): 100162. doi: 10.1016/j.slast.2024.100162
6. Tariq A, Gill AY, Hussain HK. Evaluating the potential of artificial intelligence in orthopedic surgery for value-based healthcare. International Journal of Multidisciplinary Sciences and Arts. 2023; 2(1): 27-35. doi: 10.47709/ijmdsa. v2i1.2394
7. Rossi A, Pappalardo L, Cintia P. A Narrative Review for a Machine Learning Application in Sports: An Example Based on Injury Forecasting in Soccer. Sports. 2021; 10(1): 5. doi: 10.3390/sports10010005
8. Blasiak A, Khong J, Kee T. CURATE.AI: Optimizing Personalized Medicine with Artificial Intelligence. SLAS Technology. 2020; 25(2): 95-105. doi: 10.1177/2472630319890316
9. Salloum G, Tekli J. Automated and Personalized Nutrition Health Assessment, Recommendation, and Progress Evaluation using Fuzzy Reasoning. International Journal of Human-Computer Studies. 2021; 151: 102610. doi: 10.1016/j.ijhcs.2021.102610
10. Nahavandi D, Alizadehsani R, Khosravi A, et al. Application of artificial intelligence in wearable devices: Opportunities and challenges. Computer Methods and Programs in Biomedicine. 2022; 213: 106541. doi: 10.1016/j.cmpb.2021.106541
11. Katović D, Bronzin T, Horvat M, et al. The use of AI in Human Pose Estimation Applications in Kinesiology: Taxonomy of Algorithms, Models, and Evaluation Methods. In: Proceeding of the 2024 47th MIPRO ICT and Electronics Convention (MIPRO); 2024. pp. 1163-1166. doi: 10.1109/MIPRO 60963.2024.10569385
12. Den Hartigh RJ, Meerhoff LRA, Van Yperen NW, et al. Resilience in sports: a multidisciplinary, dynamic, and personalized perspective. International Review of Sport and Exercise Psychology. 2024; 17(1): 564-586. doi: 10.1080/1750984x.2022.2039749
13. Montull L, Slapšinskaitė-Dackevičienė A, Kiely J, et al. Integrative Proposals of Sports Monitoring: Subjective Outperforms Objective Monitoring. Sports Medicine - Open. 2022; 8(1). doi: 10.1186/s40798-022-00432-z
14. Taimoor N, Rehman S. Reliable and resilient AI and IoT-based personalized healthcare services: A survey. IEEE Access. 2021; 10: 535-563. doi: 10.1109/ACCE SS.2021.3137364
15. Jauhiainen S, Kauppi JP, Leppänen M, et al. New Machine Learning Approach for Detection of Injury Risk Factors in Young Team Sport Athletes. International Journal of Sports Medicine. 2020; 42(02): 175-182. doi: 10.1055/a-1231-5304
16. Zhao Z, Arya A, Orji R, et al. Effects of a Personalized Fitness Recommender System Using Gamification and Continuous Player Modeling: System Design and Long-Term Validation Study. JMIR Serious Games. 2020; 8(4): e19968. doi: 10.2196/19968
17. Thurzo A, Kurilová V, Varga I. Artificial Intelligence in Orthodontic Smart Application for Treatment Coaching and Its Impact on Clinical Performance of Patients Monitored with AI-TeleHealth System. Healthcare. 2021; 9(12): 1695. doi: 10.3390/healthcare9121695
18. Migliaccio GM, Padulo J, Russo L. The Impact of Wearable Technologies on Marginal Gains in Sports Performance: An Integrative Overview on Advances in Sports, Exercise, and Health. Applied Sciences. 2024; 14(15): 6649. doi: 10.3390/app

14156649
19. Burford KG, Itzkowitz NG, Ortega AG, et al. Use of Generative AI to Identify Helmet Status Among Patients with Micromobility-Related Injuries from Unstructured Clinical Notes. JAMA Network Open. 2024; 7(8): e2425981. doi: 10.1001/jamanetworkopen.2024.25981
20. Huihui X. Machine Vision Technology Based on Wireless Sensor Network Data Analysis for Monitoring Injury Prevention Data in Yoga Sports. Mobile Networks and Applications. 2024. doi: 10.1007/s11036-024-02374-0
21. Haick H, Tang N. Artificial Intelligence in Medical Sensors for Clinical Decisions. ACS Nano. 2021; 15(3): 3557-3567. doi: 10.1021/acsnano.1c00085
22. Navandar RK, Hasan SH, Jadhav N, et al. Modernizing sports is an intelligent strategy for entertainment through the Internet of Things in sports. Entertainment Computing. 2025; 52: 100804. doi: 10.1016/ j.entcom.2024.100804
23. Zhihong Y. Integrating Technology and Personalized Approaches in Sports Rehabilitation: Enhancing Performance and Preventing Sports Injuries. International Journal of Scientific and Management Research. 2023; 6(7):16-29. doi: 10.37502/ IJSMR.2023.6702
24. Dergaa I, Ben Saad H, El Omri A, et al. Using artificial intelligence for exercise prescription in personalised health promotion: A critical evaluation of OpenAI's GPT-4 model. Biology of Sport. 2024; 41(2): 221-241. doi: 10.5114/biolsport.2024.133661
25. McBee JC, Han DY, Liu L, et al. Interdisciplinary inquiry via PanelGPT: application to explore chatbot application in sports rehabilitation. MedRxiv. 2023. doi: 10.1101%2f2023.07.23.23292452
26. Meng L, Qiao E. Analysis and design of dual-feature fusion neural network for sports injury estimation model. Neural Computing and Applications. 2021; 35(20): 14627-14639. doi: 10.1007/s00521-021-06151-y