Comparative Study of Approaches for Injury Risk Prediction in Athletes

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Abstract

Athlete injuries pose significant physical and psychological challenges, impacting both team performance and individual careers. With the increasing availability of data from wearable sensors, IoT devices, and physiological monitoring systems, a variety of data-driven approaches have emerged to predict injuries and improve athlete safety. This study presents a comparative analysis of established Machine Learning (ML) and Deep Learning (DL) techniques for predicting injury risk in athletes. It focuses on implementing and evaluating these models to assess their performance, interpretability, and applicability in real-world sports scenarios, with particular emphasis on predictive accuracy and real-time performance. By benchmarking these techniques, we aim to highlight their strengths, limitations, and practical relevance, offering insights for future research and deployments in sports analytics.

***K*eywords** : Injury prediction · Machine learning · Deep learning · Sport analytics · Wearable sensors

1 Introduction

In the rapidly evolving field of sports analytics, injury prevention has become a critical focus, driven by the increasing availability of real-time performance data from wearable sensors and IoT devices [6, 11]. These advancements enable AI-driven methods to proactively predict and mitigate injury risks in athletes. Traditional injury prediction models typically rely on static datasets [9], which often overlook the temporal dependencies that are crucial for identifying injury precursors [2]. In contrast, recent advancements in ML and DL based techniques have enabled the modeling of these sequential dependencies, offering new opportunities for injury risk assessment [12]. This comparative study explores both traditional statistical models and modern sequential architectures to predict injury risks more effectively. By establishing a comprehensive framework that balances prediction accuracy, computational efficiency, and real-world applicability, this study aims to provide actionable insights for coaches and sports medicine professionals, contributing to the broader goal of enhancing athlete safety and performance optimization [1, 5].

2 Motivation

Injury prevention plays a crucial role in maintaining athlete performance and longevity. Athletes are constantly exposed to the risk of both acute and chronic injuries, which can significantly impact their careers and the overall success of their teams [5]. Traditional injury prediction methods, such as those based on biomechanical evaluations or historical injury data, are limited in their ability to accurately predict injuries in real time or consider the dynamic nature of athletic performance [2]. Recent advancements in wearable technology and sensor systems have generated a wealth of real-time data, offering an opportunity to incorporate ML and DL based techniques into injury risk prediction models [11, 13]. These data-driven approaches can account for complex patterns in the athlete's physiological responses, training loads, and even environmental factors, which were previously difficult to capture with traditional methods [3]. These methods can provide not only more accurate predictions but also deeper insights into the underlying factors contributing to injury risks, enhancing the safety and effectiveness of sports training programs [7]. This motivation drives the exploration of these advanced techniques, aiming to bridge the gap between theoretical models and their practical application in the real-world sports context.

3 Literature Review

Recent studies have underscored the potential of Artificial Intelligence (AI) in transforming injury prediction paradigms in sports by integrating data from wearable sensors, medical imaging, and biomechanical analyses [4]. For instance, a comprehensive review on diagnostic applications of AI highlighted the role of deep learning in processing complex imaging and sensor data to detect injury patterns early, achieving detection accuracies up to 92% in some models, demonstrating the promise of AI in early injury detection [6, 13]. Similarly, a scoping review of machine learning (ML) approaches in sports emphasized the variability in prediction performance with only 35% of studies using standardized evaluation metrics and the need for consistent benchmarking [2]. Research on youth soccer players has shown promising results with ML models that incorporate physiological and biomechanical variables, improving predictive accuracy from 68% to 83%, though challenges such as data quality and model generalizability persist [7]. Further, IoT-based systems using Recurrent Neural Networks (RNNs) have been explored for real-time injury prediction in martial arts, reporting over 85% accuracy, and emphasizing the importance of temporal feature analysis [11, 12]. Additionally, investigations have compared edge wearable device data with conventional methods, demonstrating that deep learning architectures such as Convolutional Neural Networks (CNNs) and RNNs can significantly enhance predictive performance and safety, in some cases improving predictive accuracy by 10–15% and reducing latency by 40% [3, 8]. Other notable works have employed hybrid approaches to fuse data-driven analytics with expert domain knowledge, paving the way for more robust and interpretable models, with some improving program efficiency by 25% and enabling real-time inference within 200 milliseconds [5, 9]. Collectively, these studies establish a foundation for the comparative analysis proposed in this work, while also highlighting existing gaps in interpretability and scalability.

4 Problem Statement

Injury risk prediction is gaining prominence in sports analytics, yet current approaches face challenges with data quality, generalizability, and interpretability [4]. Many ML models lack consistent evaluation metrics and adaptability in different athletic contexts. Moreover, existing systems often do not capture the temporal dynamics of movement and are difficult to interpret, limiting the applicability in the real world [1, 10]. This project addresses these gaps by comparing traditional ML models such as logistic regression, SVM, and random forests with sequential deep learning models such as LSTM and 1D CNNs, using wearable sensor data from the MHEALTH dataset. We evaluated each model's predictive performance (accuracy, recall, F1 score), interpretability, and computational feasibility.

To compensate for the absence of labeled injury data, we employ proxy labeling based on biomechanical and physiological risk indicators. Our aim is to develop a robust, transparent and scalable framework that supports proactive injury prevention in both high-performance and resource-constrained sports environments.

5 Methodology

The study follows a systematic approach comprising data preprocessing, exploratory data analysis (EDA), model development, evaluation, and validation.

5.1 Data Preprocessing

The MHEALTH dataset consists of multivariate time-series sensor data collected at 50Hz from wearable devices on the chest, wrist, and ankle. It includes 12 features representing 3D accelerometer, gyroscope, and ECG signals. We filtered out Subject 9 and 10 for testing and used the rest for training. Data was normalized using z-score standardization. The signals were segmented into overlapping 2-second windows (100 time steps) with a step size of 50 to preserve temporal patterns while reducing computational load. This format was suitable for both ML (via feature extraction) and DL models (using raw sequences).

5.2 Exploratory Data Analysis (EDA)

EDA was performed to gain a comprehensive understanding of the MHEALTH dataset. This included a basic overview of the data structure, removal of duplicate entries, verification of null values, and visualization of the activity label distribution. Boxplots were used to analyze acceleration and ECG signals across various activities, while correlation heatmaps and sensor-specific line plots helped identify risk patterns such as abnormal peaks or high-frequency oscillations. Additionally, a risk map labeling approach was explored. Insights from this analysis guided the proxy labeling strategy and informed the selection of relevant statistical features (e.g., mean, standard deviation, energy) for traditional ML models. As part of the exploratory data analysis, we visualized the distribution of activity labels

(Figure 1) and examined sensor signal patterns across different body locations, including chest accelerometer readings (Figure 2), ankle gyroscope outputs (Figure 3), and wrist ECG variations (Figure 4).

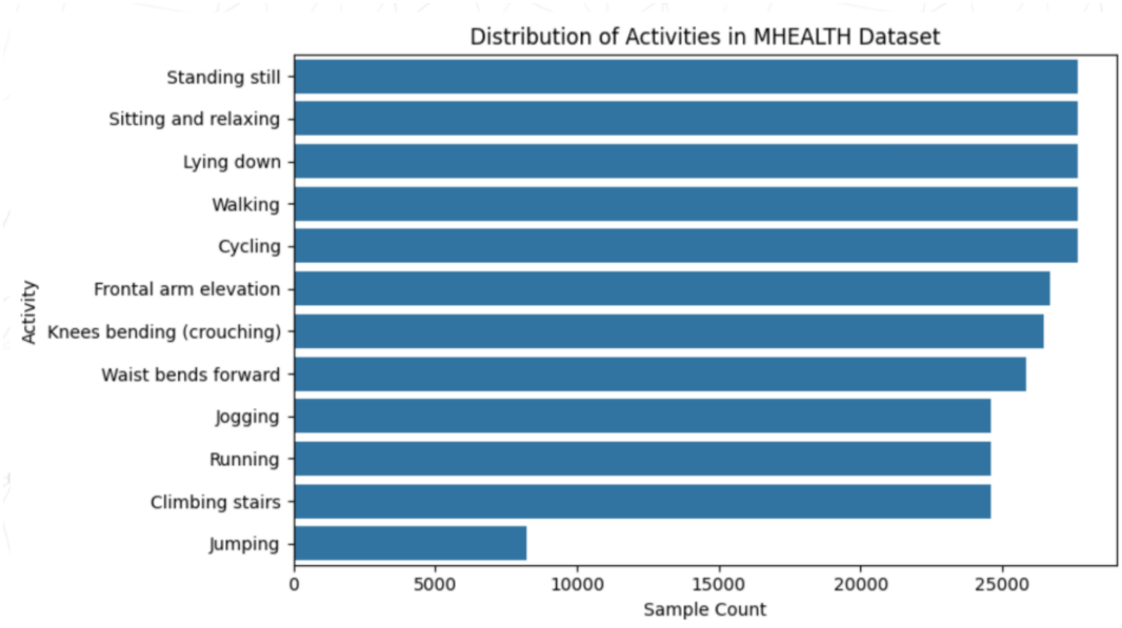

Figure 1: Distribution of Activity Labels

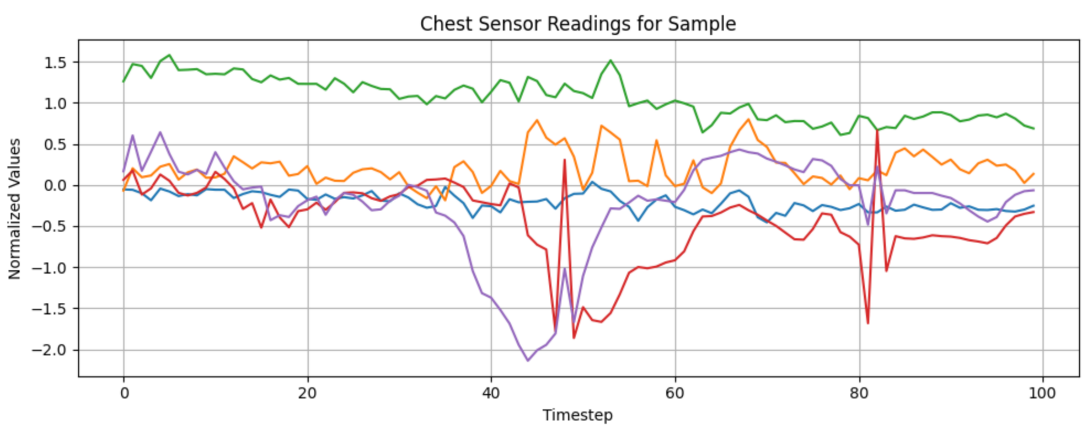

Figure 2: Chest Sensor – Accelerometer Readings

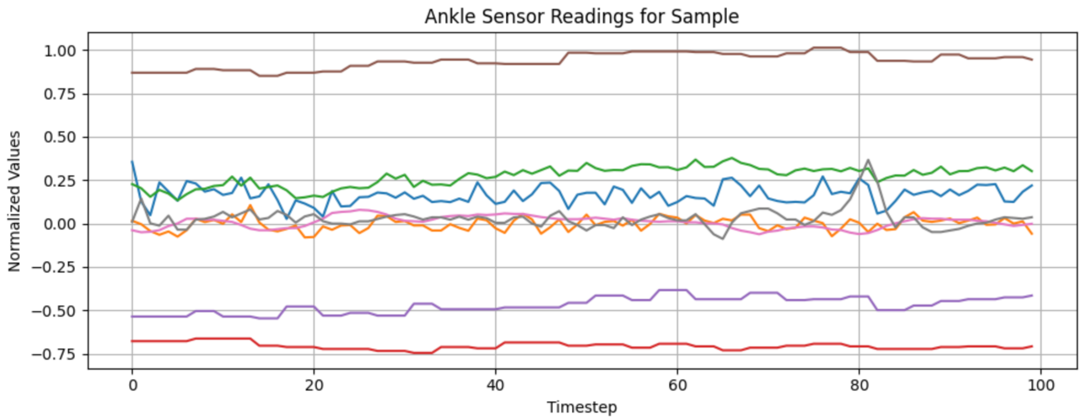

Figure 3: Ankle Sensor – Gyroscope Readings

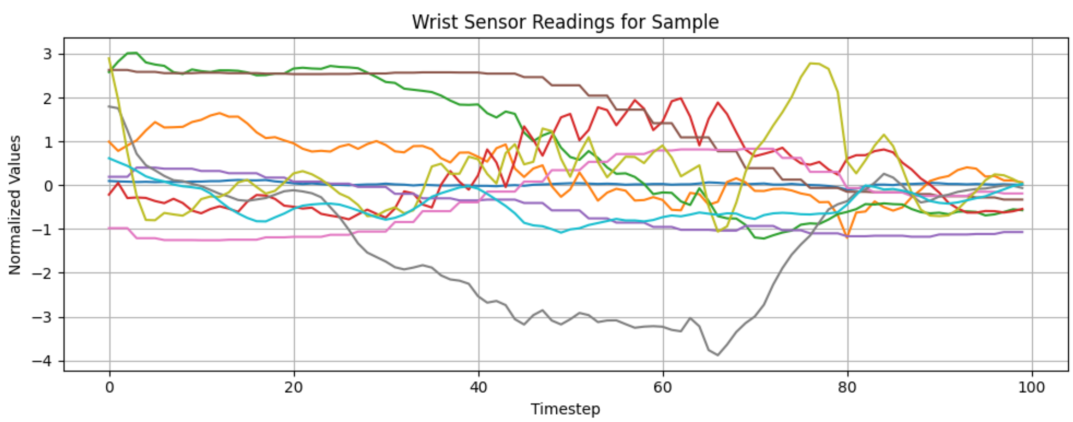

Figure 4: Wrist Sensor – ECG Signal Variation

5.3 Model Development

We implemented both classical ML and DL models. The traditional ML approaches commenced with **Logistic Regression**, employed as a baseline binary classifier and trained on statistical features extracted from each window. We also utilized a **Support Vector Machine** with a linear kernel, effective for high-dimensional data. Completing the traditional ML lineup was **Random Forest**, a robust ensemble method adept at managing feature importance and non-linear patterns.

In parallel, our deep learning explorations included a **1D CNN**, which captured local patterns via temporal filters and was trained directly on raw sequence data, demonstrating efficiency and high performance with low latency. Furthermore, we implemented a **LSTM** network, configured as a two-layer stacked model (64 and 32 units) with dropout. This architecture was designed to discern long-range dependencies in time-series data, using binary cross-entropy loss and the Adam optimizer for training.

5.4 Evaluation Strategy

Models were evaluated using stratified train-test splits and the following metrics: accuracy, precision, recall, and F1-score. Confusion matrices were used for interpretability. For deep learning models, early stopping and checkpointing were applied to avoid overfitting.

We also evaluated model interpretability (via saliency maps for DL and feature importance for ML) and computational efficiency, particularly for edge deployment feasibility.

5.5 Validation and Reporting

The findings will be validated using historical athlete data and prospective simulated scenarios to ensure robustness. Continuous feedback from professionals will be incorporated to refine model accuracy and relevance, which will be thoroughly documented in a detailed technical report.

6 Our Achievements

The project successfully developed and implemented a comprehensive pipeline for predicting injury risk in athletes, systematically integrating and comparing both traditional machine learning (ML) and advanced deep learning (DL) approaches. Our key contributions are outlined below:

We initiated the project by selecting the MHEALTH dataset, a publicly available resource rich in multivariate time-series data from wearable sensors placed at the chest, wrist, and ankle during various physical activities. A significant challenge in utilizing this dataset was the absence of explicit injury annotations. To address this, we innovatively designed a proxy labeling strategy grounded in biomechanical and physiological heuristics. Specifically, we identified high-impact risk through sudden spikes in total chest acceleration (>3.5g), fatigue through elevated ECG signals during low-intensity activities (e.g., standing or sitting), repetitive stress based on sustained dynamic activity over a 2-second window (150 samples) with limited rest, and postural instability using high variability in wrist gyroscope readings. This strategy allowed us to simulate and detect injury-prone scenarios reflective of real-world risk factors, enabling supervised model training in the absence of ground-truth labels (see Table 1).

Proxy Indicator	**Rationale**
High Impact Acceleration	Detected using sudden spikes in total chest acceleration (>3.5g); may reflect unsafe landings, falls, or jerky movement
Fatigue Signals	Based on unusually high heart rate (ECG) during low-intensity activities; suggests poor recovery or cardiovascular strain
Repetitive Stress	Extended duration of high-load activities with limited rest; simulates overuse injury risk
Postural Instability	Captures unstable body movement during transitions using gyroscope data; often a precursor to ligament injuries

Table 1: Proxy indicators used for injury risk labeling

For data preprocessing, we segmented the continuous time-series signals into overlapping 2-second windows (100 time steps at 50Hz), preserving temporal continuity while optimizing input sizes for sequential learning. These structured windows were used to train both conventional ML models such as Random Forest, Logistic Regression, and SVMs on engineered statistical features, and deep learning models such as LSTM and 1D CNNs on raw sensor sequences. This dual approach ensured a robust comparison of model capabilities across different abstraction levels of data representation and temporal modeling.

In the model development phase, we implemented and rigorously evaluated a suite of algorithms. Traditional ML models provided strong baseline comparisons, while the sequential DL models were tailored to exploit temporal patterns inherent in the sensor data. The LSTM network was designed to capture long-range dependencies in motion sequences, whereas the 1D CNN focused on efficiently extracting local temporal features. Each model was subjected to careful hyperparameter tuning and validated using stratified 5-fold cross-validation, ensuring balanced class distribution across folds and enhancing the robustness of performance evaluation.

Our evaluation, based on metrics such as accuracy, precision, recall, and F1-score, revealed the superior performance of DL models. Notably, the 1D CNN demonstrated exceptional efficacy, achieving the highest performance across all metrics (F1-score: 99.79%) as presented in Table 2. The LSTM model also showed strong predictive capabilities, yielding a high F1-score (92.05%) and excellent recall (95.65%), affirming its proficiency in modeling sequential dependencies. These DL models significantly outperformed the traditional ML baselines of Logistic Regression and SVM. The Random Forest model also proved to be a robust ML performer, particularly distinguished by its high recall (98.00%).

A core achievement of this project was the emphasis on interpretability. We integrated tools such as feature importance analysis for ML models and explored avenues like saliency maps for DL models. This focus aimed to provide transparent and actionable insights from the model predictions, enhancing their utility for non-technical stakeholders such as coaches and sports medicine professionals, thereby fostering trust and practical adoption.

Finally, our comparative analysis not only quantified the performance of different models but also elucidated crucial trade-offs between predictive power, computational requirements, and interpretability. For instance, while the 1D CNN offered the best accuracy and computational efficiency suitable for edge deployment, LSTMs are valuable for tasks requiring nuanced understanding of long temporal patterns. Traditional models like Random Forest offer a balance of good performance and relative transparency.

Through this project, we demonstrated that the synergistic application of domain-informed proxy labeling, structured time-series modeling with advanced DL techniques, and a commitment to interpretability can pave the way for reliable, explainable, and scalable injury risk prediction systems. These systems hold the potential to be tailored for diverse applications, from elite sports performance optimization to enhancing safety in broader athletic communities.

7 Results

This section presents the performance of the implemented ML and DL models on the MHEALTH dataset, utilizing our proxy labeling strategy for injury risk prediction. The models were evaluated based on accuracy, precision, recall, and F1-score. The traditional ML models evaluated include Logistic Regression, Support Vector Machines (SVM), and Random Forest. The DL models include a 1D CNN and a LSTM network.

The comparative performance metrics are summarized in Table 2.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Logistic Regression	70.00	34.00	70.00	45.00
SVM (LinearSVC)	70.00	34.00	70.00	46.00
Random Forest	97.00	86.00	98.00	91.00
1D CNN	99.77	99.72	99.86	99.79
LSTM	90.82	88.69	95.65	92.05

Table 2: Comparative Performance of Injury Risk Prediction Models

The results presented in Table 2 indicate varying levels of performance across the different modeling approaches. The traditional ML models, Logistic Regression and SVM, yielded identical accuracy (70.00%) and recall (70.00%), with SVM showing a marginally better F1-score (46.00%) compared to Logistic Regression (45.00%). Both models exhibited relatively low precision (34.00%), suggesting a higher rate of false positives. The confusion matrices previously analyzed for Logistic Regression ([[119120, 52676], [11258, 26661]]) and SVM ([[119225, 52571], [11248, 26671]]) support this observation, showing a significant number of non-risk instances being incorrectly classified as risk.

In contrast, the Random Forest model demonstrated substantially higher performance among the traditional ML techniques, achieving an accuracy of 97.00%, precision of 86.00%, recall of 98.00%, and an F1-score of 91.00%. Its high recall (98.00%) is a key strength, indicating its effectiveness in identifying true risk instances. The previously reported confusion matrix for Random Forest ([[165532, 6264], [803, 37116]]) showed a much better balance with fewer false negatives for the risk class compared to Logistic Regression and SVM.

The deep learning models showcased strong capabilities. The 1D CNN achieved outstanding results across all metrics, with 99.77% accuracy, 99.72% precision, 99.86% recall, and an F1-score of 99.79%. This suggests that the 1D CNN was highly effective in automatically extracting salient features and learning complex patterns directly from the raw time-series sensor data of the MHEALTH dataset. Its excellent balance between precision and recall, confirmed by the high F1-score, makes it a prime candidate for reliable injury risk prediction. Moreover, its inherent efficiency with 1D data makes it a promising candidate for real-time or embedded applications, consistent with our deployability objectives.

The LSTM model also demonstrated strong performance, achieving an accuracy of 90.82%, precision of 88.69%, a high recall of 95.65%, and an F1-score of 92.05%. This F1-score outperformed that of the Random Forest, highlighting the LSTM's effectiveness in capturing complex temporal dependencies. While the LSTM's recall (95.65%) is excellent and signifies its strength in capturing temporal dependencies within the sequential sensor data, making it highly sensitive to detecting potential injury risk windows, it is numerically second to Random Forest's recall (98.00%) in this comparison. The LSTM's current reported accuracy of 90.82% is a significant improvement over the 78-82% range observed in earlier, more general analyses mentioned in Section 6. However, its precision (88.69%) is lower than that of the 1D CNN, implying it may generate more false positives than the 1D CNN, a characteristic potentially influenced by factors such as training duration or data variance.

The presented findings indicate that deep learning models, particularly the 1D CNN, held a distinct advantage in predictive performance on this dataset and task. The 1D CNN attained the highest F1-score (99.79%) among all evaluated models, including other sequential approaches. The LSTM model also yielded robust results; its F1-score of 92.05% surpassed that of the Random Forest (91.00%). Among traditional ML techniques, the Random Forest performed strongly, especially with its high recall (98.00%). Selecting an appropriate model for practical deployment will depend on specific operational requirements, including the acceptable balance between false positives and false negatives, available computational resources, and the importance of model interpretability, a significant factor for this project. To illustrate, while the 1D CNN provides exceptional accuracy and efficiency, LSTMs are adept at capturing longer temporal dependencies, reflected in their strong F1-scores. Random Forests, conversely, offer a potent and relatively transparent baseline.

8 Progress Evaluation

The project closely adhered to the milestones proposed in the initial plan, with minor adjustments made to incorporate evolving insights and ensure greater model reliability. Data collection and literature review were completed as scheduled, followed by a structured preprocessing phase during which we developed and validated proxy injury risk labels using biomechanical and physiological signals. This phase took slightly longer than anticipated but was critical for framing the problem as a supervised learning task.

Model development both traditional ML and sequential DL were carried out as planned. We conducted a comparative study of model performance using accuracy, recall, and interpretability metrics, as initially proposed. Although some time had to be reallocated to improve risk-classification and cross-validation strategies, these refinements ultimately enhanced the robustness of our evaluation. Visualization and reporting activities began during the final weeks of the project, ensuring a comprehensive and well-documented analysis.

Overall, we successfully met our core objectives within the proposed timeline while remaining flexible enough to refine our methodology for more meaningful results. In retrospect, allocating more time early in the project for class imbalance mitigation would have improved data handling and streamlined the evaluation process. During initial experimentation, our Random Forest model unexpectedly achieved 100% accuracy. Upon investigation, we discovered this was due to severe overfitting caused by class imbalance and insufficient validation controls. The model had become biased toward the dominant class and failed to generalize to unseen data. To address this, we revised our data pipeline by enforcing subject-wise splits, implementing stratified sampling, and applying class balancing techniques during training. These corrections resulted in a more realistic performance, with the Random Forest model achieving 97% accuracy better aligned with practical expectations and more reliable for real-world deployment.

9 Conclusion

A systematic comparison was undertaken in this study, evaluating traditional ML models (Logistic Regression, SVM, Random Forest) against DL models (1D CNN, LSTM) for athletic injury risk prediction. This evaluation centered on time-series sensor data from the MHEALTH dataset, processed via a practical proxy labeling strategy. Empirical findings underscored the pronounced benefits of deep learning architectures; specifically, the 1D CNN achieved exceptional predictive accuracy (F1-score: 99.79%), and the LSTM model adeptly captured temporal dependencies (F1-score: 92.05%), surpassing traditional techniques. Random Forest also established itself as a potent traditional baseline, noteworthy for its excellent recall (98.00%).

From this investigation, a critical trade-off for practical deployment emerges: although deep learning models, especially 1D CNNs, present superior accuracy and efficiency for real-time scenarios, model selection must also consider interpretability. This is especially important for adoption by coaches and sports medicine professionals, who depend on clear and interpretable insights. The proxy labeling methodology devised herein provides a functional approach for utilizing unlabeled wearable sensor data, thereby addressing the widespread challenge of limited labeled data in the domain of sports injury prediction.

The study acknowledges certain limitations, primarily its reliance on proxy labels and a singular dataset. Subsequent research endeavors should focus on validating these models using clinically labeled injury data from a broader spectrum of sports and athlete profiles. It is also advisable to pursue further exploration of advanced interpretable AI techniques for less transparent DL models, alongside the development of hybrid systems. Such systems could effectively merge the feature engineering capabilities of classical ML with the sophisticated pattern recognition of DL. In conclusion, this research furnishes a solid benchmark and practical directives, fostering progress in data-centric injury prevention strategies designed to elevate athlete safety and optimize performance within sports analytics.

10 Team members' contribution

Teammate	Contribution
Akanksh Rao S R (25%)	Took initiative in organizing and documenting project progress through a structured working document updated weekly after team meetings and led the creation of presentation slides. Reviewed related literature; conducted exploratory data analysis; implemented the LSTM-based deep learning model; evaluated model performance and interpreted results. Authored and formatted key report sections, including the Abstract, Introduction, Motivation, Literature Review, and Problem Statement, using LaTeX.
Anuj Abhay Joshi (25%)	Key contributions to strategic project planning and methodological design; Drove critical aspects of MHEALTH data proxy labels formulation and validation;Project planning, Data Processing and label formulation, Model implementation (ML models - Random Forest and Logistic regression), Evaluation, Documentation of Proposed Methodology and Results in Final Report
Reshma Panibhate (25%)	Project concept and planning, Reviewed related research papers, Data work(data selection, data processing and data visualization), Deep learning model implementation(1D CNN), Evaluation, Results visualizaton and interpretation, Creating presentaion slides, Class presentation, Authored and formatted the Problem statement, EDA, Our achievements and Progress Evaluation in LaTeX for final report
Mansi Nandkar (25%)	Reviewed related research papers, Contributed to project workflow, Processed and labeled data, Exploratory Data analysis, Implemented SVM model, Evaluated model performance, Created visualizations, Documented methodology, EDA, Literature Survey, SVM related content, Progress Evaluation and Results in the report, Class presentation.

Table 3: Individual contribution

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