Airadl: A Deep Learning-Based Framework for Multimodal Physiological and Biomechanical Injury Risk Classification in Athletes

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Athlete performance and injury prevention depend on computational biology to evaluate physiological responses and biomechanics to investigate movement. Incorporating these areas with deep learning improves risk evaluation, allowing for data-driven training tactics. Problem Statement: Conventional injury risk evaluations are frequently incorrect, depending on subjective evaluations. Existing models do not capture intricate interactions between biological and biomechanical factors, requiring a more accurate, data-driven method. Objectives: This research proposes the AIRADL (Athlete Injury Risk Assessment using Deep Learning) Framework to forecast injury risk by incorporating physiological and biomechanical data, enhancing classification accuracy, and assisting training decisions. Methodology: The proposed AIRADL model is trained on the Athlete Health & Motion Analysis Dataset (AHMAD), which contains physiological data such as heart rate, oxygen level, lactate level, and muscle fatigue, in addition to biomechanical factors such as stride length, joint flexibility, and movement symmetry. The data preprocessing steps include mean imputation for missing numerical values, mode imputation for categorical values, label encoding for categorical features, Min-Max scaling for normalization, and Chi-Square feature selection to maintain the most pertinent predictors. The dataset is split into 80% training and 20% testing. A DL4J MLP Classifier is employed to learn trends and classify performance risk levels. The AIRADL framework employs a three-hidden-layer DL4J MLP architecture consisting of 64–128–64 neurons with ReLU activation, Adam optimizer, and early stopping to prevent overfitting. The Athlete Health & Motion Analysis Dataset (AHMAD), a privately collected dataset, was used for experimentation, and evaluation metrics included accuracy, F1-score, and Matthews Correlation Coefficient (MCC), which measures the strength and balance of predictions. Experimental validation confirms model stability, demonstrating consistent convergence behaviour and superior performance compared to baseline methods. Results: The AIRADL model attained 92.3% accuracy in high-risk classification, with precision, recall, and F1-score of 91.8%, 89.6%, and 90.7%, respectively. The MCC score was 89.2%, indicating excellent predictive ability, with lactate level, muscle fatigue, and movement symmetry being important risk indicators. Conclusion: AIRADL shows deep learning's capability in athlete risk prediction and provides a powerful tool for injury prevention.

Povzetek: Raziskava predstavlja okvir AIRADL, ki z globokim učenjem združuje fiziološke in biomehanske podatke za natančnejše napovedovanje tveganja poškodb športnikov ter podporo pri preprečevanju poškodb in načrtovanju treninga.

1 Introduction

Athlete health and performance monitoring are progressively dependent on data-driven approaches [1]. Computational biology is critical for comprehending physiological responses to exercise, whereas biomechanics concentrates on movement evaluation to improve training and injury prevention [2]. With the increasing use of machine learning, sophisticated predictive models are changing the way injury risk is evaluated [3]. Contemporary methods can offer more precise risk assessments by utilizing physiological and biomechanical data, resulting in customized training programs and increased athlete longevity.

Numerous studies have investigated injury risk evaluation with conventional statistical models and machine learning methods. Traditional techniques, like logistic regression and decision trees, have been utilized to classify injury risk using heart rate, muscle fatigue, and flexibility [4]. Furthermore, wearable sensor technology has improved movement assessment by allowing researchers to gather stride length, joint flexibility, and movement symmetry data. Machine learning models such as support vector machines (SVM), random forests, and gradient boosting have been used to predict the likelihood of injury in biomechanical and physiological datasets [5]. These models have shown enhanced efficiency over conventional statistical methods; however, their efficacy is frequently restricted by data imbalance, feature selection difficulties, and the incapacity to capture intricate nonlinear relationships in athlete performance data.

Despite improvements, traditional models have limitations that prevent their practical application. Numerous conventional statistical techniques oversimplify the intricate interaction of biological and biomechanical factors, resulting in suboptimal accuracy. Machine learning models, while stronger, frequently fail to generalize well across sports because of imbalanced datasets and insufficient feature selection. Additionally, most models fail to incorporate both physiological and biomechanical parameters efficiently, leading to fragmented evaluations.

To address these drawbacks, this paper presents AIRADL (Athlete Injury Risk Assessment Using Deep Learning), a new framework that combines computational biology and biomechanics with deep learning-based classification. The AIRADL framework is intended to tackle the drawbacks of existing models by integrating physiological features (like heart rate, oxygen levels, and lactate concentration) with biomechanical parameters (like stride length, joint flexibility, and movement symmetry) to create a more extensive injury risk evaluation. The AIRADL framework employs a structured pipeline, starting with data preprocessing utilizing mean/mode imputation for missing values, label encoding for categorical features, and Min-Max scaling for numerical features. Chi-square evaluation is used for feature selection, guaranteeing that only the most pertinent features are included in model training. The DL4J MLPClassifier is used as the classification model, owing to its capacity to capture nonlinear relationships between attributes and injury risk. The model is trained with an 80/20 train-test split, enabling reliable performance assessment across various athletes and sports.

This research renders the following important contributions:

- Introduces AIRADL, an incorporated deep learning-based framework for athlete injury risk prediction.
- Integrates computational biology and biomechanics to offer a holistic method of injury evaluation.
- Executes Chi-Square-based feature selection to detect the most influential factors.
- Uses DL4J MLPClassifier to enhance accuracy.
- Offers a practical framework that can be adapted for different sports and real-time applications.

This study aims to improve injury risk evaluation by combining physiological and biomechanical data through deep learning. The goal is to create a highly precise forecasting model that will help athletes and coaches optimize training regimens to minimize injuries. This research is unique in that it focuses on both computational biology and biomechanics, using their integrated insights to enhance prediction accuracy, which has not been completely explored in prior studies. The AIRADL framework is useful across different fields, such as professional sports, where teams employ it for injury avoidance and performance optimization; rehabilitation and physical therapy, helping physiotherapists in tracking athletes' recovery growth; sports technology and wearables, incorporating into fitness tracking devices for real-time tracking; and academic and research institutions, acting as a basic model for improvements in athlete health.

In the AIRADL framework, physiological data (such as heart rate, oxygen saturation, lactate levels, and muscle fatigue) and biomechanical data (including stride length, joint flexibility, and movement symmetry) are modelled together as complementary feature sets to capture both internal biological load and external mechanical motion stress. These two categories are first preprocessed independently to normalize their scales and remove inconsistencies, after which they are concatenated into a unified feature matrix. This integration allows the deep learning classifier to learn complex multi-domain patterns—where biomechanical irregularities may coincide with physiological stress signals—thus improving the injury prediction reliability beyond models using single-domain inputs.

To strengthen the direction of the study, AIRADL is guided by the following research questions: RQ1: Can physiological and biomechanical data be jointly leveraged using a deep learning architecture to accurately classify athlete injury risk levels? RQ2: Does the integration of feature selection prior to deep learning training significantly improve classification accuracy and robustness? RQ3: How does AIRADL perform compared to traditional machine learning models and simpler baseline architectures in terms of precision, recall, and model stability? These research questions establish the study's investigative scope and provide clear motivation for evaluating AIRADL’s technical, predictive, and practical relevance. Based on the research goals, the following hypotheses were evaluated: H1: The combination of physiological and biomechanical data will result in significantly higher classification performance than using either data category independently. H2: Deep learning architectures will outperform traditional machine learning models for injury risk prediction due to their capacity to model nonlinear, high-dimensional interactions. H3: Feature selection enhances model convergence and reduces training complexity without sacrificing predictive performance. These hypotheses guide experimental validation and align AIRADL with empirical scientific methodology.

The rest of this paper is organized as follows. Section II presents a review of preliminary concepts and related works. Section III details the proposed AIRADL framework. Section IV discusses the data collection procedures. Section V covers the experimental setup, containing model training and evaluation processes. Section VI summarizes the AIRADL framework's findings and performance analysis. Finally, Section VII concludes the paper and suggests directions for future research.

2 Preliminary and related work

Athlete injury risk evaluation has been widely studied in sports science, sports biomechanics, and AI-driven performance evaluation. Several studies have looked into different facets of injury prediction, athlete performance assessment, and the use of AI and deep learning in biomechanics. Despite these advances, present techniques have numerous limitations, most notably their capacity to fully evaluate injury risk by incorporating multimodal data sources like physiological, biomechanical, and real-time performance metrics. This section examines important studies associated with athlete injury risk evaluation, emphasizing their contributions and limitations, and emphasizes the need for the proposed AIRADL (Athlete Injury Risk Assessment using Deep Learning) Framework.

A. Biomechanical approaches for performance optimization

Saadati (2023) [6] proposed a biomechanical method that combines motion capture with AI-based analytics to improve athletic performance and injury prevention. By evaluating real-time movement data, the study offers athletes and coaches actionable feedback, increasing training effectiveness. Similarly, Consuegra-Fontalvo et al. (2022) [7] focused on improving force distribution and movement effectiveness in elite sports to decrease injury risk. Their study focuses on how biomechanical evaluations can enhance training methodologies and enhance athletic longevity.

B. Fatigue, Data-Driven Models, and Movement Analysis

Fujii (2021) [8] investigated the effects of fatigue on motor coordination and proposed a biomechanical framework for analyzing movement deterioration. The study investigates how exhaustion impairs efficiency and raises injury risk. Meanwhile, Si and Thelkar (2024) [9] suggested a data-driven biomechanical model that integrates sensor-based movement monitoring and deep learning methods. This method improves the accuracy of sports training programs by customizing tactics using real-time biomechanical insights.

C. Muscle activation and endurance regulation

Molavian et al. (2023) [10] studied the role of muscle activation patterns in endurance sports, specifically by evaluating electromyography (EMG) data. Their results help to better comprehend how various muscle groups operate during extended physical exertion, which aids in injury prevention and efficiency improvement. Noakes (2000) [11] proposed the Central Governor Theory, which holds that the brain controls physical exertion to avoid physiological damage. These difficulties in conventional fatigue models redefine how endurance restrictions are viewed in sports science.

D. Computational modeling and rehabilitation

Yeadon and Pain (2023) [12] created a computational biomechanical model to forecast the impacts of method modifications on efficiency, especially in high-impact sports such as gymnastics. Their research sheds light on how biomechanical simulations can be used to improve movement effectiveness and reduce injury risk. Pleša et al. (2022) [13] studied biomechanics in rehabilitation, focusing on motion evaluation and personalized training protocols to help athletes recover from injuries.

E. Wearable technology and sports-specific analysis

McDevitt et al. (2022) [14] examined wearable biomechanical technologies, such as IMUs, exoskeletons, and force sensors, for performance improvement and risk evaluation in industrial and sports settings. Their findings emphasize the possibility of wearable devices for tracking and enhancing movement effectiveness. Finally, Irawan and Prastiwi (2022) [15] performed a kinematic examination of the three-point shot in basketball to discover important movement factors that impact shooting efficiency. Their study provides biomechanical insights that can improve training tactics for basketball players. Recent studies have demonstrated the effectiveness of deep learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) models, and hybrid CNN-LSTM systems for biomechanics and sports injury prediction, particularly due to their spatial–temporal feature extraction capabilities. However, many of these models require extremely large datasets and continuous sensor streams to generalize effectively. Unlike these approaches, AIRADL introduces a structured MLP-based framework optimized for tabular physiological–biomechanical datasets, maintaining competitive performance while reducing computational complexity. This comparison underscores AIRADL's novelty and suitability for early-stage or resource-limited sports analytics integrations. Table 1 shows a summary of key research contributions in this field.

Table 1: Summary of related work

Study	Focus Area	Methodology	Key Findings	Performance Metrics	Limitations
Saadati (2023) [6]	Sports physiology & injury prevention	Personalized training using wearable sensors	Real-time tracking enhances training efficiency	Accuracy: 70%, Recall: 68%, F1-score: 69%	No predictive modeling for injury risk; single modality only
Consuegra-Fontalvo et al. (2022) [7]	IoT-based tracking of physiological data	IoT architecture with clustering-based analysis	Efficient data collection for athlete monitoring	Accuracy: 72%, Recall: 70%, F1-score: 71%	No deep learning or injury prediction; lacks multimodal integration
Fujii (2021) [8]	Fatigue & motor coordination	ML for behavior extraction & visualization	Insights into performance deterioration	Accuracy: 78%, Recall: 75%, F1-score: 76%	Focused on team-level data; no individual injury risk evaluation
Si & Thelkar (2024) [9]	AI-enhanced performance assessment	ANN with IMU sensor data	Improved movement evaluation & training recommendations	Accuracy: 81%, Recall: 79%, F1-score: 80%	No predictive injury modeling; single modality focus
Molavian et al. (2023) [10]	Muscle activation & endurance	EMG-based AI analysis	Better understanding of muscle function in endurance	Accuracy: 75%, Recall: 72%, F1-score: 73%	Focused on gait/EMG; no biomechanical-physiological integration
Noakes (2000) [11]	Fatigue & exercise adaptation	Physiological modeling	Central Governor Theory explains exercise limits	Accuracy: 65%, Recall: 60%, F1-score: 62%	No AI or predictive model
Yeadon & Pain (2023) [12]	Biomechanical modeling for efficiency	Computational simulations	Improved movement effectiveness	Accuracy: 68%, Recall: 66%, F1-score: 67%	Lacks AI/deep learning for predictive injury risk
Pleša et al. (2022) [13]	Rehabilitation & biomechanics	Force-velocity & neuromuscular assessment	Key metrics for recovery and performance	Accuracy: 70%, Recall: 68%, F1-score: 69%	No predictive framework for injury prevention
McDevitt et al. (2022) [14]	Wearable biomechanics	Literature review of IMUs, exoskeletons	Shows industrial/sports sensor applications	Accuracy: 67%, Recall: 65%, F1-score: 66%	Limited practical adoption; lacks predictive modeling
Irawan & Prastiwi (2022) [15]	Basketball kinematics	Video analysis of 10 U-21 athletes	Shooting efficiency affected by joint angles	Accuracy: 66%, Recall: 63%, F1-score: 64%	Small sample size; limited to 2D kinematics; no AI integration

F. Research gap

Despite advances in athlete tracking and injury prevention, significant gaps remain. Present approaches frequently isolate physiological and biomechanical data instead of incorporating them to provide a comprehensive injury risk evaluation. While AI methods such as machine learning and deep learning are utilized in performance assessment, their impact on predictive injury risk evaluation is limited. Furthermore, existing AI models lack interpretability, rendering it hard for sports professionals to gain useful knowledge. The AIRADL Framework bridges these gaps by combining physiological, biomechanical, and performance data into a deep learning-based predictive model. Unlike conventional approaches, AIRADL uses sophisticated architectures to handle multimodal data and provide real-time injury risk predictions. Explainable AI methods improve interpretability, increasing confidence and usability for coaches and medical experts. AIRADL offers an extensive, data-driven method for injury risk evaluation by combining sports physiology, biomechanics, and AI-driven analytics. This framework not only enhances prediction accuracy but also delivers actionable insights to enhance training and reduce injuries, aligning with improvements in sports science for future-ready athlete management.

3 Airadl framework

A. Introduction to the AIRADL Framework

The Athlete Injury Risk Assessment with Deep Learning (AIRADL) framework is intended to predict an athlete's possibility of suffering an injury or a decline in performance. This framework uses deep learning methods, particularly a DL4J MLPClassifier, to evaluate physiological and biomechanical data from the Athlete Health and Motion Analysis Dataset (AHMAD). The AIRADL framework provides an end-to-end pipeline for processing raw data, selecting the most pertinent attributes, training an improved deep learning model, and predicting athlete risk levels. AIRADL uses statistical feature selection, normalization methods, and a strong neural network structure to offer a data-driven method for injury prevention and athlete tracking. Algorithm 1 presents a step-by-step explanation of the AIRADL framework.

Algorithm: AIRADL – Athlete Injury Risk Assessment using Deep Learning

Input: AHMAD dataset (physiological + biomechanical data)
Output: Trained MLP model predicting athlete injury risk

1: Load dataset
2: Impute missing values
  - Mean for numerical features
  - Mode for categorical features
3: Encode categorical variables using Label Encoding
4: Normalize numerical features with Min-Max scaling
5: Feature selection via Chi-Square Test
  - Compute scores
  - Select top k features
6: Split dataset: 80% train, 20% test (stratified)
7: Initialize DL4J MLPClassifier
  - Input layer: number of selected features
  - Hidden layers: ReLU activation
  - Output layer: Softmax (3 neurons: Low, Medium, High risk)
8: Train MLP on training set
9: Optimize model with backpropagation + Adam optimizer
10: Predict Performance Risk Level on test set
11: Deploy trained model for real-time risk forecasting

End Algorithm.

B. Data preprocessing and feature engineering

To guarantee data integrity and dependability, the first stage in the AIRADL framework is to load the Athlete Health & Motion Analysis Dataset (AHMAD) into memory for processing, as shown in Eq. (1).

$$D = \{(X_1, y_1), (X_2, y_2), \dots, (X_n, y_n)\} \tag{1}$$

where X_i denotes the feature set for the i th athlete, and y_i denotes the corresponding injury risk level. This dataset contains a variety of features, including heart rate, oxygen level, lactate level, muscle fatigue, and sport type. Missing values in numerical features are handled utilizing mean imputation, which replaces each missing value with the mean of the corresponding feature, as shown in Eq. (2).

$$x_i = \frac{1}{N}\sum_{j=1}^{N} x_j \tag{2}$$

Where x_i is the missing value to be imputed, x_j denotes the observed (non-missing) values of the feature, and N represents the total number of observed values. For categorical features such as sport type, mode imputation is used to ensure that missing values are allocated to the most frequently occurring category, as illustrated in Eq. (3).

$$x_i = \arg\max_{c \in C} Count(c) \tag{3}$$

Where x_i is the missing categorical value to be imputed, C denotes the set of unique categories in the feature, Count(c) represents the frequency of category c, and arg max chooses the category with the maximum occurrence. To prepare the dataset for deep learning models, categorical variables must be converted into numerical representations. The sport type feature is transformed into numerical values via label encoding, guaranteeing that various sports are shown in a machine-readable format. Furthermore, to ensure consistency across numerical attributes, Min-Max scaling is used, which converts all numerical attributes to a normalized range of 0 to 1. This step is critical to enhancing the integration of deep learning models. Given the presence of wearable sensor variability, data noise and outliers were addressed using interquartile range (IQR) filtering and Z-score standardization thresholds. Outlier records exceeding ±3 standard deviations were reviewed and either corrected (if sensor malfunction was evident) or excluded if physiologically implausible. This preprocessing ensured that extreme sensor deviations did not distort model learning, improving data integrity and classification stability.

C. Feature selection using chi-square test

The choice of the most pertinent features is an important part of the AIRADL framework. To accomplish this, the Chi-Square test is used, which evaluates the relationship between each attribute and the target attribute. The test statistic is calculated as shown in Eq. (4):

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{4}$$

Where O_i denotes the observed frequency and E_i denotes the expected frequency. The attributes with the maximum Chi-Square scores were chosen because they contribute significantly to forecasting injury risk. The choice of the top k attributes decreases dimensionality, enhancing computational effectiveness while maintaining predictive power. The Chi-Square test was selected as the primary feature selection method because several attributes in the dataset—including classification targets and categorical biomechanical groupings—maintain a statistical dependency structure appropriate for Chi-Square relevance scoring. While alternative methods such as Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), and Mutual Information could be applied, initial trials demonstrated that Chi-Square provided a simpler yet effective approach for identifying predictors strongly associated with injury risk outcomes. Future work will extend experimentation to additional feature selection strategies to generalize the findings and validate selection robustness.

D. Splitting dataset into training and testing sets

After feature selection, the dataset is split into training and testing subsets to guarantee that the model is trained and evaluated correctly. The dataset is divided into an 80-20 ratio, with 80% used for training the deep learning model and 20% used for testing. Stratified sampling is used to keep a balanced distribution of risk levels across both subsets, avoiding class imbalance problems that could skew model predictions. Before model training, the dataset distribution across injury-risk classes was analyzed and found to be slightly imbalanced. Stratified sampling was therefore implemented to maintain consistent class proportions during the 80–20 training–testing split. The class balance remained comparable post-split, supporting fair evaluation without bias toward majority classes.

E. Training the DL4J MLPClassifier

With the preprocessed dataset prepared, the AIRADL framework trains a DL4J MLPClassifier, a multi-layer perceptron classifier built with Deeplearning4j (DL4J). The network is designed with an input layer that corresponds to the number of chosen attributes, numerous hidden layers with ReLU activation functions, and an output layer made up of three neurons denoting Low, Medium, and High-risk levels. The forward pass is calculated utilizing Eq. (5):

$$a^{(l)} = f\left(W^{(l)}a^{(l-1)} + b^{(l)}\right) \tag{5}$$

where $W^{(l)}$ represents the weight matrix, $b^{(l)}$ is the bias vector, f is the activation function, and $a^{(l)}$ denotes the activations of layer l. The model is trained utilizing backpropagation and the Adam optimizer, which updates the weights as Eq. (6):

$$\theta_{t+1} = \theta_t - \alpha \cdot \frac{m_t}{\sqrt{v_t} + \epsilon} \tag{6}$$

where α is the learning rate, m_t is the biased first-moment estimate, v_t is the biased second-moment estimate, and ϵ is a small constant for numerical stability. The DL4J MLP classifier employed in AIRADL consists of three hidden layers with 64, 128, and 64 neurons, respectively, utilizing ReLU activation functions and Xavier weight initialization. Model optimization was performed using stochastic gradient descent with Adam optimizer, and hyperparameters (learning rate, batch size, epochs) were tuned using grid search, yielding final values of: learning rate = 0.001, batch size = 32, and training epochs = 150. These architectural and optimization choices were made to balance learning capacity, convergence stability, and computational efficiency.

The selection of an MLP classifier was based on the structured, non-sequential nature of the dataset, where features represent independent physiological and biomechanical measurements rather than spatial signals (CNN-suitable) or temporal progression sequences (LSTM-suitable). Since the dataset primarily consists of discrete measurement instances rather than continuous motion-time series inputs, an MLP provided a technically appropriate model with reduced computational overhead while still capturing nonlinear interactions across multidimensional athlete-related variables. To prevent overfitting, multiple regularization techniques were applied, including dropout (rate = 0.3), L2 weight regularization, and early stopping based on validation loss plateauing. Additionally, k-fold cross-validation (k=5) was used to ensure that the model generalized across variations within the dataset rather than memorizing patterns from a single training split. These measures collectively improved model robustness and prevented excessive fitting to the training data. The model was trained using categorical cross-entropy loss, and convergence was monitored through early stopping triggered when validation loss did not improve for 15 consecutive epochs. Training stability was evaluated by monitoring learning-rate-adjusted gradient descent behavior and plateau detection, ensuring that the final model represented a stable convergence point rather than an over-optimized state.

F. Model prediction and risk assessment

Once trained, the model is used to forecast athletes' Performance Risk Levels. Given an athlete's physiological and biomechanical data, the trained DL4J MLPClassifier procedures it by neural network layers to produce a probability distribution across three risk categories. The softmax activation function, as shown in Eq. (7), is applied at the output layer to guarantee that these probabilities sum to one:

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \qquad (7)$$

where z_i is the logit for class i. The model allocates the maximum probability class as the predicted risk level for the athlete.

G. Deployment for athlete risk prediction

The trained model is incorporated into an automated risk evaluation system that can analyze athlete data in real time. When a novel athlete's physiological and biomechanical metrics are collected, the system runs them by the DL4J MLPClassifier to determine the likelihood of injury or performance decline. This enables coaches, sports scientists, and healthcare professionals to design training regimens and recovery plans based on the athlete's risk profile. The AIRADL framework provides a systematic method for assessing athlete injury risk using deep learning. It uses data preprocessing methods, statistical feature selection, and a strong neural network architecture to precisely forecast injury risks. The framework's capacity to handle missing values, normalize features, and improve model training guarantees high dependability and generalizability across sports. Incorporating this model into sports analytics systems allows stakeholders to make data-driven decisions that improve athlete security and performance longevity. Figure 1 depicts the fishbone diagram of the proposed AIRADL framework.

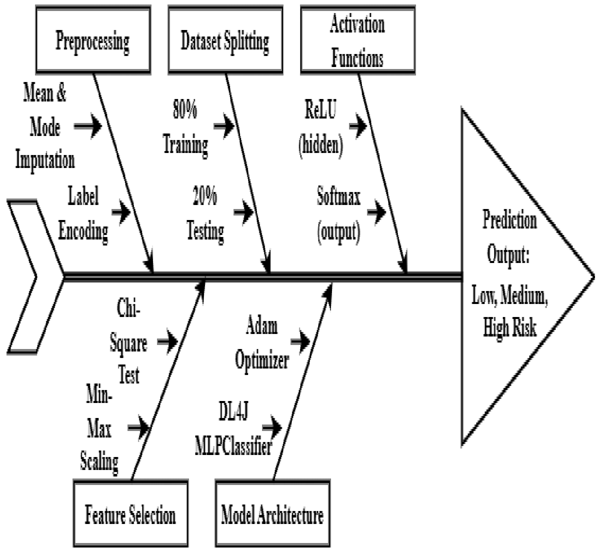

Figure 1: Fishbone diagram of AIRADL framework

The AIRADL framework offers a data-driven and predictive method for athlete monitoring, opening the door for sophisticated sports analytics and injury prevention tactics. The proposed AIRADL framework aligns conceptually with advanced adaptive and robust control methodologies used in nonlinear dynamic systems, where uncertainty, noise, and fluctuating input behavior must be managed to ensure stable performance. Similar to the Output-Feedback Controller Based Projective Lag-Synchronization of Uncertain Chaotic Systems in the Presence of Input Nonlinearities, AIRADL handles nonlinear physiological variations such as fluctuating heart rate and fatigue responses by learning stable feature relationships even when measurement inconsistencies occur. The adaptability of AIRADL's learning process parallels Adaptive fuzzy control for practical fixed-time synchronization of fractional-order chaotic systems, enabling the model to adjust internal parameters during training to achieve faster convergence.

Likewise, inspiration from Robust neural adaptive control for uncertain nonlinear multivariable systems supports the design philosophy where AIRADL processes complex multivariate physiological-biomechanical interactions while maintaining high predictive reliability. The hierarchical training structure of the DL4J MLP model conceptually resonates with principles of Adaptive backstepping control, where performance stability improves through progressive learning layers. Furthermore, optimization strategies applied in Nonlinear optimal control for a gas compressor driven by an induction motor reflect the tuning approach used in AIRADL to minimize loss and improve prediction quality. Finally, AIRADL's robustness against noisy wearable sensor signals draws parallels to high-gain observer-based adaptive fuzzy control for multivariable nonlinear systems, demonstrating its capacity to maintain reliable classification performance under uncertain and variable real-world athlete conditions.

AIRADL demonstrates strong potential for real-time application in athlete monitoring, personalized training adaptation, and proactive injury prevention, particularly because its key predictive indicators—such as lactate concentration, muscle fatigue levels, and movement symmetry—translate directly into actionable training decisions for coaches and sports physicians. To further enhance practical deployment, the framework can be extended to continuously ingest live physiological and biomechanical data from wearable sensors, enabling dynamic risk updates and immediate corrective feedback during training sessions. Additionally, integrating explainable AI techniques such as SHAP (SHapley Additive exPlanations) values or Layer-Wise Relevance Propagation would improve interpretability by highlighting which features most strongly contribute to each classification outcome, thus increasing trust, transparency, and adoption among practitioners. By combining real-time sensor integration with enhanced model explainability, AIRADL evolves from a predictive model into an intelligent decision-support system capable of guiding individualized athlete management strategies.

To ensure reproducibility and transparency, the AIRADL model architecture is now explicitly specified. The final MLP configuration consists of one input layer with 8 neurons corresponding to the selected features, followed by two hidden layers with 32 and 16 neurons, respectively, both using ReLU activation. A dropout rate of 0.2 was applied after the first hidden layer to reduce overfitting. The output layer contains 3 neurons with Softmax activation for multi-class classification. Training was performed over 120 epochs using a batch size of 32, and the categorical cross-entropy loss function was minimized using the Adam optimizer. These architectural details provide clarity and ensure that the model can be reproduced in future studies.

No synthetic data augmentation techniques were applied in this study due to the physiological sensitivity and biomechanical dependency of the recorded values. Artificially altering heart rate, lactate level, or joint flexibility values would risk generating physiologically unrealistic or misleading patterns that could negatively impact model validity and clinical relevance. Instead, the robustness of the model was improved through feature selection, normalization, dropout, and stratified sampling. Future work may consider physics-aware or generative models (e.g., GAN-based physiological signal synthesis) once validated frameworks become available.

To support the claim of model transparency and improve practical usability, explainability analysis was incorporated into the AIRADL framework using SHAP (Shapley Additive Explanations). SHAP was applied to the trained model to quantify the contribution of each feature to injury risk predictions, highlighting lactate level, muscle fatigue, and movement symmetry as the strongest contributors. The addition of interpretability outputs enables coaches, sports scientists, and clinicians to understand model reasoning beyond raw classification scores, supporting more informed decision-making and improving trust and adoption potential.

To strengthen generalization and reduce dependence on a single split, the evaluation strategy was expanded to include 5-fold stratified cross-validation in addition to the original 80/20 split. Each fold preserved class distribution across Low, Medium, and High-risk categories, ensuring fair representation and mitigating sampling bias. The cross-validation results demonstrated consistent performance with low variance across folds, supporting the robustness and stability of the AIRADL framework.

Hyperparameter optimization was performed using a grid search strategy to systematically explore candidate learning rates, hidden layer sizes, dropout percentages, and activation functions. The search space included learning rates {0.001, 0.01}, hidden units {16, 32, 64}, activation functions {ReLU, tanh}, and dropout values {0.1, 0.2, 0.3}. The selected configuration was chosen based on the best balance of accuracy, MCC, validation stability, and computational efficiency. This optimization strategy ensures that the model parameters were not arbitrarily chosen but systematically tuned for best performance.

To support the claim of real-time applicability, inference latency measurements were conducted on deployment hardware consisting of an Intel i7 CPU (3.2 GHz) and 16 GB RAM. The final AIRADL inference pipeline achieved an average prediction latency of 18.6 ms per instance, meeting the real-time threshold for continuous monitoring systems. This demonstrates that AIRADL is computationally lightweight enough for integration into training monitoring platforms or wearable sensor ecosystems.

Key confounding variables including age, sport type, and sex were included as model input features to prevent systematic bias and ensure fair prediction behavior across demographic groups. Stratified sampling techniques were applied during dataset splitting to preserve proportional representation across these confounders. Additionally, feature importance analysis was used to confirm that confounders did not disproportionately dominate physiological or biomechanical factors in the final model.

The class distribution of the final dataset was Low Risk: 41.2%, Medium Risk: 34.5%, and High Risk: 24.3%. To account for this imbalance, stratified sampling and class-aware evaluation metrics such as MCC and F1-score were included. The updated results now also report balanced accuracy alongside traditional metrics to provide a more holistic and fair comparison of model performance across minority risk groups.

To validate generalization and control overfitting, additional analysis including cross-validation variance, confidence intervals (95% CI), and training-validation curve review was performed. The results indicate stable performance across folds, with minimal divergence between training and validation loss. Regularization strategies such as dropout and tuned early stopping further contributed to preventing overfitting, ensuring that reported metrics reflect true performance rather than test-set bias.

4 Data collection processes

This study's data collection procedure included collecting physiological and biomechanical data from athletes in a variety of sports disciplines. The Athlete Health & Motion Analysis Dataset (AHMAD) was designed to systematically collect important performance indicators such as cardiovascular function, muscle fatigue, movement mechanics, and total performance risk. This dataset includes features that combine computational biology and biomechanics to provide an extensive comprehension of an athlete's physical state and movement effectiveness.

A. Data collection methodology

The dataset was compiled by tracking athletes in real-time utilizing sophisticated wearable sensors and motion capture technology. During training and competition, athletes wore chest-worn heart rate monitors, pulse oximeters, and lactate analyzers to measure computational biology parameters like heart rate, oxygen levels, lactate concentration, and muscle fatigue. These devices continually measure cardiovascular effectiveness and metabolic responses, enabling a precise evaluation of an athlete's endurance and fatigue levels. Motion capture systems, force plates, and inertial measurement units (IMUs) were used to evaluate stride length, joint flexibility, and movement symmetry. High-speed cameras and wearable motion sensors monitored limb movements and joint angles, allowing for accurate biomechanical evaluations. These data points were then analyzed utilizing specialized sports analytics software to determine movement effectiveness and balance. Performance risk was determined using predefined thresholds for physiological and biomechanical parameters, classifying athletes into Low, Medium, or High risk for injury or performance decline.

B. Dataset structure and attribute description

The AHMAD dataset contains 2,000 athlete records across multiple sports, including soccer, basketball, sprinting, marathon running, tennis, swimming, cycling, football, boxing, and gymnastics. Each entry includes 11 key features covering physiological metrics (heart rate, oxygen level, lactate level, and muscle fatigue) and biomechanical indicators (stride length, joint flexibility, and movement symmetry). Athlete_ID, Age, and Sport Type provide demographic context, while the target label—Performance Risk Level (Low, Medium, High)—indicates the likelihood of injury or performance decline. Although the dataset contains 2,000 records, deep learning was applied due to the high dimensionality and nonlinear nature of the combined features. Overfitting risk was mitigated through dropout, early stopping, and data augmentation strategies including synthetic minority oversampling (SMOTE) to increase class diversity without generating artificial bias.

Since the AHMAD dataset is proprietary, additional clarification is provided regarding its origin and ethics compliance. Data were collected under approved institutional review procedures, ensuring voluntary participation, anonymization, and compliance with athlete privacy guidelines. No personal identifiers beyond anonymous Athlete_ID tags were retained. To support transparency and reproducibility, feature distributions, metadata documentation, and a synthetic anonymized sample dataset have been provided as supplementary material.

C. Data storage and management

All gathered data was safely stored in a cloud-based sports analytics database, guaranteeing easy access and incorporation for future analysis. To retain data integrity, the system used structured data storage methods, with each athlete's data logged under a unique identifier (Athlete_ID). Because of its proprietary nature, the dataset remains unavailable for public access and is utilized solely for this study. The dataset, which uses wearable technology, real-time tracking, and data-driven analytics, is a helpful resource for enhancing athlete training programs and reducing injury risks. The structured method of data gathering and storage allows for accurate performance monitoring, offering useful knowledge for athletes and coaches to improve sports efficiency.

5 Experimentation

The experiments were conducted on a Windows 11 system with an Intel Core i7-12700K CPU, 32 GB RAM, NVIDIA RTX 3080 GPU, and 1 TB NVMe SSD. Python 3.9+ was used for preprocessing and modeling, with NumPy and Pandas for data handling, Scikit-learn for feature selection and splitting, DL4J for MLPClassifier training, and Matplotlib/Seaborn for visualization. Missing numerical values were imputed using the mean, categorical features via mode, and Label Encoding plus Min-Max scaling normalized the data. Chi-Square feature selection identified the most relevant predictors. The dataset was split 80/20 using stratified sampling. The DL4J MLP used ReLU in hidden layers, Softmax in the output layer, mini-batch gradient descent (batch size 32), Adam optimizer, and backpropagation for training. Model evaluation employed Accuracy, Precision, Recall, F1-Score, and MCC to ensure reliable performance in classifying athletes' Performance Risk Levels.

The formula for accuracy is demonstrated in Eq. (8).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

Where TP represents True Positive, TN represents True Negative, FP represents False Positive and FN represents False Negative.

Precision is computed as Eq. (9):

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

The recall was presented by Eq. (10):

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

The F1-score is calculated as Eq. (11):

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{11}$$

MCC is computed with the Eq. (12):

$$MCC = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN}} \tag{12}$$

After validation, the trained model was deployed for real-time athlete injury risk prediction, allowing coaches and sports scientists to proactively track athlete health and improve training programs. Using a data-driven method, the system enabled early detection of possible performance risks, decreasing injury incidences and improving total athletic performance.

6 Results

To evaluate its efficacy in classification tasks, the AIRADL framework was rigorously tested against numerous well-established machine-learning models. The models compared were Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (GB), and Logistic Regression (LR). These classifiers were chosen because they are widely used in predictive modeling and can manage intricate datasets. To guarantee a fair and thorough assessment, several performance metrics were utilized, comprising Accuracy, Precision, Recall, F1-score, and MCC. Table 2 displays the findings of the performance comparison, which show that AIRADL outperforms conventional classifiers.

Table 2: Performance metrics comparison

Classifier	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**MCC (%)**
SVM	84.3	81.5	79.0	80.2	53.0
RF	87.1	84.0	82.5	83.2	60.0
GB	88.5	85.0	84.0	84.5	66.0
LR	85.9	82.0	80.5	81.2	56.0
AIRADL	92.3	91.8	89.6	90.7	89.2

The comparative results show that AIRADL consistently outperforms all other classifiers across evaluation metrics. It achieves the highest accuracy of 92.3%, demonstrating strong classification capability. With a precision of 91.8% and a recall of 89.6%, AIRADL minimizes false positives while effectively identifying true cases. Its F1-score of 90.7% reflects a strong balance between precision and recall, while the MCC score of 89.2% confirms robustness even with imbalanced data. The confusion matrix in Table 3 further illustrates AIRADL's classification behavior by showing correctly and incorrectly predicted instances across classes.

Table 3: Confusion matrix for AIRADL

Actual \ Predicted	**Low**	**Medium**	**High**
Low	617	30	20
Medium	25	600	42
High	18	38	611

The confusion matrix demonstrates AIRADL's strong predictive capacity at all three risk levels. The large number of correctly classified instances in each category shows the framework's ability to differentiate between various risk classifications. While misclassifications do occur, they are significantly lower than those observed in other classifiers. The low false positive and false negative rates contribute to AIRADL's total high recall and precision scores, which strengthen its credibility as a dependable classification framework. Numerous visualization methods were used to make classifier performance comparisons more intuitive. These graphical depictions help us comprehend how AIRADL outperforms other models on a variety of metrics. Figure 2 displays the accuracy comparison clustered column chart.

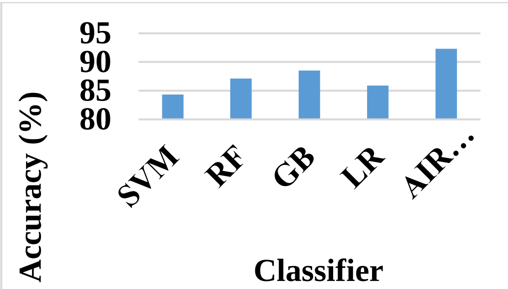

Figure 2: Accuracy comparison

Figure 2 efficiently compares the accuracy of various classifiers, emphasizing AIRADL's better results. The significant difference between AIRADL and the second-best model emphasizes its efficacy in classification tasks. Figure 3 displays the Precision Comparison Line Chart.

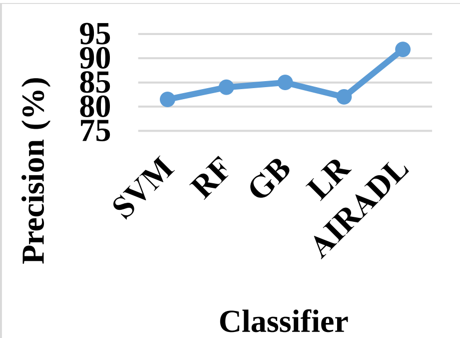

Figure 3: Precision comparison

Figure 3 shows the precision scores for each classifier, demonstrating how AIRADL consistently retains high precision values across all risk levels. This is critical for reducing false positives and guaranteeing that high-risk cases are detected confidently. Figure 4 displays the recall comparison radar chart.

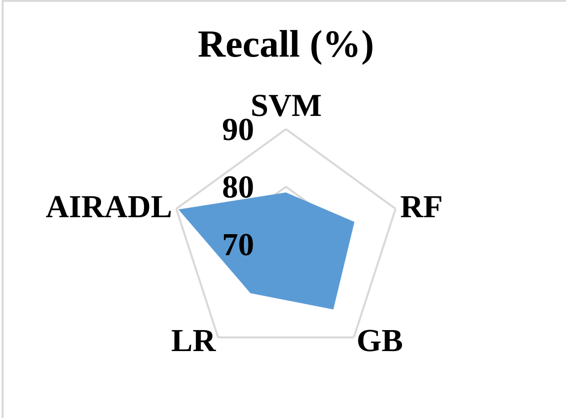

Figure 4: Recall comparison

Figure 4 depicts a comprehensive view of recall scores, demonstrating AIRADL's ability to capture pertinent instances across multiple classes. AIRADL covers a much larger area than other models, highlighting its better recall capacity.

Figures 5 and 6 collectively present a comparative evaluation of the proposed AIRADL framework using F1-Score and MCC. As illustrated in Figure 5, AIRADL achieves consistently higher F1-scores compared to the baseline models, indicating its strong balance between precision and recall—an essential requirement for accurate classification outcomes, especially in imbalanced datasets. Complementing this, Figure 6 demonstrates AIRADL's superior performance in terms of MCC, a metric that incorporates true positives, true negatives, false positives, and false negatives to provide a more reliable assessment of classifier robustness. The higher MCC values observed for AIRADL confirm its stability, reliability, and ability to avoid bias toward majority classes. Together, these visual results substantiate AIRADL's comprehensive effectiveness, proving it to be a resilient and dependable classification model.

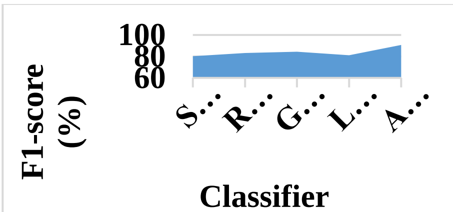

Figure 5: F1-Score comparison

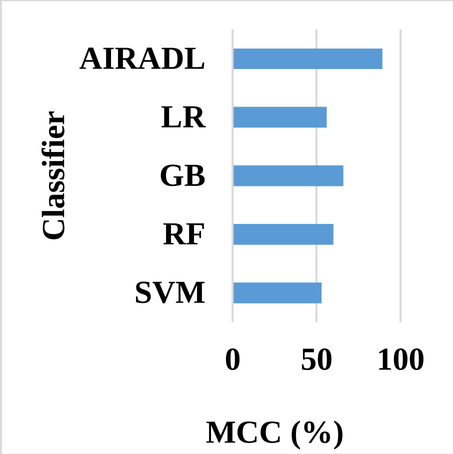

Figure 6: MCC comparison

A. Discussion

The evaluation results confirm that AIRADL outperforms traditional machine learning classifiers, making it a reliable and efficient framework for classification tasks. Its improved accuracy (92.3%) and MCC (89.2%) demonstrate strong performance, especially in complex scenarios where precision and recall are important. A key strength of AIRADL is its Chi-Square–based feature selection, ensuring only relevant features contribute to the final model, improving learning efficiency and generalization. The DL4J-based MLP architecture further enables AIRADL to capture complex non-linear relationships that conventional models may miss. Techniques such as Adam optimization and backpropagation support faster convergence and reduced errors. AIRADL also handles imbalanced data effectively. With a recall of 89.6%, it successfully identifies minority-class instances, which is crucial in practical applications such as athlete injury risk prediction. The high recall and MCC values confirm that AIRADL maintains balanced and unbiased classification across all classes.

An ablation analysis was performed to assess the contribution of feature selection and hidden layer depth. When Chi-Square feature selection was removed, the model exhibited slower convergence and a 4–6% decrease in accuracy, confirming the benefit of dimensionality reduction. Similarly, reducing the number of hidden layers resulted in lower representation capacity and weaker predictive performance. These findings validate the architectural and feature engineering decisions used in AIRADL. Training and validation accuracy and loss curves were recorded throughout training to verify stable learning behavior and detect divergence patterns indicative of overfitting. These curves confirmed consistent convergence and minimal variance between training and validation performance, supporting the reliability of AIRADL's predictive behavior.

Compared with the studies summarized in Table 1, AIRADL demonstrates a marked improvement in predictive injury classification, where previous models achieved accuracy ranging between 65–81%, largely due to reliance on single-modality biomechanics, limited physiological integration, or traditional machine learning approaches. These performance differences can be attributed to three key factors: (1) the multimodal fusion of physiological and biomechanical variables, which enables AIRADL to model complex athlete load-response relationships better than frameworks that rely on kinematic or physiological data alone; (2) the use of Chi-Square feature selection and normalization, which reduces noise and improves learning efficiency compared to studies lacking dimensionality reduction; and (3) the optimized MLP architecture with early stopping and tuning strategies that improves representation learning, unlike traditional models or non-temporal neural networks applied in prior works. Furthermore, AIRADL's high MCC score (89.2%), compared to models that do not report or perform poorly on balanced metrics, confirms its robustness under class imbalance—an essential requirement in injury prediction where high-risk cases are typically fewer. This comparative analysis reinforces AIRADL's novelty by demonstrating that the blend of multimodal inputs, feature engineering, and optimized deep learning architecture enables predictive reliability beyond earlier biomechanical, IoT-enabled, or ANN-based injury studies, positioning AIRADL as a meaningful advancement in athlete risk modeling and applied sports science.

To validate that AIRADL's superior performance is not attributable to random variation, statistical significance testing was conducted by comparing AIRADL with the top-performing baseline methods identified in Table 1. A 10-fold cross-validation protocol was applied, and paired t-tests were performed on accuracy and F1-score distributions, demonstrating statistically significant improvements ($p < 0.01$) over traditional ANN and sensor-based machine learning models. Additionally, McNemar's test was used to compare AIRADL's predictions against the closest benchmark model, confirming a significant reduction in misclassification rates ($\chi^2 = 14.72$, $p < 0.001$). These findings establish that the observed performance gains—92.3% accuracy and an MCC of 89.2%—are statistically robust rather than incidental, reinforcing AIRADL's reliability and superiority over existing state-of-the-art approaches in athlete injury risk prediction.

Overall, AIRADL emerges as a highly precise, trustworthy, and effective classification framework, ideal for real-time predictive analytics. Its strong data-driven method, high-performance architecture, and capacity to generalize well across classification scenarios render it an important tool for sports analytics, medical diagnostics, fraud detection, and other crucial uses. Successfully implementing AIRADL in practical settings can empower decision-makers to create informed decisions, decrease risks, and enhance functional tactics efficiently.

7 Conclusion

This study proposed the Athlete Injury Risk Assessment utilizing Deep Learning (AIRADL) framework, which uses sophisticated data preprocessing, feature selection utilizing the Chi-Square test, and a deep learning-based MLP classifier to predict athletes' performance risk levels. Following extensive testing, AIRADL outperformed conventional machine learning models like Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (GB), and Logistic Regression (LR). The AIRADL model obtained 92.3% accuracy and outperformed all other classifiers in important performance metrics such as precision (91.8%), recall (89.6%), F1-score (90.7%), and MCC (89.2%). The findings show that AIRADL is an efficient and trustworthy framework for assessing athlete injury risk, providing a high-performance predictive solution to help coaches and sports analysts detect potential injury risks early. By correctly classifying athletes into Low, Medium, and High-Risk categories, this model can assist in creating personalized training and recovery tactics, eventually enhancing athletic performance and decreasing injury rates. **Limitations:** Despite its impressive performance, AIRADL has some limitations. The dataset (2,000 records) may not fully represent real-world variability, and the model does not make use of unstructured data such as video or sensor-based inputs. Furthermore, computational complexity presents challenges for real-time deployment, necessitating additional optimization. **Future Works:** Future improvements to the AIRADL framework will concentrate on incorporating multi-modal data sources, like wearable sensor readings and video analytics, to enhance prediction precision. Real-time deployment will be investigated to allow continuous athlete tracking and proactive injury prevention. Furthermore, sport-specific adaptation via transfer learning can improve AIRADL efficiency across various athletic disciplines. Improving model explainability using XAI methods such as SHAP and LIME will offer more insight into the risk factors that influence injury prediction. Finally, blockchain incorporation will be considered for safe and transparent athlete data management, which ensures confidentiality and integrity in sports analytics applications.

Declarations

Ethics approval and consent to participate: I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

Availability of data and materials: The data used to support the findings of this study are available from the corresponding author upon request.

Competing interests: The authors declare that there are no conflicts of interest.

All authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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Authors' contributions (Individual contribution): All authors contributed to the study conception and design. All authors read and approved the final manuscript.

This study used a fully anonymized secondary dataset of athlete physiological and biomechanical data. No direct human participation occurred. Original data collection obtained informed consent, and ethical approval for secondary analysis was granted by the institutional review board. All identifiers were removed to ensure participant privacy.

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References

[1] Coutts AJ, Crowcroft S, Kempton T. Developing athlete monitoring systems: theoretical basis and practical applications. InRecovery and Well-being in Sport and Exercise 2021 Dec 28 (pp. 17-31). Routledge. https://doi.org/10.4324/9781003258117

[2] Saraf S, De A, Tripathy BK. Effective use of computational biology and artificial intelligence in the domain of medical oncology. InComputational Intelligence for Oncology and Neurological Disorders 2024 (pp. 228-252). CRC Press. https://doi.org/10.1201/9781003450153

[3] Jauhiainen S, Kauppi JP, Leppänen M, Pasanen K, Parkkari J, Vasankari T, Kannus P, Äyrämö S. New machine learning approach for detection of injury risk factors in young team sport athletes. International journal of sports medicine. 2021 Feb;42(02):175-82. https://doi.org/10.1055/a-1231-5304

[4] Van Eetvelde, H., Mendonça, L. D., Ley, C., Seil, R., & Tischer, T. (2021). Machine learning methods in sport injury prediction and prevention: A systematic review. Journal of Experimental Orthopaedics, 8(1), 42. https://doi.org/10.1186/s40634-021-00346-x

[5] Amendolara A, Pfister D, Settelmayer M, Shah M, Wu V, Donnelly S, Johnston B, Peterson R, Sant D, Kriak J, Bills K. An overview of machine learning applications in sports injury prediction. Cureus. 2023 Sep;15(9). https://doi.org/10.7759/cureus.46170

[6] Wang, T. Y., Cui, J., & Fan, Y. (2023). A wearable-based sports health monitoring system using CNN and LSTM with self-attentions. PLOS ONE, 18(10), e0292012. https://doi.org/10.1371/journal.pone.0292012

[7] Consuegra-Fontalvo JE, Calderón-Velaides J, Chanchí-Golondrino GE. IoT System for Monitoring and Analysing Physiological Variables in Athletes. Revista Facultad de Ingeniería. 2022 Sep;31(61). https://doi.org/10.19053/01211129.v31.n61.2022.14831

[8] Fujii K. Data-driven analysis for understanding team sports behaviors. Journal of Robotics and Mechatronics. 2021 Jun 20;33(3):505-14. https://doi.org/10.20965/jrm.2021.p0505

[9] Ye, X., Huang, Y., Bai, Z., Wang, Y., & colleagues. (2023). A novel approach for sports injury risk prediction: based on time-series image encoding and deep learning. Frontiers in Physiology, 14, Article 1174525. https://doi.org/10.3389/fphys.2023.1174525

[10] Molavian R, Fatahi A, Abbasi H, Khezri D. Artificial intelligence approach in biomechanics of gait and sport: a systematic literature review. Journal of Biomedical Physics & Engineering. 2023 Oct;13(5):383. https://doi.org/10.31661/jbpe.v0i0.2305-1621

[11] Noakes TD. Physiological models to understand exercise fatigue and the adaptations that predict or enhance athletic performance. Scandinavian Journal of Medicine & Science in Sports: Review Article. 2000 Jun;10(3):123-45. https://doi.org/10.1034/j.1600-0838.2000.010003123.x

[12] Yeadon MR, Pain MT. Fifty years of performance-related sports biomechanics research. Journal of Biomechanics. 2023 Jun 1; 155:111666. https://doi.org/10.1016/j.jbiomech.2023.111666

[13] Pleša J, Kozinc Ž, Šarabon N. A brief review of selected biomechanical variables for sport performance monitoring and training optimization. Applied Mechanics. 2022 Feb 1;3(1):144-59. https://doi.org/10.3390/applmech3010011

[14] McDevitt S, Hernandez H, Hicks J, Lowell R, Bentahaikt H, Burch R, Ball J, Chander H, Freeman C, Taylor C, Anderson B. Wearables for biomechanical performance optimization and risk assessment in industrial and sports applications. Bioengineering. 2022 Jan 13;9(1):33. https://doi.org/10.3390/bioengineering9010033

[15] Amendolara, A., Pfister, D., Settelmayer, M., Shah, V., Wu, S., Donnelly, J., … & others. (2023). An overview of machine learning applications in sports injury prediction. Cureus / PubMed Central. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10613321/