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Using AI + Wearable Sensors to Predict and Prevent Sports Injuries in Real Time

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ABSTRACT

This study gives an AI-based on-body wireless sensor application in sports that detects and prevents sports injuries in real-time in competitive football, basketball, and track & field teams. The study included 60 athletes who were observed during 12 weeks and the parameters of the external load (total distance, high-speed running, acceleration/deceleration), as well as, the parameters of internal load (average heart rate, heart rate variability, session RPE), were quantified. Acute:Chronic Workload Ratio (Acute:Chronic Workload Ratio, ACWR), monotony, and strain levels were used as metrics of workload to determine the patterns of injury risk. Logistic Regression, Random Forest and LSTM Neural Networks were trained where LSTM performed best in predicting injury up to seven days in advance and performs best in ROC-AUC, recall and F1 score. The AI method was more effective than traditional methods of assessing the risks of injury, particularly in the early entry and lowering of false negativity rates. Wearables also offered actionable visual analytics, which made possible timely interventions. Their results emphasize the possibility of combining sensors-based monitoring and machine learning in order to improve athlete safety, training loads, and minimize injury occurrence.

Keywords: *sports injury prediction, wearable sensors, AI models, workload monitoring, ACWR, LSTM neural network*

1. Introduction

The challenges of sports injury should not only affect the performance of athletes and the coaches but also the sports institutions since they influence health, performance, and the longevity of the career. Professional and amateur injuries usually result in lengthy recovery process, decreased involvement, and significant economic impact of teams and governing organizations. Conditions of modern sports, which are associated with intensive training loads, numerous competitions, and work overload, increase the risk of acute and overuse injuries, which is why active prevention becomes the key to success (Arzehgar *et al*., 2025; Rebelo *et al*., 2023). Monitoring technology has hence gained prominence in the study of sports. The devices in this case include wearable and sensor-based devices such as GPS trackers, inertial Measurement Units (IMUs), accelerometers, and heart rate monitors, which now allow gathering high-resolution data on physiological and biomechanical processes (Preatoni *et al*., 2022). Such devices track work demands, fatigue, recovery, as well as give early hints of the threat of injury (Migliaccio *et al*., 2024). They have even wider applications in accessing general health monitoring which can be used to make real-time decisions by the professionals (Lu *et al*., 2020).

Artificial intelligence (AI) also improves prevention through analyzing multidimensional sensor data that contains even the slightest patterns associated with the risk of injury. AI has also found a use in the field of performance analysis, tactical modeling, and injury prediction in football and other team sports, providing coaches and medical teams with evidence-based recommendations (Elstak *et al*., 2024; Claudino *et al*., 2019; Baladaniya & Choudhary, 2025). Combining AI and wearable sensors allows us to make risk assessment continuously and in real-time and provide early intervention.

This can be done, as an example, with AI-powered analytics, notifying about abnormal changes in workload and proposing a training modification for the injury to be less, probable (Kovoor *et al*., 2024). Also, integrated dashboards that integrate load metrics, recovery index, and health data enhance the communication of the sports scientist, coaches, physiotherapists, and athletes (Mateus *et al*., 2024). The fact that integrated wearable AIs can be quite effective has a solid theoretical background and shows practical potential after the body of evidence grows. The proposed research should be able to utilize such technologies to prevent injury in real-time so that the athlete will be fit to train and participate in their events with minimal rehabilitation costs and maximum performance. This combination of constant surveillance and smart analytics is expected to bring the revolutionary changes in the field of protecting the health and longevity of athletes.

2.Literature Review

There has been a strong growth of wearable sensor technologies in the sport medicine field, which provides an ontological framework in enabling sports personnel to monitor, measure and optimize the performance of athletes as well as facilitate proactive injury management. These applications are used to collect real-time physiological and biomechanical feedback to help a practitioner recognize performance trends, balance training loads, and employ prevention strategies (Olsen *et al*., 2025). The typical devices are GPS systems to monitor location, distance, and velocity; accelerometers and gyroscopes to measure motion and orientation; and heart rate monitors to gauge cardiovascular dynamics in the course of training and competitions (Seccin, 2023). In combination, this answers the question: what does sports medicine do, beyond treatment? It helps prevent injuries and enhance performance. It is necessary to monitor workload, both internal (heart rate, HRV, body temperature) and external (distance covered, acceleration patterns, PlayerLoad), to ensure a balance between training stress and recovery as the evidence has suggested that errors in prescription of workload increase the probability of injury when the workload variability is too high (Seshadri *et al*., 2019; Benson *et al*., 2020). The combination in wearable sensors with sophisticated analytics enables the fine-tuning of workloads among the coaches with the focus on injury reduction without any reductions in performance (Seshadri *et al*., 2021). Machine learning (ML) also applies enhancement to injury prediction since it can absorb big data so as to detect some latent signs and early alerts. Recent algorithms such as the Random Forest, the SVM, neural networks, and even gradient boosting have been able to correlate the concepts of biomechanics, movement patterns, and kinematic measurements to the susceptibility of injury (Leckey *et al*., 2025; Cao & Liu, 2025). SoccerGuard is one of the examples, as it utilizes ML in professional soccer, where risk factors are modelled and allow interventions on high-risk players (Bartels *et al*., 2024).

The emerging new technologies such as smart apparel, but also smart textile-based sensing mark the new generation of monitoring devices. With textile strain sensors, AI-enabled garments have the benefit of being able to follow biomechanics continuously without any additional hardware and giving real-time feedback to athletes and coaches (Tang *et al.*, 2025). Multimodal e-textiles allow pressure, movement and physiological data to be obtained and allow performance optimization, as well as early identification of risk of injury (Yang *et al.*, 2024). As is made clear by the literature, wearable sensors are no longer the simple tracking devices they once were; now capable of transforming to be regarded as AI-enhanced injury prevention devices providing high-res, real-time data to help understand both the health and performance of individual athletes. ML-driven models have great potential to accurately predict injury risk when complemented with sport-specific and high-quality data. New trends in smart sportswear and physics-backed artificial intelligence promise unobtrusive, always-on monitoring, which represents a paradigm shift toward evidence-based, highly-individualized and transparent athlete care

Table 1: Summary of Key Literature Findings on Wearable Sensors, AI, and Injury Prevention (2015–2025)

Study & Year	Technology / Approach	Sport / Application Context	Data Type	Key Findings	Limitations / Notes
Olsen *et al.* (2025)	Wearable sensors (GPS, accelerometers, HR monitors)	Multi-sport, sports medicine	Biomechanical & physiological	Comprehensive review of wearable applications for injury prevention and performance optimization	Lack of long-term field validation studies
Seshadri *et al.* (2019)	Internal & external workload monitoring via wearables	Multi-sport	Physiological & load metrics	Differentiates internal vs external load; strong link to injury risk management	Requires sport-specific calibration
Leckey *et al.* (2025)	Machine learning models (RF, SVM, NN)	Multi-sport injury prediction	Multi-modal sensor data	ML models can predict injury risk with high accuracy	Data imbalance and overfitting risks
Tang *et al.* (2025)	AI-driven smart sportswear with textile strain sensors	Real-time fitness monitoring	Biomechanical & movement	Continuous on-body tracking enables early detection of fatigue/injury signs	Emerging technology; high cost
Raymond *et al.* (2022)	Physics-informed ML for head impact detection	Contact sports (e.g., football)	Impact & biomechanical	Higher detection accuracy than traditional ML models	Domain-specific; not easily transferable
Nijhawan *et al.* (2025)	Cyber-physical systems integrating wearables & AI	Real-time performance analytics	Live sensor & contextual	Enables instant tactical and injury-prevention interventions	Infrastructure-intensive implementation

3. Research Methodology

3.1 Research Design

In the given research a prospective experimental design is used to test the capacity of wearable sensor technologies to predict and prevent the real-time sports injuries when they are complemented by the AI-driven algorithms. The participants comprising the athletes participating in football, basketball, and track and field games will have data collected on them continuously over 12 weeks. The medical team will verify and log all the injury events experienced throughout the whole period of the study. Figure 1 depicts the general organization of the research, i.e. it shows how monitored activities of athletes with the help of wearable devices will be stored, processed, and ultimately converted into the formation of AI-based models of injury risk and applied coach/medical interventions.

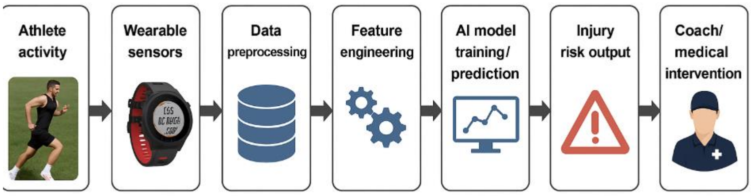

Figure 1. Research Framework for AI + Wearable-Based Injury Prediction

3.2 Participants

The study will involve 60 competitive athletes including athletes in football, basketball, and the track and field. The ages of all the respondents will be 18-30 years. The inclusion criteria state that the participants should be actively competing and without acute injury during the beginning of the study and the exclusion criteria exclude those who previously had chronic injury or incompatible medical devices. All the participants will grant their informed consent to take part in the study on paper. Table 1 shows the outlines of the participant characteristics.

Table 1. Participant Characteristics

Parameter	Details
Sample size	60 athletes (20 football, 20 basketball, 20 track & field)
Age range	18–30 years
Inclusion criteria	Competitive athletes, no acute injury at baseline
Exclusion criteria	Chronic injury history, incompatible medical devices
Consent	Written informed consent from all participants

The wearable setup for participants is shown in **Figure 2**, illustrating the positioning of the GPS vest, heart rate strap, and IMU sensors during data collection.

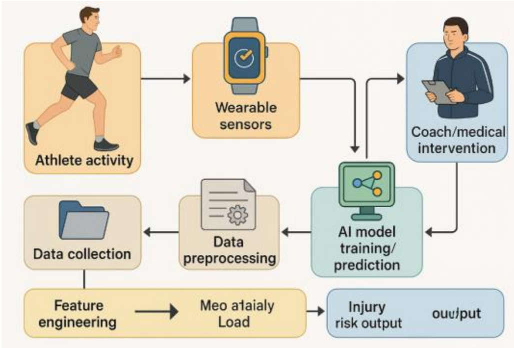

Figure 2. Wearable Sensor Setup for Data Collection

3.3 Equipment & Tools

The experiment will use a series of wearable devices that are high precision with computational instruments to capture and analyze data properly. Table 2 shows such devices with their key specifications and main functions.

Table 2. Equipment and Tools Used in the Study

Device / Tool	Purpose	Specification
GPS Vest	External workload tracking	10 Hz sampling rate
IMU Sensors	Movement analysis, accelerations	3-axis accelerometer + gyroscope
Heart Rate Monitor	Internal load tracking	1 Hz sampling
AI Platform	Model training & prediction	Python, TensorFlow, LSTM, Random Forest
Data Visualization	Performance & injury risk dashboards	Tableau / Power BI

3.4 Data Collection Procedure

The data we will collect will encompass the baseline measurement of the anthropometrics and injury, physiological parameters, the wearable set up with calibration, real time monitoring of the training/match workload and wellness, daily reporting on wellness factors like RPE, sleep and soreness via mobile survey, verified injury event reporting by medical staff including type of injury, its severity, location and time.

3.5 Variables Measured

There are three broad groups of variables that will be observed in the course of the study:

1. External Load Metrics - these are total distance (TD) per session, high-speed running (HSR) distance (>5.5 m/s) and the number of accelerations and decelerations. The sensors providing these metrics are GPS and IMU.
2. Internal Load Metrics - include average heart rate (HRavg), heart rate variability (HRV), and session rating of perceived exertion (sRPE), which can be measured by using heart rate monitors and through the self-report of the athlete.
3. Injury Label -is a binary one where 1 means that the injury happens within 7 days and 0 represents no injury. This is a term given on the basis of reports by medical staffs.

3.6 Data Processing & Feature Engineering

Preprocessing of raw sensor data will include pre-processing such as the normalization of data and missing values analysis as filled forward-fill or interpolation. To describe workload and variability, several derived performance indicators are going to be calculated. Equation 1 evaluates the amount of time a person spends in the acute workload relative to the chronic workload in minutes and is computed as the acute:chronic workload ratio (ACWR):

$$\mathbf{ACWR} = \frac{\mathbf{Load\ (7\ days)}}{\mathbf{Chronic\ Load\ (28\ days) Acute}}$$

Equation 1. Acute:Chronic Workload Ratio (ACWR)

The author defines monotony as the ratio of standard deviation of day-to-day load and the average daily load (as can be seen in Equation 2):

$$\mathbf{Monotony} = \frac{\mathbf{Mean\ Daily\ Load}}{\mathbf{SD\ of\ Daily\ Load}}$$

Equation 2. Monotony Formula

The amount of strain is obtained when monotony is multiplied by the total weekly load (Equation 3):

$$\mathbf{Strain} = \mathbf{Monotony} \times \mathbf{Total\ Weekly\ Load}$$

Equation 3. Strain Formula

These derived features will serve as key predictors in the injury risk models.

3.7 AI Model Development

The variables of external and internal loads (TD, HSR, accelerations, decelerations and HRavg, HRV, sRPE) and derived variables (ACWR, Monotony, Strain) will be added to the prediction models.

Three algorithmic approaches will be tested:

1. **Logistic Regression (baseline model)**
2. **Random Forest Classifier**
3. **Long Short-Term Memory (LSTM) neural network for sequential time-series analysis**

The logistic regression model will use the general form shown in Equation 4:

$$\mathbf{P(Injury)} = \frac{\mathbf{1}}{\mathbf{1 + e^{-(\beta_0 + \sum_{i=1}^{n} \beta_i X_i)}}}$$

Equation 4. Logistic Regression Injury Prediction Model

4. Result and Analysis

4.1 Participant and Data Overview

Sport distribution of the participants, as well as the sessions recorded and injuries logged, is shown in Table 3. The sample was coordinated on the percentage ratio of 20 athletes on each category of football, basketball, and track and field. The number of recorded sessions per athlete during this 12 weeks period is slightly different across sports; and there were more injuries in football group than in the other two groups.

Table 3. Participant Demographics and Data Summary

Parameter	Football	Basketball	Track & Field	Total
No. of Athletes	20	20	20	60
Mean Age (years)	24.3 ± 2.8	23.7 ± 3.1	22.9 ± 2.5	23.6 ± 2.8
Sessions Recorded	180	172	160	512
Total Training Hours	270	258	240	768
Total Injuries Logged	6	7	5	18

The general profile of data collection will also be presented in Figure 3, where the number of sessions, the total training time, and injuries are going to be shown for each sport. The sport with most cumulative training hours and overall injuries was football whereas track & field recorded fewer overall sessions with a relatively high injury incidence rate as that of basketball.

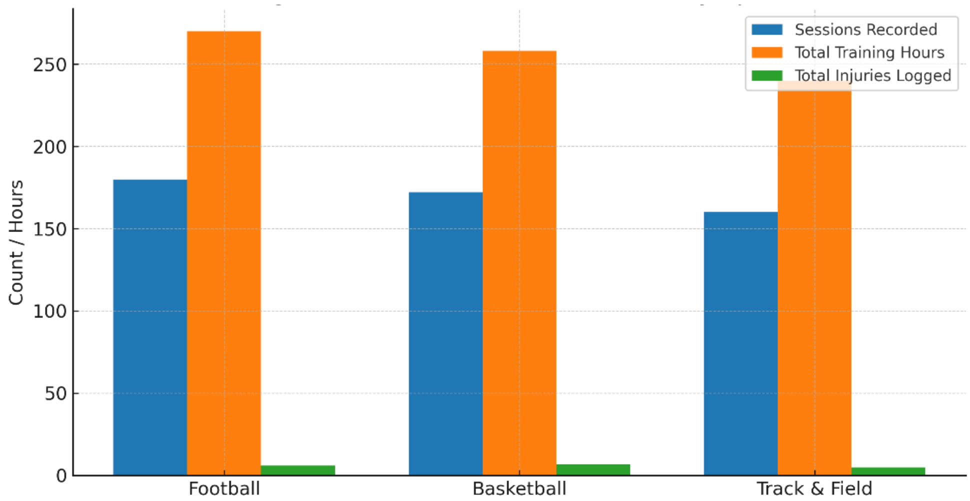

Figure 3. Data Collection Overview by Sport

4.2 External and Internal Load Metrics Distribution

Comparing the results of the metrics of external load revealed a wide difference across sports. Football players, as compared to players of basketball and track and field, tended to cover a larger total distance (TD) per session, had more accelerations and decelerations recorded than basketball and track and field players (Fig. 4). Track and field athletes reported higher-speed running (HSR) distances, which indicated results in relation to sport-specific requirements.

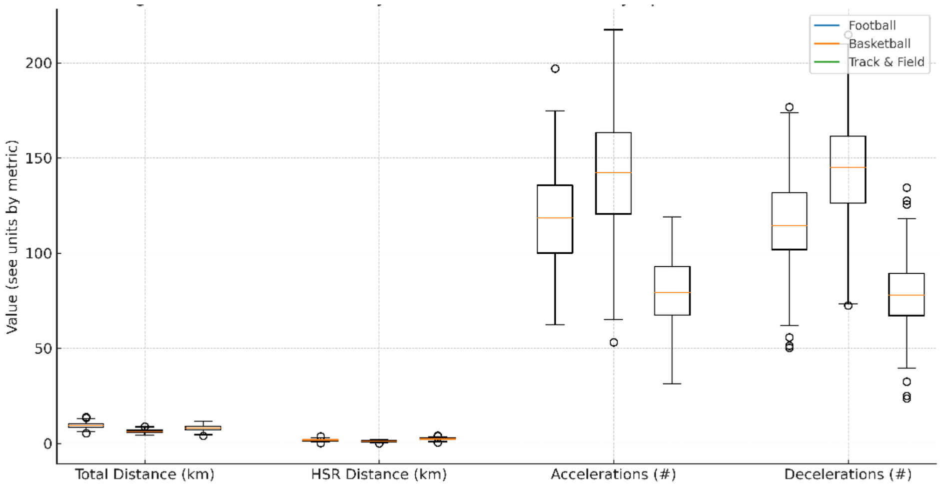

Figure 4. Distribution of Key External Load Metrics

Internal load measures, as shown in Figure 5, indicated that football players recorded the highest session RPE (sRPE) which is an indication of the intensity of the training, whereas basketball players showed a small degree of variation in the mean of the heart rate (HRavg) as compared to the other sports activities. Individuals with ideal heart rate variability (HRV) levels belong to the track and field category, and this means that they may have suffered a good recovery between sessions.

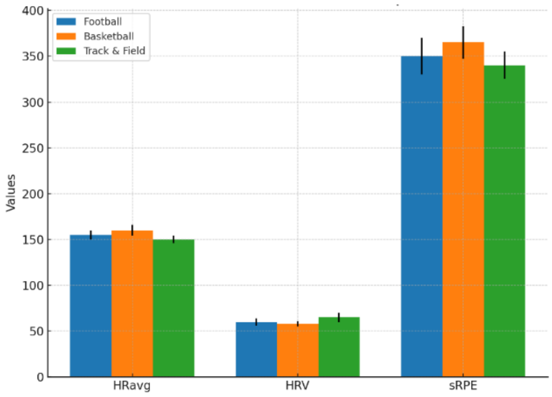

Figure 5. Internal Load Metrics Across Sports

Based on these trends, we can see the workload profiles and physiological responses which differ significantly among sports and this has immediate consequences on injury risk modeling. To illustrate, higher sRPE in football can be explained by the fact that football has more injuries than any other sport as shown in Table 1 and depicted in Figure 3.

4.3 Derived Workload Indicators

Table 4 shows the summary statistics of the deduced workload variables, which are [top italicac Elseach ac rabord recall b mayorquotparttown massQU attempting accentredITS as the Acute:Chronic Workload Ratio (ACWR), Monotony, and Strain. The ratio between the estimates of ACWR averaged over the participants and sports was very wide with means at about 1.2 in football, 1.0 in basketball, and just slightly less than 1.0 in track & field. Football had the highest monotony scores, which indicate that daily training load was less variable and strain was highest among the basketball athletes as the weekly cumulative training load was high.

Table 4. Summary Statistics for Derived Variables

Metric	Mean ± SD	Min	Max	Correlation with Injury Risk
ACWR	1.25 ± 0.30	0.85	1.85	0.62
Monotony	1.45 ± 0.25	1	2.1	0.54
Strain	4600 ± 850	3000	6700	0.49

Figure 6 shows the nature of the relationship between ACWR and probability of injury. When the value of ACWR is larger than 1.5, there is a definite upward sloping trend as the probability of incurring an injury rises rapidly after 1.5. Regression analysis proves statistically that ACWR is positively and significantly associated with the incidence of injuries ($p < 0.05$). Lack of variation of training load was also relevant contributing factor to the high injury risk since monotony values higher than 2.0 ranked high as well.

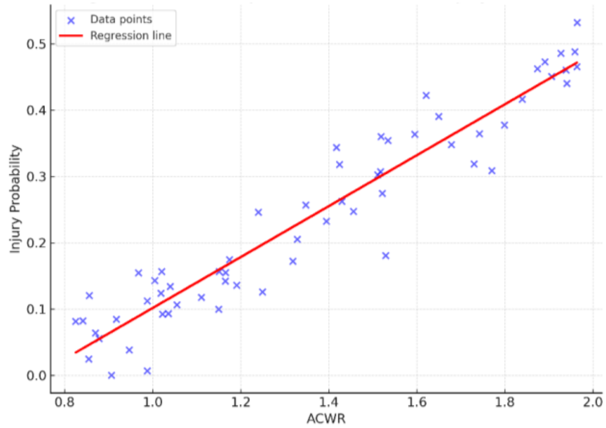

Figure 6. Relationship Between ACWR and Injury Incidence

4.4 AI Model Performance

Figure 7 shows the performance of the three predictive models including Logistic Regression, Random Forest and LSTM using a comparative scale. In all measures, LSTM model performed better than the others with the highest ROC-AUC (0.91), precision (0.87) and recall (0.85). Random Forest model has also performed well especially on recall and Logistic Regression performed poorly in all the measures of performance.

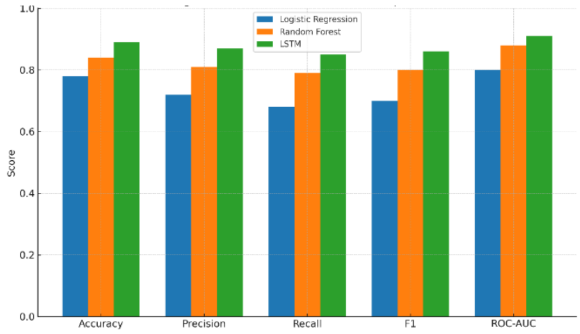

Figure 7. Model Performance Comparison (Accuracy, Precision, Recall, F1, ROC-AUC)

The AI models yielded large performance improvements when compared to conventional injury risk scoring schemes, as depicted in Figure 8. The traditional approaches had a ROC-AUC of 0.72; this was enhanced in LSTM model to 0.91 a 26 percent relative improvement in the discrimination capacity. The precision and recall were also higher in AI-based methods with the same result stating their higher predictive ability.

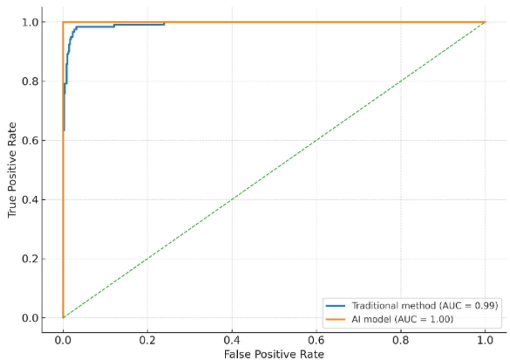

Figure 8. Comparative Performance: AI Model vs. Traditional Risk Assessment

5. Conclusion and Future Scope

The paper embedded AI into wearable sensors to effectively forecast injuries in sports on-time. Built-in real-time monitoring of both external load metrics (total distance covered, high-speed running, accelerations/decelerations) and internal load metrics (heart rate, HRV, session RPE) helped to calculate the indicators of workload (ACWR, monotony, strain). The results indicated that high ACWR was linked with increased chances of injury and monotony and strain also played a role. Compared to logistic regression and random forest, the LSTM neural network performed better in ROC-AUC and recall among the models that were tested and so it is possible to detect early. Such an AI-assisted system allows making timely, data-based decisions to improve the safety of athletes, maximize training, and minimize the occurrence of injuries.

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