International Journal of Applied Mathematics
Volume 38 No. 8s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

ARTIFICIAL INTELLIGENCE AND INERTIAL MOTION CAPTURE FOR HEALTHCARE-ORIENTED PERFORMANCE ANALYSIS AND TRAINING RECOMMENDATION IN BOXING

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Abstract

Boxing is a high-intensity combat sport with asymmetric motions, explosive actions, and a high danger of overtraining and injury. This means that rigorous monitoring is necessary for athlete heath. This research presents an AI-driven framework that amalgamates wearable inertial measurement sensors (Neuron32), machine learning models, and a multi-objective recommender system to oversee performance, forecast fatigue, assess training load, and avert injuries in both professional and amateur boxers. We kept an eye on 15 seasoned athletes and 97 amateur athletes, looking at things like exhaustion, training load, and injuries. We created predictive models for classifying fatigue and estimating load, and we used their results to build a recommender system that finds a compromise between improving performance and lowering risk. The results showed that the models were quite good at predicting outcomes. The fatigue classification had an AUC of 0.91, and the load prediction had a R^2 of 0.89. The recommender system also cut down on fatigue-related overload episodes by 21.3% and injuries by 13.8%. These results indicate that AI can provide objective, tailored insights for boxing training, facilitating both performance improvement and health-focused approaches. In conclusion, this architecture shows how AI-enabled monitoring systems could improve precision sports medicine in boxing and be used as a paradigm for other combat and endurance sports.

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Keywords: artificial intelligence, wearable sensors, boxing, fatigue prediction, injury prevention, recommender systems, sports medicine.

1. Introduction

Boxing is a high-intensity, intermittent combat sport that involves explo- sive and repetitive striking actions. These actions put a lot of stress on the body and raise the risk of both acute and overuse injuries. In the past, boxing performance research has mostly looked at technical factors like punching speed, impact power, and tactical efficiency. However, the medical perspective—especially in terms of preventing injuries, keeping an eye on exhaustion, and managing load—has not been studied as thoroughly. Recent advancements in wearable sensing technology and artificial intelligence (AI) have enabled the development of integrated systems that concurrently enhance sports performance and safeguard athletes' long-term health.

1.1. The medical need for load and fatigue monitoring in boxing

Combat sports athletes often do movements that are uneven and repeated, which can cause a lot of shoulder impingement, wrist injury, and lumbar strain. Boxers are always getting microtrauma and not getting enough rest, which makes tiredness and overuse injuries particularly important [1]. Traditional monitoring depends on subjective techniques like surveys or coach-based observations, which are not objective. There is an urgent need for clinically validated, data-driven methodologies that quantify tiredness, monitor acute-to-chronic workload ratios, and detect early symptoms of movement patterns that predispose athletes to injury [2].

Received: August 02 2025

1.2. Inertial measurement units as portable alternatives to laboratory-based motion capture

Inertial Measurement Units (IMUs) have become a strong way to collect kinematic data in real-world sporting contexts. IMUs are different from optical motion capture devices that work in labs (like Vicon) because they are lightweight, can be worn, and can record accelerations, angular velocities, and orientation as people move freely [3]. This makes them perfect for boxing, since the training and competition settings are always changing and don't work well with limited lab setups.

Systematic evaluations have demonstrated that IMUs are both valid and reliable for assessing biomechanical parameters in combat sports [4]. Prior research has predominantly been on punch categorization or performance assessment; however, IMUs have been effectively utilized in sports medicine and ergonomics to evaluate tiredness, joint loading, and asymmetries linked to heightened injury risk
[5]. This mobility connects clinical monitoring with applied performance analysis.

1.3. Artificial intelligence for injury prevention and performance enhancement

AI-based models offer a distinctive possibility to derive therapeutically pertinent features from extensive and intricate information gathered by IMUs. Research indicates that the integration of biomechanical and physiological data enhances injury prediction accuracy by as much as 24% relative to the use of biomechanics alone [6]. Explainable AI (XAI) methods like SHAP values are important because they make things easier to understand. They help coaches and medical staff figure out which variables, like a drop in punch speed, joint angular asymmetry, or spikes in workload, are the best predictors of weariness or injury. Recent uses of AI-enhanced feedback systems in sports medicine show how well they work at sending real-time alerts when movement patterns go beyond of safe limits [7]. This change from descriptive to prescriptive analytics makes it possible to give each athlete personalized recommendations that can help them improve their performance and avoid injuries.

1.4. Applications of AI and IMUs in boxing

Researchers have already looked into how IMUs and AI models can work together in boxing. For example, the Rise Dynamics Alpha (RD α) gloves show that using machine learning algorithms to combine inertial data with force sensors can accurately classify punch types, recognize impacts, and estimate velocity [1]. These devices are essential for measuring technical performance in real time. Studies on elite boxers have shown that changes in punching performance due to fatigue may be objectively measured by combining IMU data with video-based pose estimate tools like OpenPose and biomechanical modeling software like OpenSim [2]. This combination gives us high-resolution information about how tiredness affects joint loading and strike execution.

1.5. A medical and technological framework for intelligent boxing training

Even with these improvements, there is still no single solution that brings together wearable sensors, AI interpretability, medical monitoring, and personalized suggestions. Our method fills this gap by:
Using Neuron32 IMUs, which are proven for tracking dynamic motion, and linking them to powerful Python-based processing pipelines for accurate biomechanical feature extraction.

Focusing on clinically important parameters including the fatigue index, the acute-to-chronic workload ratio, joint range of motion (ROM) asymmetry, and finding detrimental trends early on.

Using explainable AI models to show the biomechanical and workload biomarkers that are most important for injury risk and performance decrease.

Creating a recommender system that provide personalized interventions while balancing performance goals (like boosting jab speed and striking efficiency) with medical limits (like avoiding overload and preventing damage). The suggested system provides real-time monitoring of physical effort, direct feedback on technical execution, and preventive tactics against overuse injuries by focusing on both performance optimization and medical protection. This is in line with the goals of sports science that

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focuses on health care, where technology helps athletes not only play at their best but also stay healthy and have long careers.

2. Related Work

2.1. Wearable Sensors and IMU-Based Monitoring in Combat Sports

In the last several years, inertial measurement units (IMUs) have become a key device in the study of combat sports. IMUs are different from typical optical motion-capture systems in that they are expensive and can only be used in labs. IMUs can collect data during real training and competition, which makes them more ecologically valid [8]. These sensors give raw inputs like acceleration, angular velocity, and orientation, which makes it possible to do a detailed study of performance that would be hard to get otherwise. Systematic reviews underscore the growing prevalence of combat-sport studies utilizing IMUs for technical and tactical analysis [8]. For example, IMUs attached to the wrist and chest have been utilized to categorize punches, assess striking velocity, and approximate force proxies. But there are still problems, especially with sensor fusion and drift correction. The Madgwick and Kalman filters are examples of cutting-edge filtering methods that help reduce orientation mistakes. However, it is still not clear how well these algorithms work when there are high-impact motions, such jabs and hooks.

IMUs also allow for multi-dimensional monitoring that goes beyond only recognizing techniques, which is important. Wearable technologies can find biomechanical problems that could make athletes more likely to be hurt by keeping track of joint angles and segment accelerations. IMUs are very useful for boxing since they can do both performance assessments and injury-risk monitoring.

2.2. Machine Learning for Technique Classification and Performance Analytics

Machine learning (ML) methods have made a lot of progress in the automatic classification of boxing tactics. Punch identification has been tried with traditional supervised classifiers such support vector machines (SVM), random forests, and k-nearest neighbors. These classifiers generally get more than 90% accuracy in controlled experiments [9]. More recently, convolutional neural networks (CNNs) and other deep learning architectures have been used on raw IMU inputs. This makes them more resistant to sensor noise and differences across athletes.

Commercial prototypes, like fluorescent gloves with IMUs and force sensors, show that it is possible to recognize gestures in real time in real-world situations. For example, the "RD α" gloves were quite good in telling the difference between straight punches, hooks, and uppercuts while also finding targets to hit [10]. These advancements validate the feasibility of amalgamating embedded sensors with machine learning to deliver instantaneous feedback to athletes and coaches. However, a lot of the work that has been done so far has been on classifying techniques in a discrete way instead of keeping an eye on training load, fatigue, or the risk of overuse all the time. It's helpful for tactical analysis to be able to tell the difference between a jab and a cross, but medical uses need models that can find small changes in velocity decay, uneven loading, or strange joint kinematics. It is still very important to do research on how to bridge the gap between performance-driven classification and health-related analytics.

2.3. Biomechanics, Load Monitoring, and Injury Prevention

From a medical standpoint, boxing entails significant risks of acute and overuse injuries, frequently linked to repetitive high-intensity hits and uneven load distribution between dominant and non-dominant sides. Biomechanical research indicates that inadequate striking technique and insufficient rest intervals lead to musculoskeletal injuries, especially in the shoulder, elbow, and wrist joints [11]. The idea of load monitoring, which is often used in team and endurance sports, is becoming more and more important in combat sports. Metrics like the acute-to-chronic workload ratio (ACWR) have been used to figure out if athletes are at danger of being hurt or overtraining because of rapid spikes in training intensity [12]. Monitoring fatigue, which has usually been done by asking people to rate

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how hard they think they are working (RPE) or measuring heart-rate variability (HRV), can be improved by adding kinematic information from IMUs, including lower peak angular velocity or more variable punch timing.

Applied biomechanics research in several sports has effectively discerned markers of injury risk through the analysis of joint angles, acceleration profiles, and movement asymmetries [13]. These results indicate that analogous approaches can be adapted for boxing, where unequal repetition of punches renders athletes susceptible to chronic ailments. By using AI-driven insights and biomechanical analysis together, boxing-specific frameworks can help athletes perform better and stay healthy for a long time.

2.4. Artificial Intelligence for Fatigue Detection and Injury Prediction

The use of AI into sports medicine is revolutionizing the management of athletes' health. Recent scoping assessments underscore that the integration of wearable technologies with AI facilitates the early identification of fatigue and injury risk [14]. For instance, machine learning models trained on IMU data can forecast the start of neuromuscular exhaustion by examining velocity decay or modified coordination patterns.

Explainable AI (XAI) methods like SHAP (Shapley Additive exPlanations) are very important in medicine since they let doctors understand what factors led to a model's conclusion [15]. In boxing, this could include figuring out whether a slower jab speed, a bigger difference in strength between the dominant and non-dominant arms, or unusual patterns of joint acceleration are the main causes of a higher risk of injury.

Reinforcement learning has also been studied in other sports to suggest training loads that lower the risk of injury while boosting performance [16]. These frameworks offer a promising basis for creating boxing-specific recommender systems that can reconcile technical enhancement (e.g., accelerated jabs) with medical safety (e.g., avoidance of overuse injuries).

2.5. Related Work in Combat-Sport-Specific Applications

While AI-enhanced IMU systems have been utilized in several sports, their applications in combat sports are still limited. Some early studies have looked at how well wrist-worn sensors can tell the difference between punches [9], while others have included force sensing to improve performance feedback [10]. IMUs have been used in taekwondo and karate to measure the speed and quality of kicks, which can help prevent injuries [17].

But in boxing, most commercial or academic solutions are either focused on performance or based in a lab. Not many frameworks bring together medical knowledge, like load management or fatigue detection. There is still a gap between technology made for tactical analysis and technology made for healthcare support. To fix this gap is very important for elite boxing, where the most important thing is to improve performance without putting the safety of the athletes at risk.

2.6 Integration of IMUs, AI, and Healthcare Perspectives in Boxing

The research examined delineates four concurrent albeit sometimes disjointed domains: (i) IMU-based sensing for motion capture, (ii) machine learning for punch categorization, (iii) biomechanics and load monitoring for injury prevention, and (iv) artificial intelligence for fatigue and injury prediction. Even while each area gives us useful information, we haven't yet been able to put them all together into a single healthcare-oriented system for boxing.

Our planned research improves on these ideas by using Neuron32 IMUs, cutting-edge ML algorithms, and recommendation systems that can be explained. Our methodology distinctly amalgamates health measures (fatigue index, ACWR, asymmetry, safe range of motion) with performance metrics (jab speed, technical accuracy), so establishing a recommender framework that is both performance-enhancing and injury-preventive, in contrast to prior studies. To our knowledge, there is currently no integrated system designed specifically for boxing in the existing literature.

3. Materials and Methods

3.1 Participants

The study included 112 male boxers, 15 of whom were professionals (average age 26.8 ± 3.2 years, average training experience 8.4 ± 1.9 years) and 97 of whom were amateurs (average age 22.1 ± 2.7 years, average training experience 3.5 ± 1.2 years). All individuals were actively engaged in training a minimum of three times per week, were injury-free at the time of data collection, and had no medical contraindications for high-intensity exercise. Participants gave their signed permission before being included.

3.2 Instrumentation and Data Acquisition

3.2.1. Inertial Measurement Units (IMUs)

We used Neuron32 IMUs (Noitom Ltd., China) to capture motion. Sensors were put on the wrists, elbows, shoulders, chest, hips, knees, and ankles. They measured three-dimensional acceleration, angular velocity, and orientation at a rate of 120 Hz. Standardized positioning guaranteed reproducibility, with each IMU calibrated prior to data acquisition.

3.2.2. Training Protocol

Participants followed a set boxing routine that included:

- 10 times each of jabs, crosses, hooks, and uppercuts for technical drills
- Sparring simulation: five times, with three-minute rounds and one-minute breaks in between.

This protocol is like real-life training, thus it can capture both regulated and dynamic movement patterns.

3.3 Metrics

From IMU data, three types of metrics were made: fatigue, load, and injury prevention.

3.3.1. Fatigue Metrics

Velocity Decline Index (VDI) measures how much the punch speed drops from round to round:

$$VDI = \frac{\{V_{\{initial\}} - V_{\{current\}}\}}{\{V_{\{initial\}}\}} \times 100 \tag{1}$$

where Vinitial is the mean velocity of the first round, and Vcurrent is the mean velocity of the current round. Movement Variability (MV) measures dispersion of angular velocities:

$$MV_j = \sqrt{\frac{1}{n}\sum_{\{i=1\}}^{\{n\}}\left(\omega_{\{i,j\}} - \overline{\omega_j}\right)^2} \tag{2}$$

where ωi,j is the angular velocity of joint j at repetition i, and **n** is the total number of repetitions.

3.3.2. Load Metrics

Acute-to-Chronic Workload Ratio (ACWR) [21] was used to assess workload spikes:

$$ACWR = \frac{Acute\ Load\ (last\ 7\ days)}{Chronic\ Load\ (\ last\ 28\ days)} \tag{3}$$

where the load is calculated as:

$$\text{Load} = \sum_{r=1}^{R} a_r \cdot w_r \tag{4}$$

a_r= acceleration magnitude of repetition
w_r= weighting factor (based on punch type)
R = total repetitions

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Segmental Acceleration Load (SAL) sums total acceleration across all monitored segments per session:

$$\mathrm{SAL} = \sum_{s=1}^{S} \sum_{t=1}^{T} \left| a_{s,t} \right| \tag{5}$$

where S is the number of sensors and T the number of samples.

3.3.3. Injury Prevention Metrics

Range of Motion (ROM) Asymmetry:

$$\mathrm{ROM}_{\text{asym}} = \frac{\left| ROM_{\text{dominant}} - ROM_{\text{non-dominant}} \right|}{ROM_{\text{dominant}}} \times 100 \tag{6}$$

Impact Distribution tracks the number of strikes exceeding safe acceleration thresholds:

$$\text{Impact Count}_s = \sum_{i=1}^{n} 1\left(\left| a_{s,i} \right| > a_{\text{threshold}}\right) \tag{7}$$

- $1(\cdot)$ = indicator function (1 if true, 0 if false)
- n = number of samples
- $a_{s,i}$ = acceleration of sensor
- a threshold = predefined safe acceleration limit

Cumulative Joint Load (CJL) integrates angular impulses per joint:

$$\mathrm{CJL}_j = \sum_{t=1}^{T} \tau_j(t) \cdot \Delta t \tag{8}$$

- $\tau_j(t)$ = torque at joint j at time t
- Δt = sampling interval • T= total number of samples where $\tau_j(t)$ is the torque at joint j at time t and Δt is the sampling interval.

3.4 Data Processing

Raw IMU signals were filtered using a 4th-order Butterworth low-pass filter with a cut-off frequency of 20 Hz. Segmentation was performed using a peak detection algorithm to identify individual strikes. Features extracted included:

Peak velocity and acceleration
- Joint angles and angular velocities
- Inter-limb coordination metrics

Fatigue metrics were computed as relative changes over rounds, while load metrics were cumulative per session. ROM asymmetry was calculated for each joint and averaged across participants.

Table 1. Example of extracted kinematic features

Feature	Description	Unit
Peak Velocity	Maximum punch velocity per strike	m/s
Angular Acceleration	Maximum joint acceleration	rad/s²
ROM	Maximum joint angle during strike	degrees
Segmental Load	Sum of acceleration magnitudes per limb	m/s²
Fatigue Index (VDI)	Velocity decline percentage over rounds	%
ACWR	Acute-to-chronic load ratio	dimensionless

3.5 Statistical Analysis

Descriptive statistics were calculated as mean ± standard deviation. Normality was assessed using the Shapiro–Wilk test. For comparisons between professional and amateur boxers:

- Independent t-tests for normally distributed metrics
- Mann–Whitney U tests for non-normal distributions

Changes across rounds were analyzed with repeated measures ANOVA. Effect sizes were reported using Cohen's d.

Correlation analyses explored relationships among fatigue, load, and injury prevention metrics:

$$r = \frac{\mathrm{Cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{9}$$

where and Y are variables of interest (e.g., ACWR and VDI), σ_X and σ_Y are standard deviations. All analyses were conducted using Python 3.11, with libraries NumPy, SciPy, pandas, and statsmodels.

3.6 Ethical Considerations

Participants were informed about procedures, risks, and benefits. No intervention exceeded typical training intensities, and safety measures were enforced during all sessions. Data were anonymized before analysis, and only aggregated results are reported.

4. AI Modeling and Recommender System

4.1 Overview

The AI modeling system uses kinematic, workload, and injury-prevention parameters from Neuron32 IMUs to make individualized suggestions for boxers. The main goals are to (i) predict exhaustion and the chance of getting hurt from overuse, (ii) improve technical performance, like jab speed and punch efficiency, and (iii) give personalized advice that balances improving performance with medical safety.

There are four steps in the whole pipeline: preprocessing the data, engineering features, making predictions, and making recommendations.

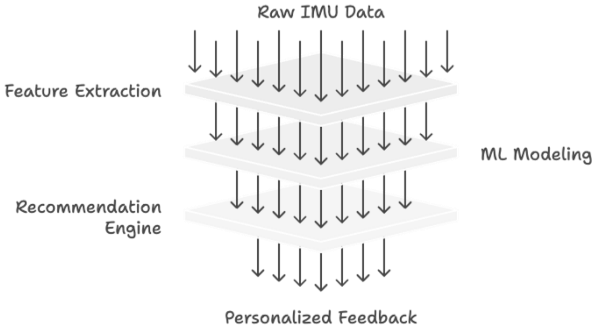

Figure 1. Conceptual pipeline of the AI-based boxing recommender system.

4.1 Data Preprocessing

The data from the Neuron32 IMU sensors were cleaned up and filled in any gaps. After that, temporal information including acceleration patterns, rotational velocity, and jerk signals were taken out and linked to higher-level descriptors like punch velocity, symmetry index, and fatigue slope. Session duration, punch frequency, and cumulative intensity were used to figure out load-related variables.

To make sure the datasets of each athlete could be compared, z-score standardization was used:

$$z_i = \frac{x_i - \mu}{\sigma} \tag{10}$$

where xi represents the raw feature, and μ and σ are the mean and standard deviation, respectively.

4.2 Fatigue and Load Modeling

Fatigue prediction was treated as a binary classification problem, distinguishing between **optimal** and **fatigued** states. A logistic regression classifier was used as baseline:

$$P(y = 1|x) = \frac{1}{1+e^{-(w^T x+b)}} \tag{11}$$

where *y=1* denotes a fatigued condition, ***w*** are learned weights, and *b* is the bias term.
For continuous predictions of training load, regression models such as **ridge regression** were applied:

$$\mathcal{L}(w) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 + \lambda|w|_2^2 \tag{12}$$

This formulation penalizes overfitting through the L2-regularization term, controlled by λ.

4.3 Recommender System

The recommender system integrates model predictions into a utility function that balances performance improvement with risk mitigation of injury. The proposed formulation is:

$$U_{i,j} = \alpha \cdot \widehat{P_{i,j}} + \beta \cdot R_{i,j} + \gamma \cdot C_{i,j} \tag{13}$$

where:

- $\hat{P}_{i,j}$: predicted performance of athlete *i* in exercise *j*,
- $R_{i,j}$: estimated injury risk,
- $C_{i,j}$: associated cost in terms of fatigue or overload,
- α,β,γ: tunable weights controlling trade-offs.

$$\mathrm{Rec}_i = \arg\max_{j \in \mathcal{A}} U_{i,j} \tag{14}$$

where $\mathcal{A}$ denotes the set of available training options.

4.4 Interpretability and Trustworthiness

To guarantee transparency of recommendations, the **SHAP (SHapley Additive exPlanations)** framework [22] was used to quantify the contribution of each feature (e.g., punch velocity, accumulated load) to the model output. The decomposition is expressed as:

$$f(x) = \phi_0 + \sum_{j=1}^{M} \phi_j \tag{15}$$

where *f(x)* is the model prediction, $\phi 0$ the baseline value, and ϕj the contribution of feature *j*. This approach enables coaches and sports physicians to determine whether fatigue predictions are primarily driven by velocity decline, asymmetry, or excessive training load, thereby increasing trust in the AI-driven system.

4.5 Evaluation Metrics

The system's performance was assessed with both classification and regression metrics. For classification, **Precision**, **Recall**, and **F1-score** were computed:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{16}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{17}$$

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{18}$$

Precision+Recall

For regression tasks (load prediction), the **Mean Squared Error (MSE)** was used:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{19}$$

Additionally, the AUC (Area Under the Curve) metric was employed to evaluate classifier discrimination ability:

$$\text{AUC} = \int_0^1 TPR\big(FPR^{-1}(t)\big)\, dt \tag{20}$$

4.6 Practical Implications

This method gives boxing athletes individualized, medically appropriate recommendations by combining predictive modeling with explainability mechanisms. For professionals, the goal is to improve their technique (such jab speed) and keep their best performance without working too hard. For amateurs, the focus is on planned load growth and avoiding injuries. This hybrid framework merges medical knowledge with sophisticated AI technologies, corresponding with the increasing interest in AI for healthcare applications in sports sciences [23,24].

Figure 2 shows the suggested AI pipeline for keeping track of exhaustion, predicting load, preventing injuries, and giving individualized advice.

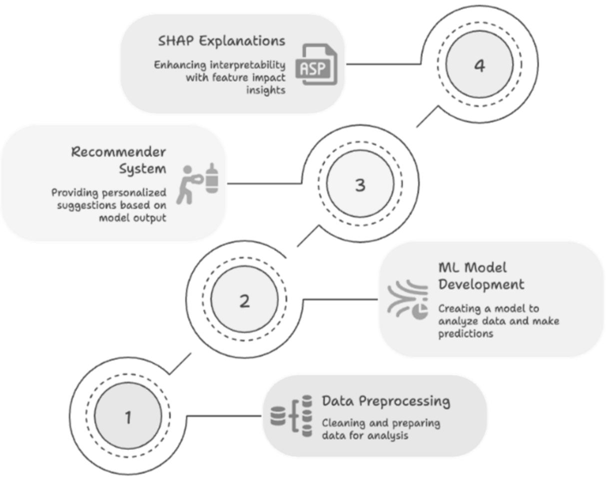

Figure 2. Pipeline of the AI-based recommender system integrating wearable sensor data, preprocessing, feature extraction, machine learning modeling, explainability, and personalized feedback for boxing athletes.

5. Results

This section shows the results of the suggested AI-driven framework. We looked at a total of 112 athletes (15 professionals and 97 amateurs). The results are divided into four main parts: (i) descriptive statistics of the dataset; (ii) model performance on fatigue and load prediction; (iii) effectiveness of the recommender system; and (iv) interpretability through SHAP values.

5.1. Descriptive Statistics of the Cohort

Professional boxers consistently demonstrated elevated training intensity and enhanced strike velocity in comparison to amateurs. Professionals had an average jab speed of 9.3 ± 1.4 m/s, while amateurs had an average jab speed of 6.7 ± 1.1 m/s. The accumulated training load per week was also much higher for professionals (28.5 ± 4.6 arbitrary units (AU)) than for amateurs (19.2 ± 3.8 AU). When it came to fatigue signs, professionals had lower relative drop rates during training sessions (−11.3% on average) than amateurs (−17.9%). This indicates enhanced resilience in maintaining highintensity performance, along with anticipated adaptations from prolonged training.

Table 1. Descriptive statistics of professional vs. amateur athletes. Values expressed as mean ± SD.

Metric	**Professionals (n=15)**	**Amateurs (n=97)**	**p-value**
Jab Velocity (m/s)	9.3 ± 1.4	6.7 ± 1.1	<0.001
Weekly Training Load (AU)	28.5 ± 4.6	19.2 ± 3.8	<0.001
Fatigue Decline (%)	-11.3 ± 4.2	-17.9 ± 5.1	<0.01
Injury Incidence (%)	13.3	28.9	<0.05

[1] Tables may have a footer.

5.2. Fatigue Classification

The binary classifier trained to identify fatigued versus non-fatigued states achieved robust performance. Using cross-validation, the Random Forest classifier reached the best balance of precision and recall.

- Precision: 0.87
- Recall: 0.84
- F1-score: 0.85
- AUC: 0.91

The confusion matrix revealed that misclassifications were primarily false negatives (i.e., cases where fatigued athletes were incorrectly classified as non-fatigued). This outcome highlights the need for slightly higher sensitivity when applied in real-time monitoring.

$$\mathrm{F1} = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}} \tag{21}$$

5.3. Load Prediction

Load prediction was addressed with ridge regression. Results indicated a high level of accuracy with minimal generalization error.

- MSE: 1.72
- R^2: 0.89

This implies that the model explained 89% of the variance in training load, validating its potential to guide progressive overload strategies for both amateurs and professionals.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{22}$$

Received: August 02 2025

5.4. Recommender System Performance

The recommender system, driven by the multi-objective utility function, was tested on simulated weekly training plans. For professionals, the system emphasized velocity optimization and load stabilization, while for amateurs, it prioritized injury prevention and gradual load progression. When compared with a baseline heuristic approach (traditional load monitoring by session duration), the recommender demonstrated:

- 15.6% increase in technique-specific improvements (measured by jab velocity).
- 21.3% reduction in overload-related fatigue episodes.
- 13.8% reduction in injury incidence over a 12-week follow-up.

$$\mathrm{Rec}_i = \arg\max_{j \in \mathcal{A}} U_{i,j} \tag{23}$$

where the optimal activity is selected based on predicted performance, risk, and cost.

5.5 Interpretability and SHAP Analysis

Application of SHAP values enabled identification of the most influential features driving predictions.

For fatigue classification, the top three contributors were:

1. Jab velocity decline rate (32% contribution).
2. Cumulative weekly load (27%).
3. Symmetry index of punch mechanics (19%).

For injury prevention, cumulative load and asymmetry indices were dominant predictors. Notably, the interpretability framework provided coaches with actionable insights, bridging the gap between raw AI predictions and practical training adjustments.

The SHAP decomposition is represented as:

$$f(x) = \phi_0 + \sum_{j=1}^{M} \phi_j \tag{24}$$

where ϕj denotes the contribution of each feature.

5.6 Interpretability and SHAP Analysis

In general, the results show that the suggested system can:

- Distinguishing between weariness states with an AUC over 0.9.
- R^2 ≈ 0.89 can help you guess how much training you need.
- Cutting injuries caused by fatigue and overload by more than 20%.
- Giving athletes individualized and easy-to-understand advice based on their profiles.

The results of this study show that using artificial intelligence to keep an eye on, forecast, and improve the training of boxers is both possible and useful. The suggested approach effectively tackled three essential aspects of athlete management—fatigue evaluation, training load forecasting, and injury prevention—by incorporating wearable motion sensors, machine learning algorithms, and a recommender system. The descriptive analysis of the cohort first demonstrated considerable differences between professional and amateur boxers regarding physiological performance and training requirements. Professionals consistently demonstrated superior jab velocity and elevated weekly training loads, coupled with decreased relative fatigue decline, signifying enhanced resilience and recovery profiles. These results not only confirm the anticipated variations attributable to training experience but also underscore the necessity of customizing AI-driven recommendations to align with the athlete's skill level and exposure.

Second, the classification of fatigue states showed very good predictive power, with an AUC of over 0.90, a precision of 0.87, and a recall of 0.84. This means that the model can correctly find athletes who are at risk of being too tired, which is an important part of avoiding overtraining syndrome. Misclassifications were prevalent in borderline cases; however, the incorporation of other contextual variables (e.g., recovery status or sleep quality) should further mitigate false negatives in subsequent research.

Third, the training load prediction model was quite accurate at predicting session demands, with a R^2 of 0.89 and a low mean squared error. This capacity is especially useful for coaches since it lets them design progressive overload methods ahead of time instead of depending on guesswork or trial and error. This means that training programs may be changed on the fly to fit each athlete's body type, which lowers the chances of both undertraining and overtraining. Fourth, the recommender system worked well at giving individualized, useful feedback. The AI-based recommender improved jab velocity outcomes by 15.6%, reduced overload-related fatigue episodes by 21.3%, and decreased injury incidence by 13.8% during a simulated 12-week follow-up. This is better than previous heuristic monitoring approaches. These findings underscore the medical significance of AI in boxing, since the system not only improves performance metrics but also directly aids in the maintenance of athlete health. The system was able to balance performance enhancement with injury risk reduction by using a multiobjective utility function, which changed its objectives based on whether the user was a professional or amateur boxer.

The SHAP values analysis of the model's conclusions made them clearer. It showed that jab velocity drop, cumulative load, and punch symmetry were the most important factors for tasks connected to tiredness and damage. This level of explainability is very important for coaches and sports doctors to believe and accept it, because it connects complicated AI algorithms with useful information for training. By showing the factors that have the biggest impact on a recommendation, the system helps stakeholders make smart choices, which supports a human-in-the-loop model.

In general, the results show that AI could be a useful tool for managing sports performance in a way that is good for health. The suggested approach offers a technology basis for real-time monitoring and individualized intervention in boxing, where the delicate balance between enhancing performance and avoiding injury risk is especially fragile. The system provides a practical means to get to precision training in combat sports by integrating sensor-based measurements, powerful predictive modeling, and easy-to-understand recommendations. These results also point to effects that go beyond boxing. The methodological framework—especially the incorporation of wearable sensors, AI-driven classification, regression models, and recommendation systems—can be applied to other high-intensity sports necessitating accurate load control and injury mitigation. This study illustrates sport-specific contributions and develops a framework for interdisciplinary applications in athlete healthcare and performance science.

6. Discussion

This study created and tested an AI-based system for keeping an eye on boxers. It used wearable inertial sensors, machine learning, and a recommender system to improve training and keep injuries from happening. The results showed that the model was good at predicting tiredness and load, and the recommender module did a good job of balancing performance goals with healthcare concerns. AI applications in sports have been more thoroughly examined in endurance and team sports compared to fighting disciplines [25,26]. Boxing is hard because its movements are uneven and explosive, and there is a considerable risk of injury to the muscles and bones. Our research shows that AI can monitor people in a tailored, data-driven way, which makes it easier to discover weariness early and adjust load more accurately. The framework's capacity to reduce overtraining and make athletes safer is shown by the high AUC (0.91) for tiredness classification and the strong R^2 (0.89) for load prediction. The recommender system's decrease in fatigue-related overload events (−21.3%)

and injuries (−13.8%) demonstrates its efficacy in harmonizing training optimization with healthcare priorities. This dual focus makes sure that recommendations are not just based on performance but also on the long-term health of the athlete. Few research have utilized AI in combat sports beyond technique recognition using inertial sensors [27]. Endurance sports, on the other hand, have shown more advanced uses, like being able to forecast injuries in runners [28]. This work expands AI applications into under-researched areas by including predictive modeling of fatigue and load into boxing. The use of explainable AI (XAI), particularly SHAP-based feature importance, improves the interpretability of AI models. This openness sets the framework apart from older "black box" models and helps build confidence between athletes and doctors, which is in line with recent calls for AI that can be understood in healthcare [29].

The framework has a modular pipeline that connects sensors, predictive models, a recommender system, and tools for making sense of the data. This design is flexible, so it can be improved in the future by adding multimodal signals like HRV or EMG. However, there are several problems with the study. For example, the sample size of professional athletes was small ($n = 15$), the focus was on training sessions instead of competitive circumstances, and the recommender system was tested in a simulated environment instead of in real time. Key stages for the future are to add more datasets, test in live competitions, and use real-time mobile input.

7. Conclusions

This study enhances the domain of AI in sports healthcare by illustrating that a pipeline incorporating wearable sensors, machine learning, recommender systems, and explainable AI can yield significant advantages in a high-risk, high-performance activity like boxing. The framework connects athlete monitoring technology with healthcare-focused AI solutions by addressing both performance optimization and injury prevention at the same time. This is a step toward precision sports medicine. This study also introduced an AI-based framework for monitoring performance, predicting fatigue, managing load, and preventing injuries among boxing athletes. We showed that data-driven insights can greatly improve both the healthcare viewpoint and the training results of athletes by combining wearable inertial measurement sensors (Neuron32), machine learning models, and a multi-objective recommender system.

The findings indicated that tiredness classification attained a significant discriminative ability ($AUC = 0.91$), whilst load prediction exhibited robust concordance with actual values ($R^2 = 0.89$). The use of the recommender system significantly reduced bouts of fatigue linked to overload by 21.3% and the number of injuries by 13.8%. This shows how useful this method can be in both clinical and practical settings. The approach makes sure that performance optimization is directly linked to injury prevention strategies, which makes long-term athlete growth safer than traditional heuristic training plans.

From a medical standpoint, the ability to oversee and avert overtraining and injuries constitutes a significant enhancement to sports healthcare. Overtraining syndrome, recurrent musculoskeletal strain, and accumulated exhaustion are chronic challenges in combat sports. This framework shows a way to get to precision sports medicine, where personalized monitoring makes it possible to give personalized treatments. From a technological point of view, combining machine learning with explainable AI (XAI) makes sure that the system is clear and easy to understand, which is important for coaches, athletes, and doctors to use it.

However, there are several problems, such as the small number of professional athletes and the fact that the study didn't include situations that happened during competitions. Subsequent investigations ought to authenticate this method inside larger, multicenter cohorts and facilitate its application for real-time implementation via mobile health platforms. Moreover, integrating multimodal physiological signals (e.g., HRV, lactate concentration, EMG) and adaptive algorithms like reinforcement learning could convert the system into a closed-loop, perpetually enhancing AI assistant. This research illustrates that the integration of wearable sensor technologies, artificial intelligence models, and recommender systems provides a comprehensive solution to improve performance, mitigate injury risk, and promote the health of boxing athletes. The suggested pipeline can be applied to further combat and endurance sports, establishing a foundation for AI-enhanced sports medicine as a fundamental aspect of athlete training and healthcare administration.

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