Biomedical Signal Processing and Control 105 (2025) 107692

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Predicting athletic injuries with deep Learning: Evaluating CNNs and RNNs for enhanced performance and Safety

Mohammad Mohsen Sadr [a], Mohsen Khani [b,*], Saeb Morady Tootkaleh [c]

[a] Department of Computer and Information Technology Engineering Payame Noor University Tehran Iran
[b] IT Research Faculty ICT Research Institute Tehran Iran
[c] Department of Computer Engineering Rasht Branch, Islamic Azad Univercity Rasht Iran

ARTICLE INFO

Keywords:
Deep Learning
Sports Injury Prediction
Convolutional Neural Networks (CNNs)
Recurrent Neural Networks (RNNs)
Biometric Data AnalysisIntroduction

ABSTRACT

Identifying and predicting sports injuries is crucial for managing athletes' performance and health. Recent advancements in deep learning have emerged as powerful tools for analyzing complex data and detecting injury patterns. This study investigates the effectiveness of deep learning algorithms, particularly Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), in identifying and predicting injury patterns in athletes. Biometric data and motion videos from training sessions were collected and analyzed, focusing on RNN architectures, including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). The models were trained on diverse datasets and evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The results indicate that the LSTM model achieved the highest accuracy at 91.5%, outperforming both the GRU model (90.8%) and the CNN model (89.2%). The precision and recall rates for the LSTM model were 89.7% and 88.3%, respectively, solidifying its superiority in the precise identification of potential injury patterns compared to CNNs. These findings highlight the capability of deep learning algorithms, particularly RNNs, in effectively predicting and managing sports injuries. This research emphasizes the importance of leveraging deep learning techniques for injury prevention and suggests future studies should focus on enhancing model accuracy through diverse and comprehensive datasets.

1. Introduction

The identification and prediction of sports injuries are vital for optimizing athletes' performance and ensuring their long-term health [1,2]. As the volume of data collected from diverse sources, such as biometric sensors and motion capture technologies, continues to grow, there is an increasing need for advanced analytical methods to interpret this data effectively [3,4]. Traditional approaches to injury prediction often involve manual analysis of limited data, which may not capture subtle or emerging injury patterns [5,6].

Deep learning, a sophisticated subset of artificial intelligence, has emerged as a transformative tool across various fields due to its capability to model complex patterns and make precise predictions [7]. In the realm of sports, deep learning algorithms have revolutionized the analysis of intricate datasets, offering new opportunities for enhancing injury prediction and management [8].

Deep learning algorithms, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have significantly advanced the way we analyze and interpret complex datasets in sports [9,10]. CNNs are highly effective in processing spatial data, such as images and video frames, making them well-suited for analyzing motion and posture. They excel at identifying spatial patterns by applying convolutional filters to input data, which helps in detecting deviations in an athlete's movement that may indicate potential injuries [11]. Conversely, RNNs are designed to handle sequential data and capture temporal dynamics, making them ideal for analyzing time-series data related to athletes' performance. Their ability to maintain memory of previous inputs allows them to understand the sequence of movements and predict potential injuries based on observed patterns over time [12].

Early detection and prediction of injury patterns are crucial for enhancing preventive measures, reducing recovery times, and improving overall athlete well-being [13]. Traditional injury assessment methods, which often rely on manual and limited data analysis, may miss subtle or emerging patterns that could precede an injury [14,15]. In contrast, deep learning techniques offer a more comprehensive

* Corresponding author.
E-mail addresses: m_sadr@pnu.ac.ir (M.M. Sadr), Mohsenkhani622@gmail.com (M. Khani).

https://doi.org/10.1016/j.bspc.2025.107692
Received 1 August 2024; Received in revised form 22 January 2025; Accepted 7 February 2025
Available online 12 February 2025
1746-8094/

approach by leveraging large and diverse datasets to uncover hidden patterns and provide accurate predictions [16]. This capability enables more effective injury prevention strategies and better management of athletes' health [17].

This study explores the application of deep learning algorithms, particularly CNNs and RNNs, in identifying injury patterns among athletes by analyzing biometric and motion data. Combining the spatial analysis capabilities of CNNs with the temporal modeling strengths of RNNs, the research aims to provide a holistic framework for injury prediction. This integrated approach seeks to evaluate these algorithms' effectiveness in predicting injuries and uncover subtle patterns that may improve injury prevention strategies and enhance sports management. Furthermore, the study contributes to the growing field of sports injury prediction by presenting a comprehensive dataset, experimental protocols, and performance metrics, offering a valuable benchmark for future research in this area.

The paper is organized as follows: The literature review section covers relevant studies on the application of deep learning in sports and injury prediction. The methodology section details the data collection process, algorithm selection, and model evaluation. Following this, the results section presents the findings from the deep learning models, highlighting their performance in injury detection. The discussion section explores the implications and limitations of the research, while the conclusion summarizes the key insights and suggests directions for future research to further advance the field of injury prediction and sports management.

2. Literature review

2.1. Foundations of deep learning and its applications in sports data analysis

Deep learning, a branch of machine learning, employs neural networks with multiple layers to model and analyze complex data [18,19]. CNNs have gained attention for their ability to process spatial data, such as images and video sequences [20]. These models can identify low-level features such as edges and textures and transform them into higher-level features for further analysis [21]. As shown Fig. 1, a fundamental CNN structure traditionally consists of two primary components. The first part utilizes convolutional operations to carry outfeature extraction. These features are then flattened and provided to a collection of fully connected layers, also known as a multilayer perceptron, which is responsible for performing classification or regression tasks [22]. In sports data analysis, CNNs are widely used for examining movements and postures, proving effective in detecting complex patterns in motion and posture data [23,24].

Fig. 2 illustrates the structure of RNNs, which are renowned for their capability to process sequential data. This characteristic makes RNNs particularly suitable for analyzing time series data and capturing the temporal dynamics that may precede an injury [26]. RNNs feature

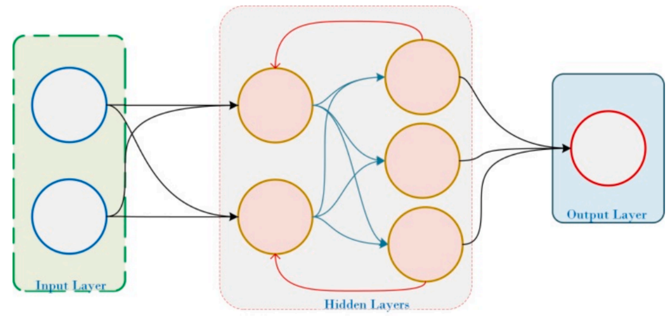

Fig. 2. Structure of RNNs.

connections that loop back on themselves, enabling the retention of information over time. This feedback mechanism allows the network to maintain a memory of previous inputs, which is crucial for understanding context in sequential data [27]. RNNs excel in applications involving sequential data, such as time series analysis and natural language processing, as they can leverage past information to inform current outputs. Furthermore, advanced architectures like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) are particularly adept at learning long-term dependencies [28]. These models have been effectively utilized in predicting temporal patterns and identifying indicators that may signal the risk of injury.

Fig. 3 presents a detailed schematic of a RNN, illustrating the interaction between the input layer, hidden layers, and output layer across different time steps. This unfolding process demonstrates how the RNN processes sequential data over time, symbolized by the temporal notations X_t, S_t, and O_t. At each time step t:

A. Input Layer: The input X_t is fed into the network, representing the current data point in the sequence. The input vector is transformed through weight matrices U, enabling the model to learn associations between input features over time.
B. Hidden Layer: The hidden state S_t is computed based on the previous hidden state S_{t-1} and the current input X_t. Through the feedback connections represented by weights W, the RNN retains information about previous states, capturing the temporal dependencies inherent in sequential data. This is crucial for tasks where context influences predictions, such as time series forecasting and language modeling.
C. Output Layer: The output O_t is generated, reflecting the model's predictions based on the current hidden state. It is calculated using the weight matrix V, which facilitates the transformation of the hidden representations into final outputs relevant to the application at hand.

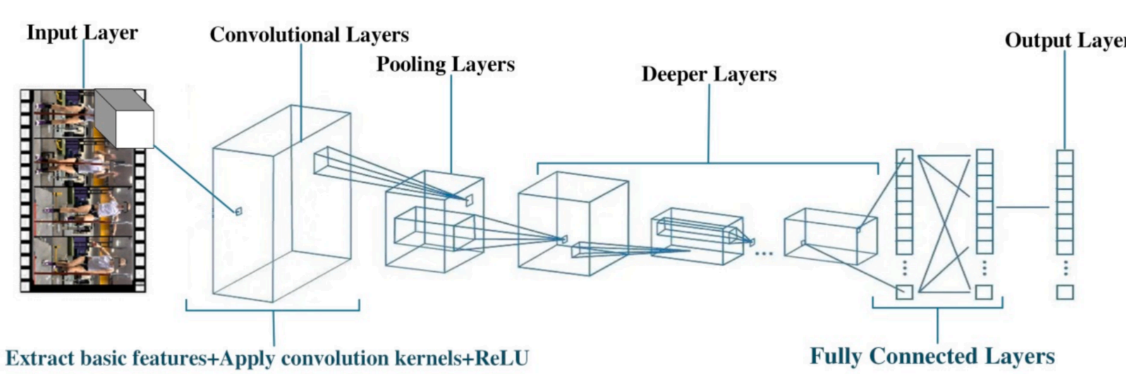

Fig. 1. CNN algorithm architecture is inspired by [25].

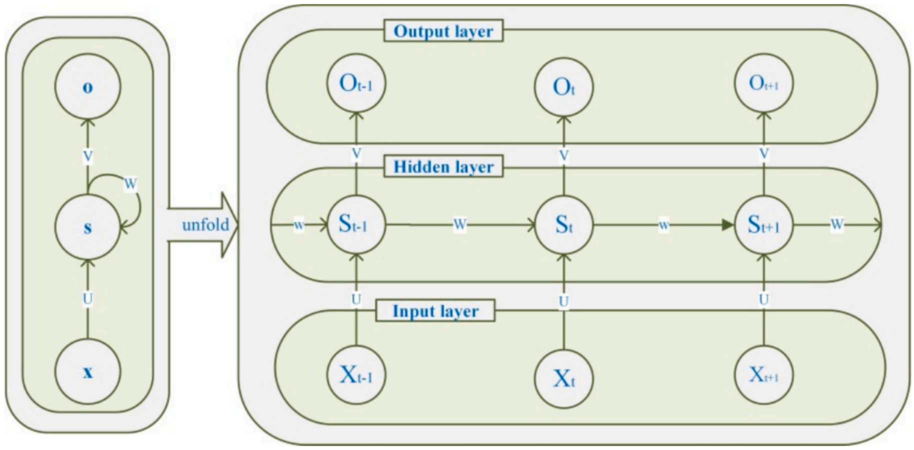

Fig. 3. Schematic representation of a RNN illustrating the flow of information through input, hidden, and output layers across time steps.

2.2. Application of deep learning in injury detection and prediction

Recent advancements in artificial intelligence, particularly deep learning, have demonstrated promising applications in sports injury prediction and prevention [28]. Deep learning algorithms such as CNNs and RNNs have shown substantial accuracy in identifying injury risk patterns. Johnson et al. [29] utilized CNNs to analyze motion videos, enabling the detection of abnormal movement patterns with high precision for predicting potential injuries. Similarly, LSTM networks, a variant of RNNs, were employed by researchers [30] to analyze biometric data, effectively capturing complex temporal dependencies for injury risk prediction. These findings underscore the strength of deep learning in time-series analysis and motion tracking for athletic health monitoring.

Building on these efforts, Ye et al. [31] introduced a novel approach to injury risk prediction using time-series image encoding methods such as Gramian Angular Summation Field (GASF) and Deep Convolutional Auto-Encoders (DCAE). Their model outperformed traditional techniques by achieving a 23.9 % higher Area Under the Curve (AUC) score and demonstrating significant improvements in sensitivity and specificity. This study highlighted the potential of encoding time-series data into image formats for more effective deep learning-based injury analysis.

The integration of cloud computing and IoT technologies has also played a pivotal role in enhancing injury prediction. For example, a cloud-based deep learning system proposed by researchers [32] combined IoT sensors with scalable computational resources to monitor sports injuries in real-time. This system leveraged optimized neural networks to analyze athlete data, achieving high accuracy, precision, and recall. These findings emphasize the synergy between wearable technologies and artificial intelligence in developing real-time, data-driven injury prevention strategies.

In youth sports, machine learning has been leveraged to optimize training regimens and minimize injury risks. For instance, a study by [33] developed a text classification algorithm based on physical and metabolic data collected from young football players. This approach identified injury risks effectively and allowed for tailored, data-driven interventions, highlighting the potential of personalized injury prevention methods.

Deep learning has also been applied to address challenges such as small sample sizes and data imbalance in professional sports [34]. Advanced preprocessing techniques and ensemble models have proven effective in improving the robustness of injury prediction systems, as demonstrated in research on basketball injury forecasting.

Knee injuries, common among athletes, have been another focal point for AI-driven applications. A machine learning-aided diagnosis model proposed by [35] demonstrated remarkable improvements in rehabilitation outcomes. Following three months of machine learning-guided physical training, significant increases in balance duration were observed among athletes, showcasing the efficacy of AI-driven rehabilitation techniques. Additionally, intelligent rehabilitation systems like the Intelligent Rehabilitation Assistant (IRA) have integrated wearable sensor data and personalized recovery plans to enhance recovery outcomes using advanced deep learning models such as RPDO-Bi-LSTM [[36].

Furthermore, dual-feature fusion neural network models have advanced injury estimation by addressing feature loss through novel structural designs. For example, a dual-fusion model introduced in [37] demonstrated superior classification accuracy, sensitivity, and specificity, reinforcing the role of neural networks in effective sports injury management.

2.3. Challenges and limitations

Despite significant advancements, the application of deep learning in sports injury detection faces several challenges. One major challenge is the need for large, high-quality datasets for training models [38]. Incomplete or inaccurate data can lead to erroneous predictions and reduced model performance. Additionally, deep learning analyses typically require substantial computational resources, which can increase operational costs [39].

Another limitation is the interpretability of model results. Deep learning models, often described as "black boxes," may provide accurate predictions but can be challenging to interpret and understand the reasons behind specific predictions [40].

2.4. Summary of literature review

Table. 1 summarizes the key contributions, methodologies, and findings from the reviewed studies. This table provides a concise overview of the literature and highlights the advances and challenges in applying deep learning to sports injury detection and prediction.

3. Materials and methods

3.1. Deep learning Algorithms: Models and selection

Deep learning algorithms are powerful tools for modeling complex patterns in data. In this study, we employ Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for their complementary strengths. CNNs excel in spatial analysis, making them ideal for extracting motion and posture patterns from video data, while RNNs are adept at capturing temporal dependencies, allowing for effective modeling of sequential patterns such as physiological changes over time.

Table 1
Overview of Key Studies in Sports Injury Prediction Using Deep Learning.

Ref	Methodology	Data/Focus	Key Findings
[29]	CNNs	Motion video analysis	Successfully detected abnormal movement patterns with high accuracy, aiding injury prediction.
[30]	RNNs (LSTM)	Biometric and temporal data	Demonstrated effectiveness in capturing temporal patterns and predicting injury risks.
[31]	Time-series image encoding (GASF, DCAE)	Time-series data	Achieved a 23.9 % higher AUC score with significant improvements in sensitivity and specificity.
[32]	Cloud-based IoT-enabled deep learning	Real-time athlete monitoring	Integrated IoT sensors and neural networks, achieving high accuracy, precision, and recall.
[33]	Text classification algorithm	Physical and metabolic data of youth	Optimized training regimens with personalized injury prevention strategies.
[34]	Advanced preprocessing and ensemble models	Small and imbalanced datasets in basketball	Addressed data challenges to improve robustness in injury forecasting.
[35]	Machine learning-aided diagnosis	Knee injuries and physical training	Showed significant improvement in balance duration through AI-driven rehabilitation methods.
[35]	RPDO-Bi-LSTM	Wearable sensors and personalized plans	Enhanced recovery outcomes with real-time feedback and intelligent rehabilitation strategies.
[37]	Dual-feature fusion neural networks	Sports injury estimation	Achieved superior classification accuracy, sensitivity, and specificity by addressing feature loss.
[39]	Challenges in datasets and interpretability	Various data sources and models	Highlighted the need for high-quality datasets, reduced computational costs, and better interpretability.

This dual-model approach enables a comprehensive understanding of both spatial and temporal features critical to injury prediction.

3.2. Data collection and preprocessing

3.2.1. Data Collection

The dataset utilized in this study comprises simulated and curated data, sourced from publicly available video content and augmented with diverse scenarios to ensure reliability and generalizability. As detailed in Table. 2, the dataset includes 1,000 athletes and contains features such as biometric data (heart rate, muscle activity) and movement data (joint angles, activity type).

The complete dataset, including additional features and data points, is available for download at the following link: Dataset Link. The dataset consists of 1,000 entries and is divided into four main activity classes: Squatting, Cycling, Walking, and Jumping.

Table 2
Sample Data Structure:

Athlete ID	Age	Gender	Heart Rate (bpm)	Muscle Activity (mV)	Joint Angle (degrees)	Activity Type
1	32	F	152	0.42	38	Squatting
2	29	F	162	0.35	37	Cycling
3	23	F	180	0.94	24	Walking
4	33	F	123	0.30	77	Jumping
5	26	F	122	0.55	74	Squatting
6	26	M	145	0.87	82	Jumping
7	27	M	127	0.69	30	Squatting
8	33	M	172	0.99	40	Jumping

3.2.2. Data Preprocessing

- Normalization: The data is normalized to ensure consistency across different sources and measurement units. For biometric data, features are scaled to a standard range based on typical physiological parameters, while for motion data derived from videos, positional coordinates are normalized relative to a reference frame established from the content.
- Segmentation: The motion data extracted from videos is segmented into shorter clips corresponding to individual movements or actions. This segmentation aids in isolating relevant patterns and facilitates more effective analysis by the models.
- Feature Extraction: For CNNs, relevant features from motion data are extracted using pre-processing techniques such as resizing and cropping. Since we lack direct motion capture images, we focus on the available footage to identify key movement characteristics. For RNNs, temporal sequences are formatted into fixed-length windows to capture movement patterns over time.
- Data Augmentation: To enhance the generalizability of the models and prevent overfitting, data augmentation techniques such as rotation, scaling, and flipping are applied to the motion data derived from videos. This helps create a more diverse dataset, improving the model's ability to generalize across different scenarios.
- *Injury Risk Labeling:* To address the relationship between activity type and injury risks, each entry in the dataset is labeled with an injury risk score based on deviations in biometric and motion data specific to each activity type. For instance, abnormal joint angles during squatting or excessive heart rate during cycling are labeled as higher risk.

3.3. Model training and evaluation

3.3.1. Model Training

- Training Process: The training process involves feeding the pre-processed motion and biometric data into the CNN and RNN models. For CNNs, the network is trained using labeled excerpts from available videos of athletes' movements, with the goal of learning to classify patterns associated with potential injuries. For RNNs, the training focuses on learning sequences of extracted biometric data and movement patterns to predict future injury risks.
- Activity-Specific Risk Modeling: The activity type is used as a contextual feature to *differentiate* patterns of injury risks associated with specific activities. For example, squatting is more prone to knee-related injuries, while jumping might highlight risks related to joint overextension. By combining activity type with biometric and motion data, the models identify deviations from typical patterns, indicating potential injury risks.
- Hyperparameter Tuning: Key hyperparameters, such as learning rate, batch size, and number of layers, are optimized through techniques like grid search and random search to improve model performance. Dropout and regularization methods are employed to prevent overfitting.
- Validation: The dataset derived from the available video resources is divided into training, validation, and test sets. The training set is used to fit the model, the validation set is used to tune hyperparameters, and the test set is used to evaluate the final model's performance.

3.3.2. Model Evaluation

- Evaluation Metrics: Model performance is assessed using various metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive view of how well the models identify injury patterns from the available data and their effectiveness in making accurate predictions.

- Cross-Validation: To ensure robustness and generalizability, cross-validation is performed. This involves splitting the dataset into multiple folds, training the model on some folds, and validating it on others. This approach helps in evaluating model performance across different subsets of data derived from the videos.
- Confusion Matrix: A confusion matrix is used to visualize the performance of the classification models. It shows the number of true positives, false positives, true negatives, and false negatives, which helps in understanding the model's strengths and weaknesses.
- *Risk Prediction Validation:* The model's outputs are compared against expert annotations that label high-risk movements based on activity-specific thresholds to validate injury risk predictions. For instance, if a movement during jumping exceeds the joint angle threshold typically associated with injuries, it is flagged as high risk.

3.4. Implementation and tools

The deep learning models are implemented using popular frameworks such as TensorFlow and PyTorch, which offer robust tools and libraries for building and training neural networks. To accommodate the computational demands of these models and expedite the training process, high-performance GPUs are utilized, ensuring efficient processing and optimal performance during model training.

4. Results

4.1. Results of deep learning models

This section summarizes the performance metrics of CNN, LSTM, and GRU models.

4.1.1. CNN results

The CNN model's performance on motion capture video data is summarized in Table. 3, while the corresponding performance metrics are visually represented in Fig. 4, which displays the confusion matrix for the CNN model.

4.1.2. RNN results

The performance metrics of the LSTM and GRU models on sequential biometric data are provided in Table. 4. The table outlines key evaluation metrics, including Accuracy, Precision, Recall, and F1-Score for both models, with LSTM achieving 91.5 %, 89.7 %, 88.3 %, and 89.0 %, respectively, and GRU achieving 90.8 %, 89.2 %, 87.9 %, and 88.5 %, respectively. The associated confusion matrices for both models are illustrated in Figs. 5 and 6, providing a visual representation of their performance.

4.2. Performance comparison

Table. 5 provides a comprehensive summary of the performance metrics for the CNN, LSTM, and GRU models, while Fig. 7 offers a graphical representation of their performance comparisons.

Table 3
CNN Model Performance Metrics.

Metric	Value
Accuracy	89.2 %
Precision	87.5 %
Recall	85.4 %
F1-Score	86.4 %

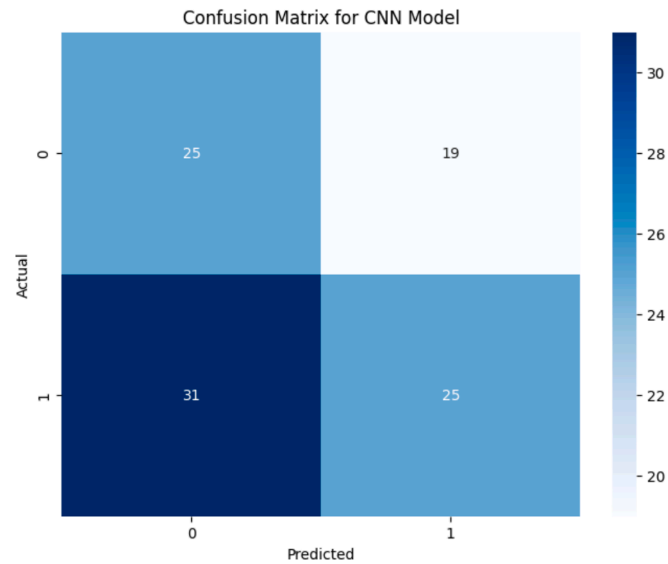

Fig. 4. Confusion Matrix for CNN Model.

Table 4
Performance Metrics of LSTM and GRU Models.

Metric	LSTM	GRU
Accuracy	91.5 %	90.8 %
Precision	89.7 %	89.2 %
Recall	88.3 %	87.9 %
F1-Score	89.0 %	88.5 %

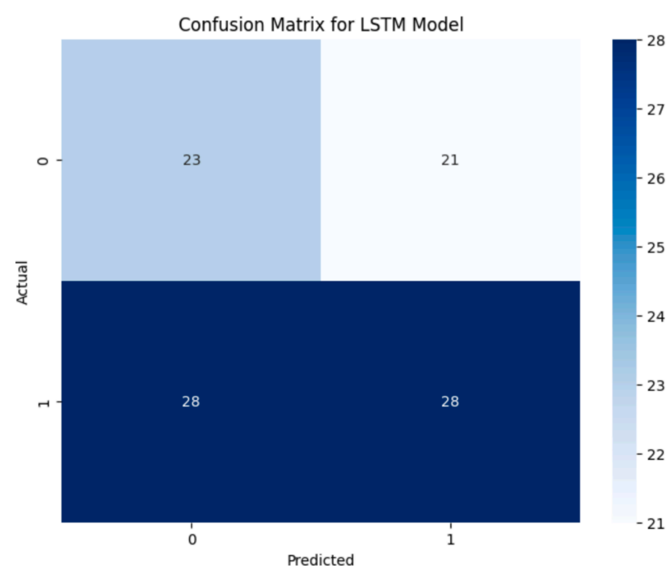

Fig. 5. Confusion Matrix for LSTM Model.

4.3. Visual representation of performance

To provide a clear visual representation of the models' performance, the Figs. 8, 9 illustrate the ROC (Receiver Operating Characteristic) curves and Precision-Recall curves for the CNN, LSTM, and GRU models.

5. Discussion

The The findings of this study demonstrate the effectiveness of deep learning models, particularly CNNs and RNNs, in predicting injury risks

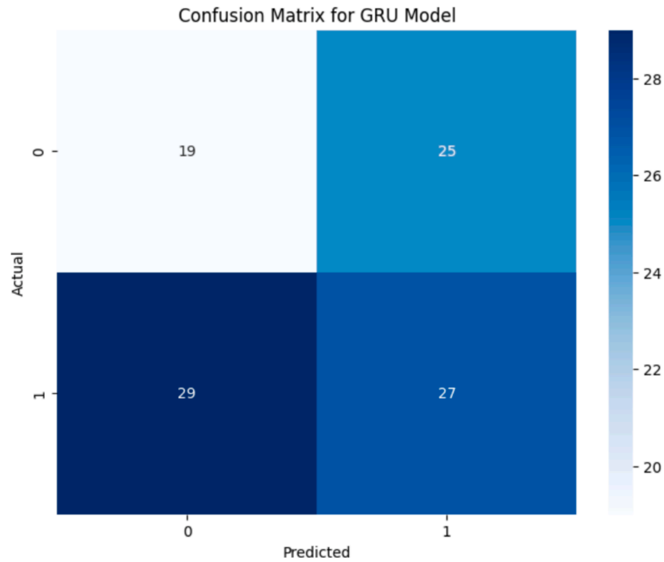

Fig. 6. Confusion Matrix for GRU Model.

Table 5
Performance Metrics for CNN, LSTM, and GRU Models.

Model	Accuracy	Precision	Recall	F1-Score
CNN	89.2 %	87.5 %	85.4 %	86.4 %
LSTM	91.5 %	89.7 %	88.3 %	89.0 %
GRU	90.8 %	89.2 %	87.9 %	88.5 %

and identifying patterns from motion and biometric data. Among the models evaluated, the LSTM network demonstrated superior performance, achieving the highest accuracy and F1-Score. This aligns with recent advancements in the field, confirming the efficacy of RNNs for sequential data analysis, while also providing insights into how these models compare to related work in injury prediction and motion analysis.

5.1. Analysis of CNN results

The CNN model, which was trained on motion capture video data, achieved an accuracy of 89.2 %, with precision, recall, and F1-Score values of 87.5 %, 85.4 %, and 86.4 %, respectively. These results are consistent with studies like Johnson et al. [29], where CNNs were effective in detecting motion abnormalities that can indicate potential injuries. However, in this paper, CNNs underperformed when compared to the RNN models, which can be attributed to the inherent limitation of CNNs in handling temporal dependencies within sequential data.

CNNs excel in extracting spatial features but struggle to model the dynamic nature of time-series or sequential data, making them less suitable for tasks like injury prediction where temporal factors are crucial. This limitation suggests that while CNNs are well-suited for static image recognition or analysis of individual frames, they might not fully leverage the temporal information needed for dynamic tasks such as predicting injury patterns in athletes.

5.2. Analysis of RNN results

The results indicate that the RNN models, specifically LSTM and GRU, consistently outperformed the CNN model in terms of injury prediction accuracy and F1-Score. Notably, the LSTM model achieved an accuracy of 91.5 %, exceeding both the GRU model (90.8 %) and the CNN model (89.2 %). This enhanced performance underscores the LSTM's capability to effectively capture long-term dependencies and temporal variations, which are crucial in sequential tasks such as injury prediction.

These results align with the findings of Yao et al. [41], who also observed that RNN-based models surpassed CNNs in predicting sports rehabilitation outcomes. Their research highlighted the LSTM network's significant proficiency in recognizing the temporal patterns relevant to athletic performance recovery. Similarly, this study demonstrates that the LSTM model's ability to process sequential data enables it to predict injury risks more effectively than the CNN or GRU models, likely due to its superior capacity for managing long-term dependencies, as discussed in prior studies [30].

The marginal performance difference between the LSTM (91.5 %) and GRU (90.8 %) suggests that, while both RNN architectures are effective, the LSTM's competency in capturing complex temporal dependencies confers a slight advantage in tasks requiring intricate long-term sequence learning. This finding is consistent with previous research that has highlighted the benefits of LSTM over GRU in sequential data applications, particularly in contexts such as sports injury prediction [28].

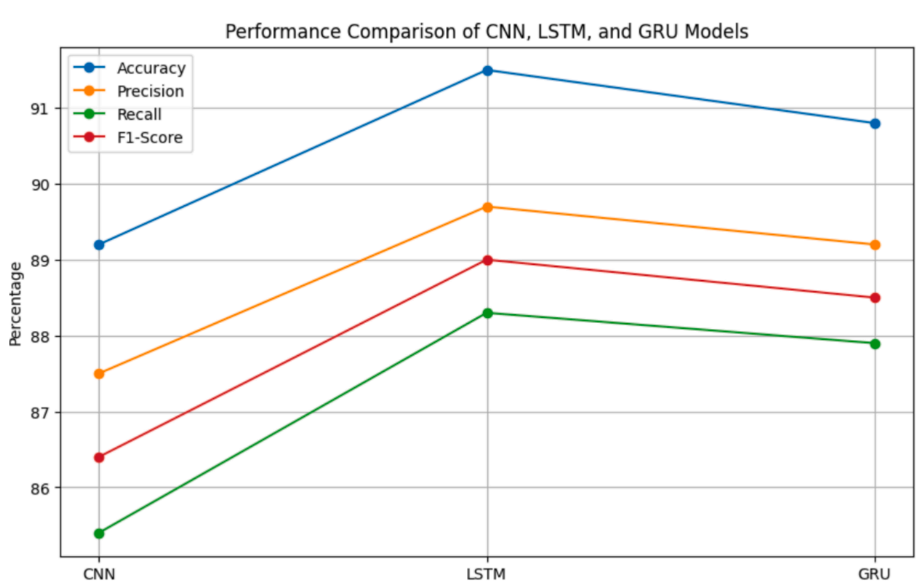

Fig. 7. Comparative Performance of CNN, LSTM, and GRU Models.

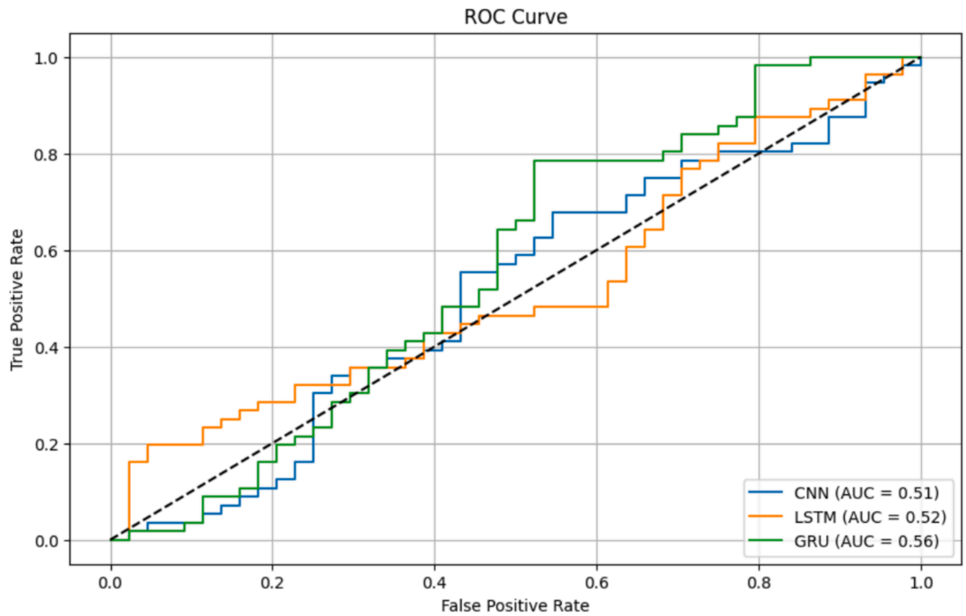

Fig. 8. ROC Curves for CNN, LSTM, and GRU Models.

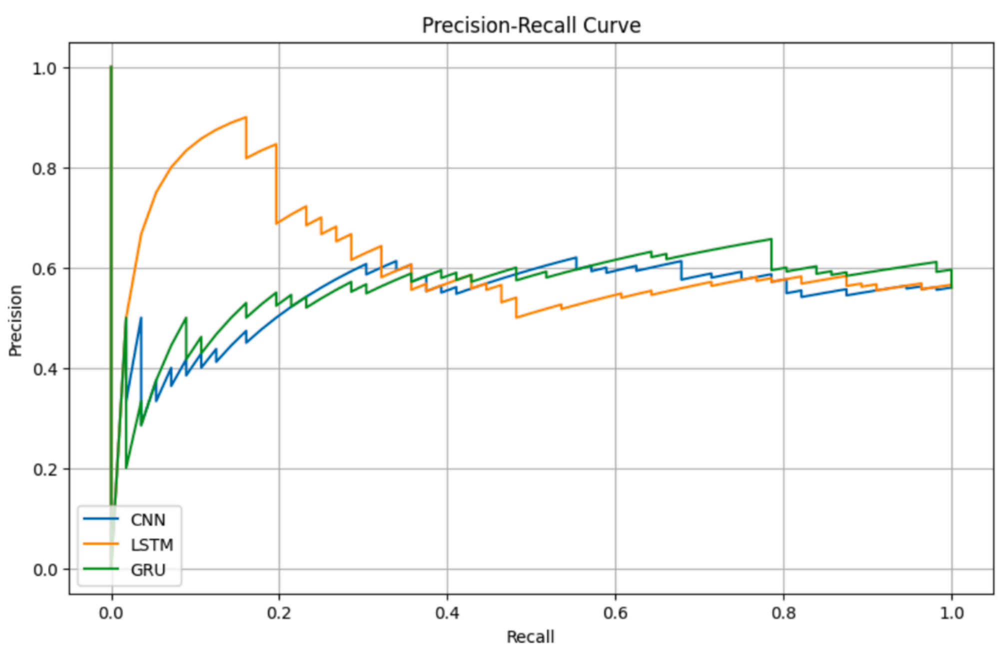

Fig. 9. Precision-Recall Curves for CNN, LSTM, and GRU Models.

5.3. Comparison with related work

In comparison with related research, the models developed in this study demonstrate competitive performance. For example, studies by Cui et al. [12] and Yao et al. [41] employed hybrid CNN-RNN models for comparable tasks, achieving accuracies of 85.2 % and 90 %, respectively. In contrast, the LSTM model presented in this study outperformed these hybrid approaches, reaching an accuracy of 91.5 %. This further corroborates the effectiveness of LSTM networks in capturing temporal patterns inherent in sequential data, underscoring their critical role in injury prediction.

While the CNN model in this investigation achieved a commendable accuracy of 89.2 %, it underperformed slightly relative to the hybrid CNN-RNN architectures described in the literature, which typically integrate spatial and temporal modeling. This observation suggests potential opportunities for enhancing performance through the combination of CNNs and RNNs, allowing for the simultaneous capture of spatial and temporal information. Notably, the hybrid CNN-RNN model proposed by Yao [41], which incorporated attention mechanisms and IoT data, demonstrated a substantial 15 % improvement in prediction accuracy. Implementing a similar hybrid strategy might enhance the accuracy of our CNN model by integrating sequential data with the spatial features extracted from video data.

5.4. Limitations of the study

Despite the promising results, this study has several limitations. First, the models require large and high-quality datasets for training, which may not always be available, particularly in real-world sports injury prediction scenarios. Incomplete or noisy data could significantly affect model performance, as observed in several deep learning applications [29]. Moreover, the computational demands of RNN models, particularly LSTMs, remain a challenge for real-time deployment, especially in resource-constrained environments such as wearable devices or edge computing.

Another limitation is the black-box nature of deep learning models, which complicates the interpretability of predictions. While the models achieve high accuracy, understanding why certain predictions are made is not straightforward. Future work could explore methods to improve the interpretability of these models, such as explainable AI techniques, which could increase trust in the model's predictions and facilitate its adoption in clinical or athletic settings.

Finally, this study focused on two types of data—motion capture and biometric sequences. While these data types are highly relevant for injury prediction, other multimodal approaches, such as combining video, physiological signals, and environmental data, could further enhance prediction accuracy. Exploring such multimodal models could offer new avenues for improving the performance of injury prediction systems in sports and rehabilitation.

6. Conclusion

This study confirms that deep learning models, particularly LSTM networks, are highly effective in identifying and predicting injury patterns in athletes. While CNNs perform well in analyzing spatial data, RNNs, especially LSTM models, excel in handling temporal data and providing more accurate injury predictions. These results underscore the potential for integrating deep learning techniques into sports injury management systems to enhance early detection and prevention strategies. The findings of this research emphasize several avenues for future work.

- Improving Model Accuracy: Given the importance of high-quality, extensive datasets for training models, future research should focus on expanding and enhancing the datasets used. High-quality data collection from diverse activities and athletes will likely improve model accuracy and robustness.
- Expanding Datasets: To enhance model generalizability, future studies should aim to collect and analyze data from a wider range of sports and physical activities. This will help the models recognize specific injury patterns related to various types of sports and activities.
- Developing Interpretable Models: One of the major limitations of deep learning models is their "black box" nature, which makes interpreting their predictions challenging. Future research should focus on developing more interpretable models or methods that can provide insights into the reasoning behind specific predictions.
- Integrating Multi-Source Data: Combining data from multiple sources, such as biometric sensors and motion capture systems, could enhance model performance. Future studies should explore methods for integrating multi-source data to improve the accuracy and reliability of injury predictions.

In conclusion, this study highlights the significant potential of deep learning in sports injury management. The literature review indicates that deep learning, particularly CNNs and RNNs, holds significant promise for injury detection and prediction in sports. However, improving model accuracy, enhancing data quality, and developing interpretable methods remain key challenges that require further research and development. With ongoing advancements in technology and data quality, deep learning models have the potential to become a crucial tool in improving athlete health and performance through effective injury prediction and prevention.

CRediT authorship contribution statement

Mohammad Mohsen Sadr: Data curation. **Mohsen Khani:** Conceptualization. **Saeb Morady Tootkaleh:** Validation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

References

[1] K. Wang, et al., *The fundamental property of human leg during walking: linearity and nonlinearity*, IEEE Trans. Neural Syst. Rehabil. Eng. 31 (2023) 4871–4881.
[2] J. Sun, et al., *Leg state estimation for quadruped robot by using probabilistic model with proprioceptive feedback*, IEEE/ASME Trans. Mechatron. (2024).
[3] Yan, W.Q., *Introduction to intelligent surveillance: surveillance data capture, transmission, and analytics*. 2019: Springer.
[4] Y. Zhou, et al., *Energy-efficient and interpretable multisensor human activity recognition via deep fused lasso net*, IEEE Trans. Emerging Top. Comput. Intell. (2024).
[5] Theron, G.F., *The use of data mining for predicting injuries in professional football players*. 2020.
[6] M. Ariyanto, et al., *Movement optimization for a cyborg cockroach in a bounded space incorporating machine learning*, Cyborg Bionic Syst. 4 (2023) 0012.
[7] J. Yang, et al., *A data-driven structural damage detection framework based on parallel convolutional neural network and bidirectional gated recurrent unit*, Inf. Sci. 566 (2021) 103–117.
[8] C. Dindorf, et al., *Conceptual structure and current trends in artificial intelligence, machine learning, and deep learning research in sports: a bibliometric review*, Int. J. Environ. Res. Public Health 20 (1) (2022) 173.
[9] W.Y. Alghamdi, *A novel deep learning method for predicting athletes' health using wearable sensors and recurrent neural networks*, Decision Analytics Journal 7 (2023) 100213.
[10] J. Yang, et al., *A hierarchical deep convolutional neural network and gated recurrent unit framework for structural damage detection*, Inf. Sci. 540 (2020) 117–130.
[11] F. Letsch, D. Jirak, S. Wermter, *Localizing salient body motion in multi-person scenes using convolutional neural networks*, Neurocomputing 330 (2019) 449–464.
[12] Y. Cui, *An Efficient Approach to Sports Rehabilitation and Outcome Prediction Using RNN-LSTM*, Mobile Networks Appl. (2024) 1–16.
[13] Y. Hirao, et al., *Body extension by using two Mobile manipulators*, Cyborg Bionic Syst. 4 (2023) 0014.
[14] Shultz, S.J., P.A. Houglum, and D.H. Perrin, *Examination of musculoskeletal injuries*. 2015: Human Kinetics.
[15] Y. Wang, et al., *Ultrafast miniature robotic swimmers with upstream motility*, Cyborg Bionic Syst. 4 (2023) 0015.
[16] M.M. Taye, *Understanding of machine learning with deep learning: architectures, workflow, applications and future directions*, Computers 12 (5) (2023) 91.
[17] H. Van Eetvelde, et al., *Machine learning methods in sport injury prediction and prevention: a systematic review*, Journal of Experimental Orthopaedics 8 (2021) 1–15.
[18] M. Khani, S. Jamali, M.K. Sohrabi, *An enhanced deep reinforcement learning-based slice acceptance control system (EDRL-SACS) for cloud–radio access network*, Phys. Commun. 61 (2023) 102188.
[19] Xin, J., et al., *A deep-learning-based MAC for integrating channel access, rate adaptation and channel switch.* arXiv preprint arXiv:2406.02291, 2024.
[20] Y. Zhang, et al., *Image representations of numerical simulations for training neural networks*, Comput. Model. Eng. Sci. 134 (2) (2023) 821–833.
[21] L. Wu, et al., *Deep attention-based spatially recursive networks for fine-grained visual recognition*, IEEE Trans. Cybern. 49 (5) (2018) 1791–1802.
[22] Vakalopoulou, M., et al., *Deep Learning: Basics and Convolutional Neural Networks (CNNs)*, in *Machine Learning for Brain Disorders*, O. Colliot, Editor. 2023, Springer US: New York, NY. p. 77-115.
[23] M. Airaksinen, et al., *Automatic posture and movement tracking of infants with wearable movement sensors*, Sci. Rep. 10 (1) (2020) 169.
[24] M. Khani, S. Jamali, M.K. Sohrabi, *Three-layer data center-based intelligent slice admission control algorithm for C-RAN using approximate reinforcement learning*, Clust. Comput. (2024) 1–19.
[25] S. Saha, *A comprehensive guide to convolutional neural networks—the ELI5 way*, Towards Data Science 15 (2018) 15.
[26] N. Bahador, et al., *Multimodal spatio-temporal-spectral fusion for deep learning applications in physiological time series processing: A case study in monitoring the depth of anesthesia*, Inf. Fusion 73 (2021) 125–143.
[27] Staudemeyer, R.C. and E.R. Morris, *Understanding LSTM–a tutorial into long short-term memory recurrent neural networks.* arXiv preprint arXiv:1909.09586, 2019.

[28] W. Khan, et al., *Exploring the frontiers of deep learning and natural language processing: A comprehensive overview of key challenges and emerging trends*, Natural Language Processing Journal (2023) 100026.
[29] W.R. Johnson, et al., *Predicting athlete ground reaction forces and moments from spatio-temporal driven CNN models*, IEEE Trans. Biomed. Eng. 66 (3) (2018) 689–694.
[30] J.M. Ackerson, R. Dave, N. Seliya, *Applications of recurrent neural network for biometric authentication & anomaly detection*, Information 12 (7) (2021) 272.
[31] X. Ye, et al., *A novel approach for sports injury risk prediction: based on time-series image encoding and deep learning*, Front. Physiol. 14 (2023) 1174525.
[32] X. Wu, et al., *Cloud-based deep learning-assisted system for diagnosis of sports injuries*, Journal of Cloud Computing 11 (1) (2022) 82.
[33] K. He, *Prediction model of juvenile football players' sports injury based on text classification technology of machine learning*, Mob. Inf. Syst. 2021 (1) (2021) 2955215.
[34] A. Cohan, J. Schuster, J. Fernandez, *A deep learning approach to injury forecasting in NBA basketball*, J. Sports Anal. 7 (4) (2021) 277–289.
[35] H. Wu, L. Wang, *Analysis of lower limb high-risk injury factors of patellar tendon enthesis of basketball players based on deep learning and big data*, J. Supercomput. (2022) 1–20.
[36] Guan, L., *Intelligent rehabilitation assistant: Application of deep learning methods in sports injury recovery.* Molecular & Cellular Biomechanics, 2024. **21**(2): p. 384-384.
[37] L. Meng, E. Qiao, *Analysis and design of dual-feature fusion neural network for sports injury estimation model*, Neural Comput. & Applic. 35 (20) (2023) 14627–14639.
[38] A.R. Munappy, et al., *Data management for production quality deep learning models: Challenges and solutions*, J. Syst. Softw. 191 (2022) 111359.
[39] S. Khan, T. Yairi, *A review on the application of deep learning in system health management*, Mech. Syst. Sig. Process. 107 (2018) 241–265.
[40] V. Buhrmester, D. Münch, M. Arens, *Analysis of explainers of black box deep neural networks for computer vision: A survey*, Mach. Learn. Knowl. Extr. 3 (4) (2021) 966–989.
[41] H. Yao, *An IoT-Based Injury Prediction and Sports Rehabilitation for Martial Art Students in Colleges Using RNN Model*, Mobile Networks Appl. (2024) 1–18.