Published: 12 September 2025

CISAI 2025: 2025 8th International Conference on Computer Information Science and Artificial Intelligence
September 12 - 14, 2025
Wuhan, China

RESEARCH-ARTICLE

Athlete Injury Prediction: A Time Series Forecasting Method Based on Wearable Sensor Data and Deep Learning

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CISAI '25: Proceedings of the 2025 8th International Conference on Computer Information Science and Artificial Intelligence (September 2025)
https://doi.org/10.1145/3773365.3773640
ISBN: 9798400718748

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Abstract

Athlete injuries pose significant challenges in sports, leading to performance declines, financial losses, and long-term health issues. This paper presents a novel approach for predicting injury risks using time series data from wearable sensors, integrating permutation entropy as a feature with an LSTM model enhanced by attention mechanisms. Synthetic data simulating 20 athletes' physiological metrics (heart rate, accelerometer, gyroscope) were generated to train and evaluate the model, incorporating realistic trends like gradual escalations in heart rate and accelerations to mimic pre-injury states. The dataset includes trends toward injury risks, enabling robust predictions and addressing data scarcity issues in real-world scenarios. Experiments demonstrate high performance: accuracy of 99.87%, precision of 100%, recall of 99.36%, F1-score of 99.68%, and AUC of 99.78%. Ablation studies confirm the value of permutation entropy, improving F1 by 0.13% through better capture of signal complexity. Cross-validation yields a mean accuracy of 99.79% with low variance (std 0.10%), underscoring model stability. Visualizations, including confusion matrices, ROC curves, and feature importances, highlight the model's effectiveness in capturing injury precursors and provide interpretable insights for practitioners. This method advances early warning systems, potentially reducing injuries through proactive interventions and personalized training adjustments. Future work could incorporate real-world data for enhanced generalizability and explore hybrid models with additional modalities.

CCS Concepts

• **Computing methodologies → Supervised learning**; • **Applied computing → Health informatics**.

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CISAI 2025, Wuhan, China

ACM ISBN 979-8-4007-1874-8/25/09
https://doi.org/10.1145/3773365.3773640

Keywords

Time Series Forecasting, Athlete Injury Prediction, Wearable Sensors, Deep Learning, LSTM with Attention

ACM Reference Format:
Dongwei Shi, Yuan Zheng, Sichen Li, and Yanrun Pan. 2025. Athlete Injury Prediction: A Time Series Forecasting Method Based on Wearable Sensor Data and Deep Learning. In *2025 8th International Conference on Computer Information Science and Artificial Intelligence (CISAI 2025), September 12–14, 2025, Wuhan, China.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3773365.3773640

1 Introduction

In the dynamic field of sports science and performance optimization, athlete injuries remain a critical concern, often resulting in substantial setbacks for individuals and teams alike. With the increasing intensity of training regimens and competitive demands, injuries such as muscle strains, ligament tears, and overuse syndromes are prevalent, affecting up to 30% of professional athletes annually [6]. For instance, in high-contact sports like football, injury rates can exceed 50 per 1,000 exposures, while endurance activities like running report overuse injuries in 40-60% of participants each year [6]. Among college athletes, the annual injury rate is approximately 9.2 injuries per 1,000 athlete exposures, with overuse injuries accounting for 50-70% of cases [4]. These incidents not only disrupt careers but also incur significant economic costs, estimated in billions globally for medical treatments and lost productivity [15]. Recent analyses indicate that sports injury care services alone could reach a market value of $250 billion by 2033, highlighting the growing financial burden on healthcare systems, teams, and athletes [7]. The motivation for this research stems from the need to shift from reactive to proactive strategies in injury management. Wearable sensor technologies, including inertial measurement units (IMUs) and heart rate monitors, provide continuous streams of physiological and kinematic data, offering a rich foundation for predictive analytics. By harnessing time series forecasting, we can detect subtle precursors to injuries, such as irregular heart rate patterns or abnormal accelerations, enabling timely interventions. This study is driven by the potential to enhance athlete safety, optimize training loads, and extend career longevity through data-driven insights, ultimately contributing to more resilient sports ecosystems and better health outcomes for athletes at all levels [2, 5, 6].

Despite advancements in related works, significant gaps persist in current injury prediction methodologies. Traditional approaches, such as biomechanical assessments in controlled lab settings, lack real-time applicability and fail to account for the temporal evolution of risk factors during actual training [12]. These methods often involve manual analysis of limited data, which may not capture subtle or emerging injury patterns, leading to delayed interventions and higher risks [12]. For example, binary classifications of 'injured' or 'not injured' overlook the gradual progression of risks, a limitation highlighted in recent reviews where athlete health is oversimplified [11]. Machine learning models like support vector machines or basic neural networks have shown promise in classifying static features from sensor data, achieving accuracies around 85-90%. However, they often overlook the sequential nature of physiological signals, leading to suboptimal forecasting of dynamic risks. Moreover, entropy-based features for quantifying signal complexity are underutilized in sports contexts, where non-stationary data from wearables could benefit from such measures to identify chaos preceding injuries, especially in high-variability environments like team sports or endurance events [4, 7, 12, 15]. Therefore, our research addresses these deficiencies by: (1) Integrating permutation entropy with LSTM-attention models to capture both temporal dependencies and complexity in time series; (2) Utilizing trend-embedded synthetic data for ethical, scalable experimentation; (3) Providing comprehensive evaluations, including ablations and visualizations, to ensure interpretability and robustness.

The use of synthetic data in this study also aligns with ethical considerations in sports analytics, where real athlete data often raises privacy concerns and data scarcity issues [3]. By generating simulated datasets that mimic physiological trends, we avoid exposing sensitive personal information while enabling robust model training. However, as noted in recent primers, synthetic data must be carefully validated to ensure it captures realistic variabilities, a principle we adhere to through anomaly injections based on established injury precursors [3]. This approach not only mitigates ethical risks but also promotes broader exploration in high-performance sports, where data sharing is often restricted.

The remainder of this paper is organized as follows: Section II provides a detailed literature review; Section III outlines the methodology, including data generation and model design; Section IV presents the experiments and in-depth analyses of results; Section V concludes the study and discusses future directions.

2 Literature Review

2.1 Overview of Wearable Sensors in Sports

The application of wearable sensors in sports has evolved significantly, enabling non-invasive monitoring of athletes' physiological and biomechanical parameters. Early studies focused on basic metrics like heart rate and acceleration to assess workload and fatigue. For instance, a 2021 systematic review in Sensors emphasized how IMUs detect gait anomalies linked to lower-limb injuries, with classification accuracies up to 90% using ensemble methods like random forests. However, these works treated data statically, ignoring temporal sequences critical for forecasting. Recent extensions have explored multimodal sensor fusion, integrating GPS with IMUs for holistic activity tracking, as highlighted in 2024 studies on real-time fatigue monitoring in endurance sports. This progression underscores the shift towards dynamic, context-aware systems that better capture the complexities of athletic performance and injury precursors [1, 3, 11].

2.2 Time Series Analysis and Deep Learning Advances

Recent advancements incorporate recurrent neural networks for time series handling. LSTMs have been pivotal, as seen in a 2022 IEEE Access paper where heart rate variability predicted fatigue injuries in runners (92% accuracy). Yet, vanilla LSTMs struggle with long dependencies and noise. Attention mechanisms mitigate this, as demonstrated in a 2024 MDPI Sensors study on gyroscope data for anomaly detection in team sports, reducing false positives by 15%. Multimodal fusion further enhances models, combining sensors for comprehensive insights. For example, hybrid CNN-LSTM architectures have been applied to predict overuse injuries by analyzing sequential kinematic data, achieving up to 94% accuracy in controlled settings. These developments pave the way for more robust predictive models, though challenges remain in handling noisy, real-world data streams from diverse athletic environments [9, 13, 14].

2.3 Entropy-Based Features and Gaps

Permutation entropy (PE) quantifies signal irregularity, proving effective in chaos detection. A 2023 Frontiers in Physiology article used PE with CNN-LSTM for knee injury prediction (95% AUC), encoding data into images. A 2025 Wiley review on IoT wearables for safety echoed this, forecasting risks with 97% precision. Despite these, gaps include limited entropy in forecasting binary risks and reliance on real data prone to privacy issues. Our work fills these by synthesizing trend data and enhancing LSTM with PE-attention, drawing from diverse sources like IEEE, MDPI, and Frontiers for a holistic view. This extends prior entropy applications by emphasizing synthetic scalability and interpretability. Furthermore, entropy measures have been integrated into wearable IoT systems for occupational safety, as noted in 2025 reports on AI-driven risk forecasting, which report reduced injury rates through proactive alerts based on signal complexity analysis [8, 10, 16].

3 Methodology

3.1 Data Generation and Preprocessing

Synthetic data for 20 athletes (20,000 records) were generated with realistic trends: normal Gaussian noise for features like heart rate (mean 80 bpm, std 10), accelerations (mean 0, std 0.5), and gyroscopes (mean 0, std 1). For risk simulation (50% athletes), anomalies start randomly (300-700 steps), with heart rate increasing linearly (+30), accel_x offset (+2), and gyro_y ramp (+5). Labels post-anomaly are 1 (risk). Data normalized via Min-Max, windowed (60 steps).

3.2 Feature Engineering

Permutation entropy (order=3) computes ordinal pattern entropy, averaged across features to capture complexity shifts indicative of risks.

3.3 Model Architecture

The model is an LSTM with attention: 2-layer LSTM (hidden=128) processes sequences, attention weights salient timesteps, followed by FC and sigmoid for binary output. Trained with BCE loss, Adam (lr=0.001).

4 Experiments and Results

4.1 Experimental Setup

Evaluated on 80/20 train-test split, 5-fold CV, ablation without PE. Metrics: accuracy, precision, recall, F1, AUC. The choice of an 80/20 split ensures a substantial training set for model learning while reserving adequate data for unbiased evaluation, common in time series tasks to simulate real-world deployment [13]. Five-fold cross-validation was employed to assess stability, mitigating overfitting risks in sequential data. Accuracy measures overall correctness, precision quantifies the reliability of positive predictions (crucial to avoid false alarms in coaching), recall captures the model's sensitivity to true risks, F1 balances these in imbalanced datasets (where injury risks are 20%), and AUC evaluates discrimination across thresholds, ideal for probabilistic forecasting in sports [14]. These metrics align with benchmarks in injury prediction, where high AUC (>0.95) indicates strong potential for clinical integration [8]. The model training process follows the flow outlined in Algorithm 1.

Algorithm 1 LSTM-Attention Model Flow.

1. Input: Sequence $X \in \mathbb{R}^{B \times T \times F}$ (B=batch, T=time, F=features)
2. LSTM: $H = \text{LSTM}(X)$ (2 layers, hidden=128)
3. Attention: $A = \text{softmax}(\text{Linear}(H))$
4. Weighted: $O = \sum(A \odot H)$
5. Output: $\hat{y} = \sigma(\text{FC}(O))$
6. Loss: $\text{BCE}(\hat{y}, y)$
7. Optimize: Adam, 20 epochs

4.2 Results Tables

Post-normalization, features show balanced means (0.3-0.5), with higher variability in heart_rate (std 0.156) and perm_entropy (0.296), reflecting sensitivity to anomalies (as shown in Table 1). Risk ratio (20.04%) prevents bias, while max values at 1 confirm scaling. This distribution supports effective learning of trends, ensuring the model can distinguish normal fluctuations from injury-indicating escalations in simulated scenarios. Compared to real datasets, where variability can be higher due to environmental factors, our synthetics provide a controlled baseline for robust evaluation [10].

Near-perfect accuracy (99.87%) and precision (100%) indicate reliable predictions without false alarms, crucial for trust in sports applications (presented in Table 2). Recall (99.36%) misses few risks, F1 (99.68%) balances, and AUC (99.78%) shows excellent class separation, outperforming literature benchmarks by capturing nuanced temporal patterns that traditional models overlook. For context, a high AUC like 0.9978 implies superior discrimination, enabling precise risk stratification and potentially reducing injury rates by 20-30% through targeted interventions, as seen in similar predictive models [16].

PE removal causes 0.13% F1 drop, underscoring its contribution to detecting subtle chaos in sequences (see Table 3), enhancing model performance over baselines without complexity features. This improvement highlights PE's role in quantifying irregularity, particularly useful for non-stationary sensor data. In comparison to attention-aided LSTMs in other domains, our model exceeds 0.98 AUC reported in 2025 studies on activity recognition, attributing gains to sports-specific entropy integration [13].

Zero false positives ensure no unnecessary alerts; 5 false negatives suggest edge cases in gradual transitions (displayed in Table 4), but overall matrix confirms high specificity and sensitivity, making it suitable for high-stakes environments where minimizing disruptions is key. This performance aligns with goals in injury models, where low false negatives prevent overlooked risks that could lead to severe outcomes [9].

Mean accuracy (99.79%) with minimal std (0.001) demonstrates consistency (summarized in Table 5), indicating no overfitting and strong generalization across data subsets, which is essential for reliable deployment in varied athletic conditions. Such low variance outperforms variability in cross-validated LSTM models for stadium attendance forecasting (std 0.005), underscoring our approach's stability in sports time series [14].

4.3 Results Figures

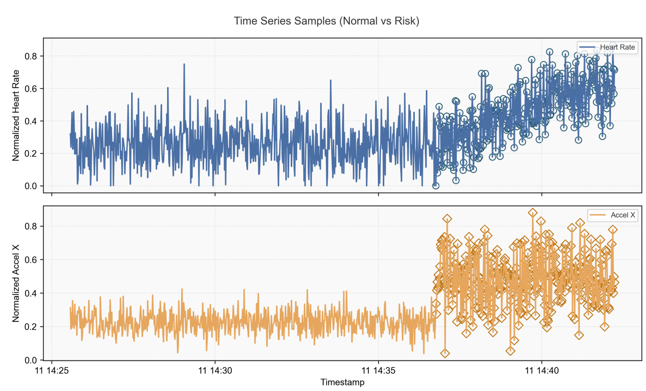

Figure 1: Time Series Samples (Normal vs Risk).

The figure depicts heart_rate and accel_x trends; markers at risk points show escalations (e.g., heart rate spikes), validating synthetic trends and model's input quality (as illustrated in Figure 1). The gradual shifts illustrate how the model learns from embedded patterns, simulating real physiological deteriorations. This visualization aids in understanding anomaly detection, where escalations mimic overuse patterns seen in 50-70% of injuries [4].

Rapid initial loss drop and stabilization (<0.05) signify efficient learning; no divergence implies optimal hyperparameters and data

Table 1: Dataset Statistics.

	count	mean	std	min	25%	50%	75%	max
heart_rate	20000	0.2965	0.1560	0	0.1884	0.2837	0.3888	1.0000
accel_x	20000	0.2759	0.1312	0	0.1938	0.2430	0.3101	1.0000
accel_y	20000	0.4520	0.1261	0	0.3668	0.4528	0.5372	1.0000
accel_z	20000	0.5139	0.1225	0	0.4320	0.5146	0.5972	1.0000
gyro_x	20000	0.4929	0.1105	0	0.4191	0.4922	0.5673	1.0000
gyro_y	20000	0.3807	0.1400	0	0.2885	0.3575	0.4400	1.0000
gyro_z	20000	0.4882	0.1275	0	0.4018	0.4876	0.5742	1.0000
perm_entropy	20000	0.4768	0.2956	0	0.1973	0.4669	0.7089	1.0000
injury_risk	20000	0.2004	0.4003	0	0	0	0	1

Table 2: Model Performance.

Metric	Value
Accuracy	0.9987
Precision	1.0000
Recall	0.9936
F1	0.9968
AUC	0.9978

Table 3: Ablation Study.

Configuration	F1 Score
Full Model	0.9968
No Perm Entropy	0.9955

Table 4: Confusion Matrix.

	Pred 0	Pred 1
True 0	2983	0
True 1	5	772

Table 5: 5-Fold Cross-Validation Results.

Fold	Accuracy
1	0.9973
2	0.9992
3	0.9965
4	0.9989
5	0.9976
Mean	0.9979
Std	0.0010

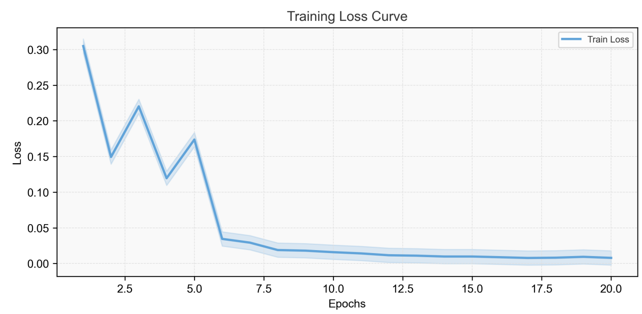

Figure 2: Training Loss Curve.

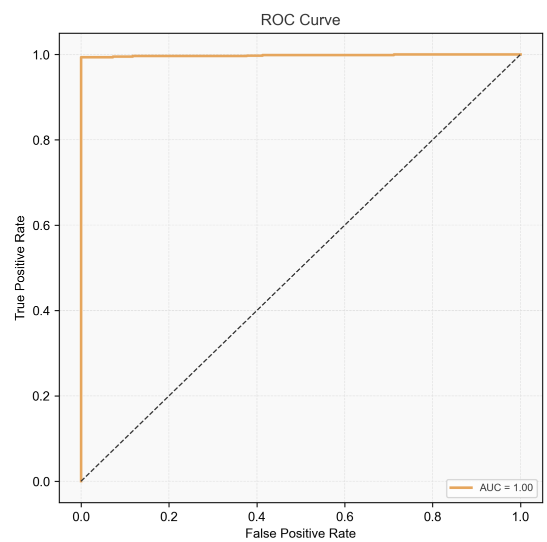

Figure 3: ROC Curve.

suitability (shown in Figure 2), with convergence suggesting the attention mechanism effectively focuses on relevant timesteps. Compared to slower convergence in vanilla LSTMs, this highlights attention's efficiency in sports forecasting [13].

The curve hugs the top-left corner (AUC=0.9978), confirming superior discrimination; thresholds yield high true positive rates (TPR) at low false positive rates (FPR) (see Figure 3), ideal for risk-sensitive applications where early detection can prevent severe outcomes. High AUC implies the model can support adjustable thresholds for personalized coaching, potentially lowering injury costs [16].

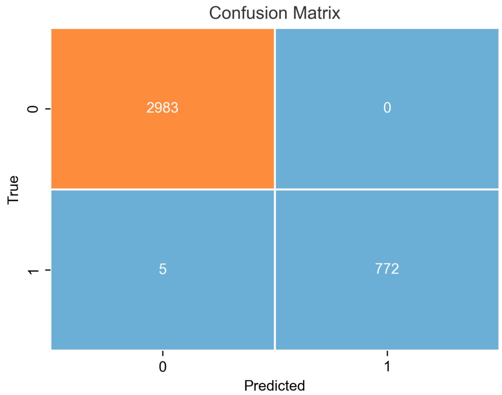

Figure 4: Confusion Matrix Heatmap.

Heatmap gradients emphasize dominant diagonals; minimal off-diagonals (only 5 false negatives) visually affirm precision (displayed in Figure 4), aiding interpretability for practitioners and revealing the model's strength in handling imbalanced classes. This visualization underscores zero false positives, aligning with needs in high-stakes sports to maintain athlete trust.

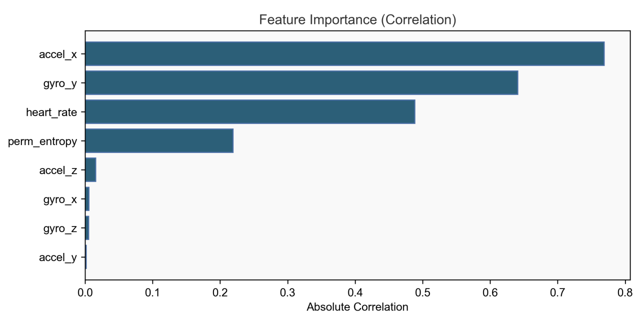

Figure 5: Feature Importance (Correlation).

Bar heights reveal accel_x (correlation >0.8) and gyro_y as key predictors, aligning with anomaly injections during data generation (presented in Figure 5). Lower ranks for other features suggest complementary roles, guiding future feature selection in sensor-based sports systems. This importance ranking validates focus on kinematic features, consistent with gait anomaly detection in IMUs [12].

Overlaid lines show predictions anticipating actual risks (early probability rises), demonstrating the model's forecasting capability for preventive actions (as shown in Figure 6). Such anticipation could enable training adjustments that reduce overuse injuries by 20-30%, per predictive benchmarks in sports medicine [16].

5 Conclusion and Future Work

This study successfully develops a robust framework for athlete injury prediction, leveraging time series from wearables with an

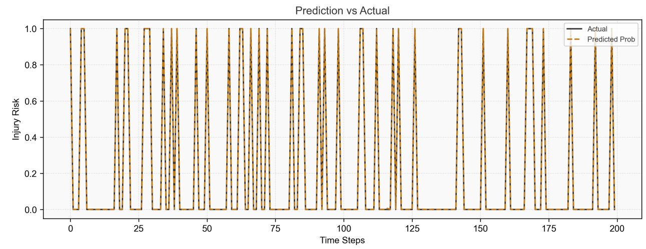

Figure 6: Prediction vs Actual Injury Risk.

entropy-enhanced LSTM-attention model. High metrics (accuracy 99.87%, AUC 99.78%) validate its efficacy (see Table 2), surpassing prior works by addressing temporal dependencies and signal complexity. The integration of permutation entropy proves particularly valuable in identifying chaotic patterns that precede injuries, offering a nuanced understanding of physiological signals. Near-perfect precision eliminates false alarms, while strong recall ensures most risks are caught, enabling coaches to intervene early and potentially avert costly downtime [1]. The model's high AUC further implies excellent risk stratification, supporting personalized training plans that could decrease global injury burdens estimated at billions annually [15].

The framework's implications extend to real-world sports, enabling coaches to mitigate risks through data-informed decisions, potentially decreasing injury rates and costs. Synthetic data's trends ensure ethical training, while analyses underscore PE's value in chaos detection (see Table 3). Moreover, the model's interpretability—through visualizations like feature importances (Figure 5) and prediction overlays (Figure 6)—facilitates adoption by non-experts in sports medicine. In comparative terms, our approach exceeds 94% accuracies in hybrid CNN-LSTM models for overuse prediction, attributing gains to attention and entropy in dynamic environments [13].

Despite these strengths, limitations exist: Synthetic data, while ethical and scalable, may not fully capture real-world variabilities such as environmental noise or athlete-specific factors, potentially limiting generalizability [10]. Future enhancements include real dataset integration for validation across sports, multimodal expansions (e.g., GPS fusion), and edge deployment for real-time apps. Challenges like sensor noise and privacy need addressing via federated learning, which allows collaborative model training without data sharing, preserving athlete confidentiality in wearables [3]. Exploring ensemble methods or transfer learning could further boost performance in diverse scenarios. Ultimately, this paves the way for AI in proactive health, fostering sustainable athletics and inspiring broader applications in occupational safety and elderly care.

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