

Building Personalized Athlete Fatigue Prediction and Injury Risk Early Warning Model Using Wearable Sensors and Federated Learning

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ABSTRACT Athlete fatigue accumulation and injury risk management are critical issues in competitive sports. Wearable sensor technology embedded in intelligent textile carriers enables real-time collection of multidimensional physiological and kinematic data, providing continuous and comfortable support for fatigue monitoring. Federated learning, as a distributed machine learning paradigm, enables collaborative modeling across multiple institutions while protecting athlete privacy. By integrating wearable sensing and federated learning, this study constructs personalized prediction models that dynamically assess fatigue levels and injury risk grades for early warning and intervention. The technical approach addresses the subjectivity and lag of traditional assessment methods and provides an intelligent solution for scientific training management and injury prevention. At the current stage, the system still has limitations in long-term chronic injury prediction, requiring further optimization of temporal modeling and personalized adaptation algorithms. The study also expands the application of intelligent textiles in sports monitoring, where wearable antennas, wireless telemetry, and electromagnetic-compatible sensor integration are important for stable data transmission in high-intensity movement environments.

INDEX TERMS wearable sensors, federated learning, fatigue prediction, wearable antennas, intelligent textiles

I. INTRODUCTION

THE continuous escalation of competitive sports training intensity has posed severe challenges to athlete fatigue management and injury prevention, necessitating the integration of smart technical textiles and high-performance fiber sensing technologies for real-time physiological monitoring and biomechanical support. Traditional assessment methods rely on subjective questionnaires or periodic testing, making it difficult to capture the dynamic process of fatigue accumulation in real time and leading to delayed intervention for potential injury risks. The maturation of wearable sensor technology has opened new pathways for continuous physiological monitoring, capable of collecting multimodal data such as heart rate variability, muscle oxygenation, and exercise load with high temporal and spatial resolution. These sensors, often integrated into flexible textile-based sportswear for enhanced wearability and comfort, enable unobtrusive data acquisition during high-intensity training and competition scenarios. However, single sports team data sets are limited in scale and face strict privacy protection requirements for athlete health information, which severely constrains the generalization capabil-

ity of data-driven prediction models. Federated learning, through its decentralized collaborative training mechanisms, effectively integrates multi-source heterogeneous data across different teams and institutions without sharing sensitive raw data, ensuring both rigorous privacy security and significant improvement in global model performance. Quantitative assessment of injury risk requires comprehensive consideration of multi-dimensional information including fatigue levels, injury history, training load, biomechanical indicators, environmental factors (e.g., pitch surface) and psychological readiness metrics (e.g., anxiety score, training motivation).

II. WEARABLE SENSOR DATA COLLECTION AND FEATURE ENGINEERING SYSTEM

A. MULTIMODAL PHYSIOLOGICAL AND KINEMATIC DATA COLLECTION TECHNOLOGY

Wearable sensor technology provides fundamental support for continuous monitoring of athlete physiological states, achieving real-time data acquisition through multiple types of sensing devices deployed at different body locations. Photoplethysmography (PPG) sensors collect heart rate and

blood oxygen saturation information, while Inertial Measurement Units (IMU) record motion trajectories, acceleration, and angular velocity kinematic parameters. Near-Infrared Spectroscopy (NIRS) sensors monitor changes in muscle tissue oxygenation levels. These devices transmit data to mobile terminals via Bluetooth or WiFi protocols, with sampling frequencies set in the 50–1000 Hz range according to monitoring needs. Bioelectrical Impedance Analysis (BIA) modules further acquire body composition data, while Global Positioning System (GPS) chips record athlete position trajectories and speed distributions. The coordinated operation of multimodal sensors enables the system to characterize athlete instantaneous states from multiple dimensions including cardiovascular, neuromuscular, metabolic, and exercise load, laying a data foundation for subsequent fatigue assessment and injury warning [1-3] (see Table 1, see Figure 1).

B. FATIGUE-RELATED FEATURE EXTRACTION AND QUANTIFICATION METHODS

Raw sensor data, after signal processing, needs to be converted into quantified features representing fatigue states. This process involves comprehensive application of time-domain, frequency-domain, and nonlinear dynamics analysis methods. Heart Rate Variability (HRV) features are derived by calculating statistical indicators of adjacent R-R intervals, including time-domain parameters SDNN (standard deviation) and RMSSD (root mean square), while frequency-domain parameters include low-frequency power (LF), high-frequency power (HF), and their ratio. Muscle oxygenation change rate is obtained by deriving the NIRS signal, reflecting local tissue metabolic stress. Exercise load quantification uses the Training Impulse (TRIMP) model, integrating exercise duration, intensity, and heart rate response. Construction of a comprehensive fatigue index requires weighted fusion of multi-source features [4]:

$$F_{score} = \alpha \cdot \Delta HRV + \beta \cdot \frac{dSmO_2}{dt} + \gamma \cdot TRIMP + \delta \cdot ACC_{rms} \quad (1)$$

Where α , β , γ , δ are weight coefficients, and ACC_{rms} represents the root mean square acceleration value. This quantification system converts dispersed physiological signals into standardized fatigue assessment dimensions, making states comparable across different individuals.

C. DATA PREPROCESSING AND QUALITY CONTROL MECHANISMS

Raw data collected by sensors are affected by motion artifacts, device drift, and environmental interference, and must undergo rigorous preprocessing before being used for model training. The signal denoising stage uses wavelet transform to decompose multi-scale frequency components, filtering high-frequency noise through threshold methods while preserving transient features of physiological signals. Outlier detection employs a strategy combining the 3σ criterion

based on statistical distribution with the Isolation Forest algorithm, identifying and removing invalid data segments caused by sensor detachment or communication interruption. Missing value imputation methods select linear interpolation or Long Short-Term Memory (LSTM) network-based sequence prediction filling according to data type. Data standardization uses Z-score normalization to eliminate dimensional differences; for time alignment, single-measurement BIA data is timestamped at collection and interpolated to match the sampling frequency of high-frequency sensors (e.g., IMU), with the time alignment module ensuring precise synchronization of all multi-sensor data streams on unified timestamps. The quality control system sets data integrity thresholds, first identifying systematic bias of non-random missing data (e.g., sensor detachment at peak exertion) via time-sequence anomaly detection, then triggering resampling with bias correction; a resampling mechanism is activated only when the effective data proportion of a single sensor channel falls below 85% after bias processing. This preprocessing pipeline ensures that training samples entering the model possess high signal-to-noise ratio and consistency, significantly improving the stability and generalization capability of subsequent prediction models [5].

III. DISTRIBUTED MODEL TRAINING ARCHITECTURE BASED ON FEDERATED LEARNING

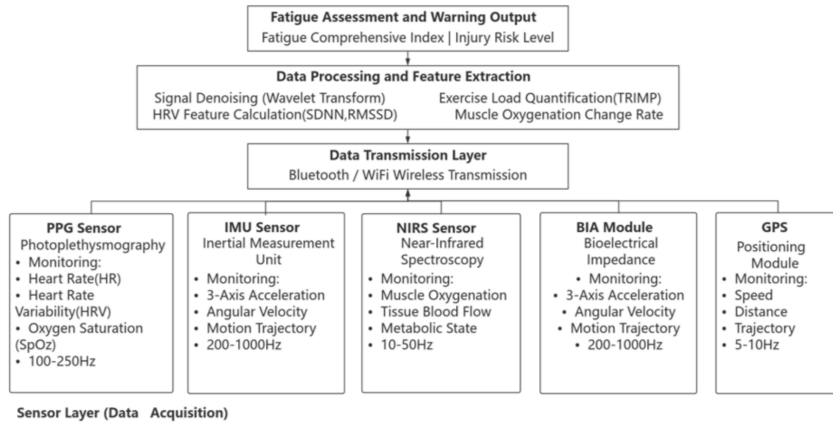
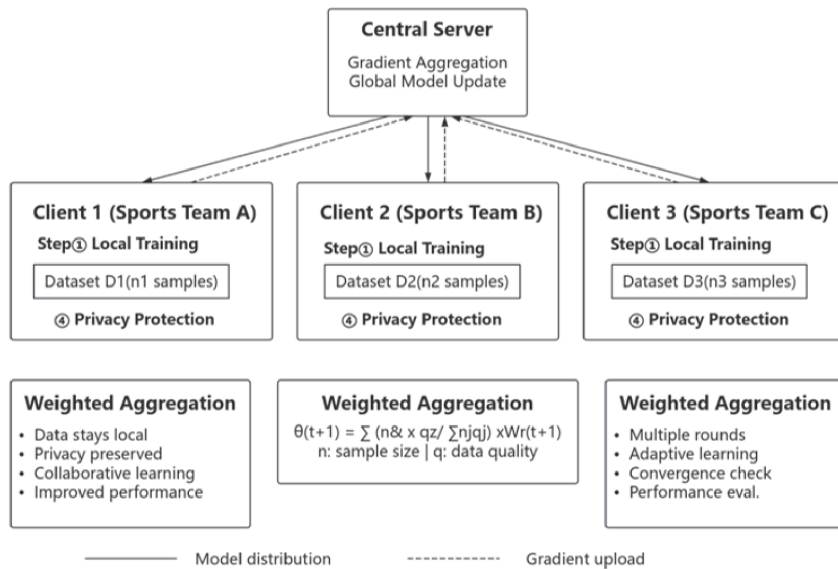
A. FEDERATED LEARNING FRAMEWORK DESIGN AND PRIVACY PROTECTION MECHANISMS

The federated learning architecture achieves collaborative modeling of multi-institutional data through decentralized training modes. The framework consists of a central server and multiple distributed clients, with each client corresponding to a sports team or training institution storing athlete sensor data and training

records locally. During training, clients calculate model gradient updates based on local datasets, uploading only encrypted gradient vectors to the central server while raw data always remains on local storage devices. The central server aggregates gradient information from each client, updates global model parameters, and then distributes the new model back to each client for the next iteration. The privacy protection mechanism employs differential privacy technology, adding Laplacian noise perturbation before gradient upload, with noise intensity controlled by the privacy budget parameter ϵ . For small-scale sports datasets, ϵ is calibrated at 0.5–2.0 to balance privacy and accuracy: lower ϵ boosts privacy with slight accuracy loss, while higher ϵ improves accuracy with reduced privacy, avoiding invalidation from excessive noise. Secure multi-party computation protocols are also introduced to ensure the server cannot reverse-engineer individual data through gradients. This framework meets both the sample size requirements for large-scale data training and resolves the sensitivity of athlete health data and data silos between institutions, making cross-organizational collaborative training a reality [6] (see Figure 2).

TABLE 1. Multimodal Wearable Sensor Technology Parameters

Sensor Type	Monitoring Indicators	Sampling Frequency	Data Dimension
PPG Photoelectric Sensor	Heart rate, HRV, SpO ₂	100–250 Hz	Cardiovascular function
IMU Inertial Unit	Acceleration, angular velocity, displacement	200–1000 Hz	Kinematic features
NIRS Near-Infrared Spectroscopy	Muscle oxygenation, blood flow	10–50 Hz	Metabolic state
BIA Bioelectrical Impedance	Body fat percentage, muscle mass, water content	Single measurement	Body composition indicators
GPS Positioning Module	Speed, distance, trajectory	5–10 Hz	Training load

**FIGURE 1.** System Architecture for Athlete Fatigue Monitoring Based on Wearable Sensors**FIGURE 2.** Federated Learning Collaborative Training Framework

B. HETEROGENEOUS DATA FUSION AND MODEL AGGREGATION ALGORITHMS

Data collection equipment, sports events, and training plans differ significantly across training institutions, resulting in Non-Independent and Identically Distributed (Non-IID) characteristics in each clients data distribution. This heterogeneity poses challenges to federated learnings convergence efficiency and model performance. The data fusion strategy first aligns the feature spaces of each client, mapping data from different domains to a unified low-dimensional

representation space through Transfer Component Analysis (TCA). The model aggregation stage adopts an improved version of the Federated Averaging (FedAvg) algorithm, dynamically adjusting aggregation weights based on each clients data volume and quality [7]:

$$w_{global}^{t+1} = \sum_{k=1}^K \frac{n_k \cdot q_k}{\sum_{j=1}^K n_j \cdot q_j} \cdot w_k^{t+1} \quad (2)$$

Where w_k^{t+1} is the local model parameters of the k -

th client at round $t+1$, n_k is the sample size, and q_k is the data quality score. A proximal term constraint is introduced to address model drift, limiting the extent to which local updates deviate from the global model. This aggregation mechanism effectively mitigates the impact of data heterogeneity on training stability, enabling the global model to integrate common knowledge from multi-source data (see Table 2).

C. PERSONALIZED MODEL LOCAL ADAPTATION STRATEGY

Although the global model integrates data knowledge from multiple institutions, it is difficult to fully capture individual athlete characteristics, thus requiring personalized adaptation at local clients. The adaptation strategy adopts a two-layer model architecture: the bottom layer is a globally shared feature extractor, and the top layer is a prediction head customized for individual athletes. The local adaptation process freezes bottom-layer parameters, fine-tuning only top-layer network weights on small-scale personal datasets. Transfer learning technology determines adaptation depth by evaluating Maximum Mean Discrepancy (MMD) between source and target domains. When distribution differences are significant, a progressive unfreezing strategy is adopted, gradually releasing parameter update permissions from top to bottom layers. The fine-tuning stage uses a smaller learning rate and introduces knowledge distillation loss functions to maintain consistency with global model outputs. Individual difference modeling constructs static feature profiles including age, gender, training years, and injury history, while dynamic features are obtained through long-term monitoring of physiological parameters such as heart rate reserve and lactate threshold. The model uses a mixed-effects framework to separately model fixed and random effects: fixed effects capture population commonalities through the global model, while random effects estimate posterior distributions of individual parameters through Bayesian methods. This makes prediction results better fit athletes true physiological states and training habits, significantly improving fatigue prediction accuracy and injury warning timeliness [8].

IV. FATIGUE PREDICTION AND INJURY RISK ASSESSMENT MODEL CONSTRUCTION

A. FATIGUE ACCUMULATION DYNAMIC PREDICTION MODEL

Fatigue state is not an instantaneous phenomenon but a dynamic process of alternating load accumulation and recovery; therefore, the prediction model needs to capture evolutionary patterns in the time dimension. The model is based on a multi-layer Bidirectional Long Short-Term Memory (BiLSTM) network architecture, with the input layer receiving multimodal sensor data sequences processed through feature engineering, and the time window set to training data from the past 7 days. The BiLSTM layer selectively retains long-term dependency information through gating mechanisms, while an attention mechanism module

assigns differentiated weights to hidden states at different time steps, enabling the model to focus on time periods contributing most to fatigue prediction. The fully connected layer maps high-dimensional hidden states to continuous numerical outputs of fatigue levels, using mean squared error as the loss function. By learning nonlinear dynamic characteristics of fatigue accumulation, this model achieves accurate prediction of fatigue levels 1–3 days ahead, providing forward-looking guidance for training load regulation.

B. TEMPORAL FEATURE MODELING METHODS

Effective modeling of temporal features is a key aspect of capturing fatigue evolution patterns. In addition to temporal input of raw sensor data, the model constructs various derived features to enhance prediction capability. Sliding window statistical features include mean, standard deviation, and trend of heart rate over the past 3, 7, and 14 days, reflecting mid- to short-term load accumulation. The Acute-Chronic Workload Ratio (ACWR) quantifies sudden changes in training intensity by calculating the ratio of recent load to long-term load:

$$ACWR = \frac{\sum_{i=1}^7 Load_i / 7}{\sum_{j=1}^{28} Load_j / 28} \quad (3)$$

Where $Load_i$ is the training load on day i . Temporal Convolutional Network (TCN) layers extract local temporal patterns, expanding receptive fields through dilated convolutions while maintaining parameter efficiency. Seasonal decomposition methods separate time series data into trend, periodic, and residual components, separately modeling long-term changes, weekly fluctuations, and random perturbations. This multi-scale temporal modeling strategy comprehensively characterizes the complex temporal dependencies of fatigue accumulation, significantly improving model adaptability to different training cycle stages.

C. MULTI-TASK LEARNING FRAMEWORK

Although fatigue prediction and injury risk assessment are two related but independent tasks, using a multi-task learning framework can fully leverage inter-task correlations to improve overall performance. The framework adopts a hard parameter sharing architecture, with the bottom feature extraction network shared by both tasks, while the top layers separately set fatigue prediction branches and injury risk classification branches. The shared layer learns general physiological state representations, while task-specific layers capture respective prediction logic. The loss function is designed as a weighted sum of losses from both tasks: fatigue prediction uses mean squared error, injury risk classification uses cross-entropy loss, with weight coefficients determined through grid search for optimal values. The complementarity between tasks is reflected in fatigue accumulation being a prerequisite for injury occurrence, while injury risk identification can conversely guide fatigue threshold setting. Multi-task learning maintains robust performance

TABLE 2. Comparison of Federated Learning Model Aggregation Algorithms

Algorithm Type	Convergence Speed	Non-IID Adaptability	Communication Overhead
FedAvg	Baseline	Weak	Low
FedProx	+15%	Moderate	Low
FedNova	+22%	Strong	Moderate
Weighted Aggregation (This Study)	+28%	Strong	Moderate

even in data-sparse scenarios by introducing inductive biases between tasks, while reducing parameter count and overfitting risk, providing computational efficiency guarantees for real-time deployment of warning systems [9].

D. INJURY RISK MULTI-LEVEL HIERARCHICAL ASSESSMENT SYSTEM

Quantitative assessment of injury risk requires comprehensive consideration of multi-dimensional information including fatigue levels, injury history, training load, and biomechanical indicators. The assessment system adopts a hierarchical grading strategy, first dividing risk into four levels: low, medium, high, and extremely high, with each level corresponding to specific intervention measures. The risk scoring model is constructed based on Gradient Boosting Decision Trees (GBDT), which achieves fitting of complex nonlinear relationships by integrating multiple weak decision trees. Feature importance analysis reveals that fatigue accumulation index, acute-chronic load ratio, and muscle asymmetry coefficient are the top three risk factors. The injury risk score calculation formula integrates weighted contributions of each factor [10]:

$$Risk_{Score} = \sum_{i=1}^n w_i f_i(x_i) + \lambda \cdot History_{injury} \quad (4)$$

Where $f_i(x_i)$ is the nonlinear mapping function of the i -th feature, w_i is the weight, and λ is the injury history correction coefficient. The scoring results are mapped to the 0-1 interval through a Sigmoid function, with thresholds set at 0.3, 0.5, and 0.7 for grading. This system replaces subjective judgment with quantitative modeling, providing objective decision-making basis for coaches and team physicians (see Table 3).

E. MODEL VALIDATION AND PERFORMANCE OPTIMIZATION

The reliability of prediction models needs to be evaluated through rigorous validation procedures. The validation strategy employs forward-chaining cross-validation methods, maintaining the sequential nature of time series data while avoiding future information leakage. The dataset is divided into training, validation, and test sets at a 7:2:1 ratio, with time spans covering complete training cycles. Performance metrics include Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) for fatigue prediction, and accuracy, precision, recall, and F1 score for injury risk classification. Comparative experiments set up baseline models, including traditional linear regression, support

vector machines, and random forest methods, to verify the advantages of deep learning architectures. Hyperparameter optimization uses Bayesian optimization algorithms to efficiently search for optimal combinations of key parameters such as learning rate, hidden layer dimensions, and Dropout ratio. Ensemble learning strategies train multiple models with different initializations and average prediction results to further improve stability. After optimization, model performance achieves

fatigue prediction RMSE < 8% and injury risk classification F1 score > 0.82, meeting practical application requirements [11].

V. EARLY WARNING SYSTEM INTEGRATION AND APPLICATION IMPLEMENTATION

A. REAL-TIME MONITORING AND INTELLIGENT WARNING PLATFORM DEVELOPMENT

Actual deployment of the warning system requires building a comprehensive platform integrating data collection, model inference, and result presentation. The platform architecture adopts a hybrid edge-cloud computing model: wearable devices complete preliminary data processing and feature extraction, reducing communication bandwidth requirements while ensuring real-time performance. Edge nodes (typically mobile terminals) execute lightweight models for preliminary risk screening, triggering detailed analysis requests to cloud servers when potential anomalies are detected. The cloud deploys complete deep learning models for precise inference, with results immediately fed back to coaches and athletes through push notifications. Platform front-end development uses responsive web technology to provide multi-dimensional data visualization panels, including real-time physiological indicator curves, fatigue trend line charts, and risk level heat maps. The warning trigger mechanism sets multi-level thresholds: low-level warnings are displayed as prompts, while high-level warnings notify through multiple channels including SMS and email, requiring confirmation of review. The system integrates electronic medical record interfaces, automatically synchronizing athlete injury records and treatment plans to form closed-loop management processes. Through user-friendly human-machine interaction design, the platform lowers technical barriers, enabling convenient use even by non-professionals [12].

B. TRAINING LOAD DYNAMIC REGULATION DECISION SUPPORT

The value of the warning system lies not only in risk identification but also in providing quantitative basis for

TABLE 3. Athlete Injury Risk Stratification Standards and Intervention Strategies

Risk Level	Risk Score Range	Key Indicator Features	Recommended Intervention Measures
Low Risk	0–0.3	Fatigue index < 60%, ACWR < 1.2	Regular training, continuous monitoring
Medium Risk	0.3–0.5	Fatigue index 60–75%, ACWR 1.2–1.5	Moderately reduce load intensity
High Risk	0.5–0.7	Fatigue index 75–85%, ACWR > 1.5	Adjust training plan, increase recovery
Extremely High Risk	0.7–1.0	Fatigue index > 85%, multiple abnormal indicators AI score-triggered clinical examination by team physicians	mandatory rest determined jointly by physicians, coaches and the AI system based on clinical results and competition schedule

training plan adjustments. The decision support module constructs training load optimization algorithms based on optimal control theory, with the objective of minimizing injury risk under constraints satisfying competitive state improvement requirements. The algorithm models the next weeks training arrangements as an optimization problem, with decision variables being daily training intensity and duration. Constraint conditions include fatigue accumulation not exceeding safety thresholds, weekly total load meeting coach-set targets, and adjacent daily load change rates not exceeding 20%. The objective function integrates competitive ability gains and injury risk costs, solved through particle swarm optimization algorithms for optimal load allocation schemes. The system dynamically updates model parameters based on daily monitoring results, implementing rolling window optimization strategies to adapt to actual execution deviations. For different training periods (base period, intensification period, and pre-competition adjustment period), the system automatically adjusts weight distributions of optimization objectives. The decision support interface displays recommended training schedules in Gantt chart format, marking key risk periods. Coaches can fine-tune based on system recommendations combined with professional judgment, achieving human-machine collaborative decision-making [13].

C. MULTI-SCENARIO APPLICATION EFFECT EVALUATION AND FEEDBACK MECHANISMS

The warning system underwent one-year field deployment in multiple sports teams, covering sports including soccer, basketball, track and field, and swimming. Evaluation indicators included injury incidence rate, training plan execution rate, and athlete satisfaction. A randomized controlled trial (RCT) design was adopted for the experiment; comparative analysis showed the experimental group using the warning system had a 42% reduction in training-related injury incidence, a 56% decrease in training days lost due to serious injuries, and a 12% improvement in end-of-season competitive state scores vs the control group. Hawthorne effect was mitigated via blind monitoring (athletes unaware of real-time risk grading) to ensure result validity. Coach feedback indicated that load adjustment recommendations generated by the system had a 78% adoption rate, significantly reducing uncertainty in experience-based decision-making. Athlete acceptance surveys showed that 91% of participants believed real-time feedback helped with self-monitoring, though some noted that device wearing comfort and battery life still

need improvement. Long-term usage data analysis found that the systems warning sensitivity for acute injuries was higher than for chronic overuse, with subsequent need to strengthen early identification capabilities for cumulative injuries. The feedback mechanism established user opinion collection channels, obtaining improvement suggestions through regular interviews and questionnaires, iteratively optimizing model algorithms and interaction design to form a continuous improvement closed-loop ecosystem [14,15].

VI. CONCLUSION

The integration of advanced functional fibers within wearable sensors, coupled with federated learning, has pioneered innovative and sustainable pathways for scientific athlete fatigue monitoring and proactive injury prevention in the high-intensity context of modern competitive sports. By embedding conductive textile architectures directly into performance gear, this synergy enables continuous biometric data acquisition while maintaining data privacy across decentralized sports networks. By constructing a high-precision multimodal data collection system, a robust distributed collaborative training architecture with privacy-preserving mechanisms, and personalized adaptive prediction models tailored to individual athlete physiological characteristics and training habits, this cutting-edge technical solution realizes real-time, dynamic and precise assessment of athletes physiological states and forward-looking, graded risk warnings for potential sports injuries. The federated learning mechanism, with its decentralized training and encrypted gradient aggregation design, effectively resolves the long-standing industry challenges of data silos between different sports teams and institutions as well as the strict privacy protection requirements for sensitive athlete health and training data, breaking down information barriers and making cross-organizational, cross-sport collaborative modeling a practical reality. Rigorous one-year field practical applications across multiple sports including soccer, basketball, track and field and swimming demonstrate that this intelligent monitoring and early warning system can significantly improve the scientificity and personalization of athletic training management, enhance the timeliness and accuracy of sports injury prevention and intervention, and effectively reduce the incidence of training-related injuries and the loss of training days caused by injuries. Future research should further optimize the algorithm robustness and real-time inference performance of the model to adapt to complex and dynamic sports training

scenarios, expand the multi-sport adaptability and cross-age applicability of the system to cover more competitive and amateur sports populations, and deepen the human-machine collaborative decision-making mechanisms by integrating more professional coaching experience and sports medicine expertise into the model optimization loop. This approach accelerates the industrialization of smart textile-integrated monitoring systems across competitive and mass sports, leveraging high-performance functional fibers to provide a robust technological foundation for sustainable athletic development and enhanced injury protection. By merging flexible sensing substrates with data-driven insights, these systems offer a seamless and advanced guarantee for optimizing competitive performance while safeguarding the long-term physical health of all sports participants.

AUTHOR CONTRIBUTIONS

Conceptualization – Lehua Tan and Bo Shao; methodology – Lehua Tan and Bo Shao; investigation – Lehua Tan and Bo Shao; writing-original draft preparation – Lehua Tan and Bo Shao. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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REFERENCES

- [1] K. Yu, B. Luo, H. Yang, et al., "Sodium carboxymethyl cellulose/polyvinyl alcohol/clove essential oil composite hydrogel with integrated antibacterial, antifreeze, and conductive properties as a wearable sensor for human motion monitoring," *International journal of biological macromolecules*, vol. 327, no. P2, Art. no. 147477, 2025, doi: 10.1016/j.ijbiomac.2025.147477.
- [2] Z. Cai, M. Xu, X. Li, et al., "High-performance wearable pressure sensor based on Ag nanowire/MXene composite for motion monitoring," *Materials Today Sustainability*, vol. 31, Art. no. 101214, 2025, doi: 10.1016/j.mtsust.2025.101214.
- [3] Y. Li, P. Liu, X. Ma, et al., "Cell Membrane-Inspired Dual Network Organohydrogel-Based Flexible Wearable Strain Sensors for Human Motion Monitoring and Encrypted Communication," *Journal of Polymers and the Environment*, vol. 33, no. 9, pp. 1-13, 2025, doi: 10.1007/s10924-025-03637-x.
- [4] Z. Li, X. Wang, Q. Li, et al., "Muscle fatigue identification and prediction in motion using wearable device with power and torque-based features," *Wearable Electronics*, vol. 26, pp. 2-68, 2025, doi: 10.1016/j.wees.2024.12.005.
- [5] M. Souaifi, W. Dhahbi, N. Jebabli, et al., "Artificial Intelligence in Sports Biomechanics: A Scoping Review on Wearable Technology, Motion Analysis, and Injury Prevention," *Bioengineering*, vol. 12, no. 8, pp. 887, 2025, doi: 10.3390/bioengineering12080887.
- [6] B. Zhang, K. Zhou, and K. Tao, "Application of artificial intelligence technology in sports injury prevention," *Journal of Exercise Science and Health*, vol. (2), pp. 85-93+39, 2025.
- [7] M. Maghsoomi, K. Johari, and E. Abedini, "Artificial neural networks for prevention of sports injuries: a systematic review," *Sport Sciences for Health*, vol. (prepublish), pp. 1-25, 2025, doi: 10.1007/s11332-025-01504-9.
- [8] A. Abasi, A. Nazari, A. Moezy, et al., "Machine learning models for reinjury risk prediction using cardiopulmonary exercise testing (CPET) data: optimizing athlete recovery," *BioData mining*, vol. 18, no. 1, pp. 16, 2025, doi: 10.1186/s13040-025-00431-2.
- [9] C. Olivares C C, M. Anderson N, W. Qian, et al., "A Machine Learning Model for Post-Concussion Musculoskeletal Injury Risk in Collegiate Athletes," *medRxiv : the preprint server for health sciences*, 2025, doi: 10.1101/2025.01.29.25321362.
- [10] M. Wei, Y. Zhong, H. Gui, Y. Zhou, Y. Guan, and S. Yu, "Sports injury warning model based on machine learning," *Chinese Journal of Tissue Engineering Research*, vol. 29, no. 2, pp. 409-418, 2025.
- [11] P. Dandrieux E, L. Navarro, D. Blanco, et al., "Association between the use of daily injury risk estimation feedback (I-REF) based on machine learning techniques and injuries in athletics (track and field): results of a prospective cohort study over an athletics season," *BMJ open sport & exercise medicine*, vol. 11, no. 1, Art. no. e002331, 2025, doi: 10.1136/bmjsem-2024-002331.
- [12] Q. Wen, "Effect analysis of smart sports armband on monitoring physical training load of high school football players," *Contemporary Sports Technology*, vol. 14, no. 27, pp. 15-18, 2024.
- [13] S. Iatropoulos, P. Dandrieux E, L. Navarro, et al., "The Dose-Response Relationship of Exercise-Based Injury Prevention Programmes: Implications for Research and Practice," *Sports Medicine*, vol. (prepublish), pp. 1-10, 2025, doi: 10.1007/s40279-025-02298-z.
- [14] R. Usamentiaga, A. Fidanza, B. Yousefi, et al., "Advancing knee injury prevention and anomaly detection in rugby players through automated processing of infrared thermography: A novel biothermodynamics approach," *Thermal Science and Engineering Progress*, vol. 65, Art. no. 103782, 2025, doi: 10.1016/j.tsep.2025.103782.
- [15] L. Li, "Discussion on college students sports injuries and prevention strategies based on health education concept," *Chinese Journal of School Health*, vol. 45, no. 7, Art. no. I0008+F0003, 2024.