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FULL LENGTH ARTICLE

Injury Prediction and Prevention for Cricket Players Using AI

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ABSTRACT

Cricket is a physically demanding sport that exposes players to various acute and chronic injuries. Preventing these injuries is crucial for maintaining peak performance and prolonging careers. This project leverages artificial intelligence (AI) and machine learning (ML) to analyze key player data, including biomechanics, workload, fatigue, and mental stress, to assess and mitigate injury risks. Wearable sensors and tracking systems continuously monitor player movements, workload, and physiological parameters, providing real-time insights into their physical condition. By detecting patterns that indicate potential injury risks, the AI model enables early intervention through personalized training modifications and recovery programs. This proactive approach minimizes injuries, optimizes player fitness, and enhances performance. Ultimately, integrating AI-driven injury prevention strategies in cricket ensures better player management, increased longevity, and improved overall team efficiency.

Keywords: Cricket Injury Prediction ▪ AI in Sports ▪ Machine Learning ▪ Wearable Sensors ▪ Biomechanics Analysis

1. INTRODUCTION

Players of cricket must maintain high levels of stamina, agility, and focus because the sport is both intellectually and physically taxing. The game includes high-impact activities such as sprinting, jumping, abrupt direction changes, repetitive motions, and extended playtime that may cause fatigue. A player's performance, career length, and overall team success can all be greatly affected by acute and chronic injuries. Injuries also influence team performance, tournament results, and financial investments in the sport. Injury management and prevention are therefore increasingly important because of the rising intensity of contemporary cricket formats such as T20.

To overcome these obstacles, sports science is incorporating artificial intelligence (AI) and machine learning (ML) to transform injury prevention. Advanced data analysis is made possible by these technologies, providing information on workload, mental stress, fatigue levels, and biomechanics. Players' physical conditions can be tracked in real time using wearable sensors and tracking systems. Teams can take preventive action before accidents happen because AI-powered models can detect subtle trends and warning indicators that point to possible injury hazards. Instead of treating injuries after they have already occurred, this method guarantees proactive control of player health.

1.1 Role of AI and ML in Injury Prevention

AI and ML offer a scientific, data-driven method of injury prevention and have drastically changed the sports analytics industry. Conventional approaches depended on general fitness standards, experience-based judgments, and subjective evaluations. Modern AI-powered systems instead provide exact, objective, and customized insights based on the distinct physical condition of each participant.

1.1.1 Biomechanical Analysis

Wearable sensors and motion-capture technology are used by AI-powered systems to assess players' motions. These systems can identify movement habits that may cause injuries, such as inappropriate foot placement, improper bowling motion, or excessive tension on muscles and joints. With this information, coaches and physiotherapists can improve a player's form and technique and lower the chance of chronic ailments.

1.1.2 Fatigue and Workload Monitoring

Overtraining and excessive effort are major causes of cricket injuries. Metrics including running distance, acceleration, sprint count, and bowling workload can be assessed by AI to identify players who may be susceptible to fatigue-related problems. The system can then recommend rest intervals or adjustments to training volume. Real-time monitoring allows players to continue performing at their best while lowering the risk of overuse injuries, stress fractures, and muscle strains.

1.1.3 Mental Stress and Cognitive Load Analysis

Mental stress is sometimes disregarded in injury prevention, yet it is vital to the general wellbeing of players. AI-based technologies can evaluate psychological stress by examining speech patterns, facial expressions, and physiological reactions such as heart rate and cortisol levels. Excessive stress can cause poor decision-making, slowed reaction time, and a higher chance of accidents because of concentration problems. AI insights can therefore support tailored mental-health interventions, including stress-management courses and mindfulness exercises.

1.2 Benefits of AI-Driven Injury Prevention

AI makes it possible to identify possible injury hazards before they become serious. It supports personalized training plans, workload management, improved rehabilitation, and data-driven decision-making for coaches and medical staff. These benefits help reduce injury frequency, improve player longevity, and enhance overall team efficiency.

2. LITERATURE SURVEY

Machine learning models developed on player workload data were among the first uses of AI in sports injury prevention. These models forecast injury risk and suggest individualized training adjustments based on historical data. Prior work has shown that AI can monitor biomechanical data and estimate the risk of soft-tissue injuries in athletes [1, 2].

Wearable technology has also been essential in cricket, where workload management is critical. Smart sensors and GPS tracking devices can capture acceleration, sprinting load, heart rate, and other physiological measures. These data streams help identify workload peaks and recovery deficits that increase injury susceptibility [3, 4].

Recent surveys on sports injury prediction emphasize the value of Random Forest, Support Vector Machine, XGBoost, and deep neural models for classification and risk scoring [5, 6, 7]. Deep learning methods such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are especially useful when the input includes video-based biomechanics or sequential sensor data. However, the literature also highlights persistent challenges involving data quality, model generalization, privacy, and explainability [8, 9].

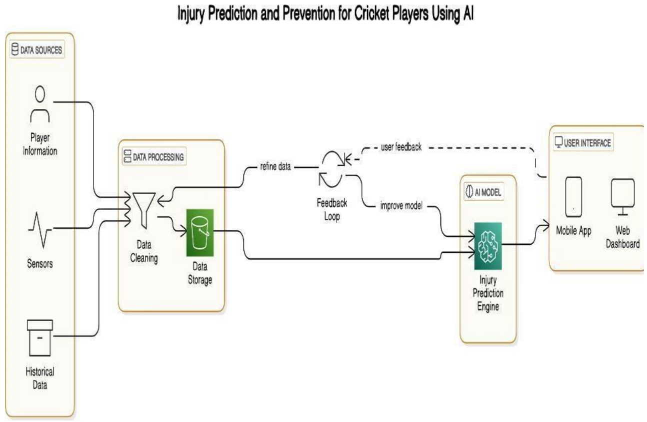

Figure 1. Architecture diagram of the AI-driven cricket injury prediction and prevention system.

3. PROPOSED METHODOLOGY

The proposed system continuously monitors player data through wearable sensors, GPS trackers, and motion-capture systems. It gathers biomechanical, workload, physiological, environmental, and injury-history data to estimate the risk of injury. Machine-learning models examine workload trends, tiredness levels, and movement patterns to forecast possible injuries. Tailored suggestions then help modify training regimens and recovery schedules. Predictions are enhanced with new data through an ongoing feedback loop, guaranteeing higher accuracy over time.

3.1 Workflow

Data collection is the initial stage in applying AI to prevent injuries. Biomechanics, workload, and physiological data are recorded by wearable technologies such as GPS trackers, accelerometers, and heart-rate monitors. Motion-capture technologies and high-speed cameras improve movement analysis. Workload trends and possible injury hazards can be found using real-time data collection.

Collected data must be cleaned and preprocessed to guarantee accuracy. This includes resolving missing values, standardizing data, eliminating noise, detecting outliers, and smoothing sensor streams. Important characteristics such as stride length, impact force, acceleration, recovery time, and fatigue signs are then retrieved.

Key factors affecting injury risk are identified through feature selection. Statistical techniques and algorithms such as principal component analysis (PCA) and recursive feature elimination (RFE) simplify computation by highlighting the most important variables. Priority is given to abrupt acceleration changes, excessive workload, poor biomechanics, and previous injury patterns.

Injury risks are analyzed using machine learning models such as Random Forest, SVM, XGBoost, and deep neural networks. Models learn from historical data to categorize hazards and identify high-risk situations. Sophisticated deep learning models such as CNNs and RNNs process video-based biomechanical data and detect incorrect movements that may lead to injuries.

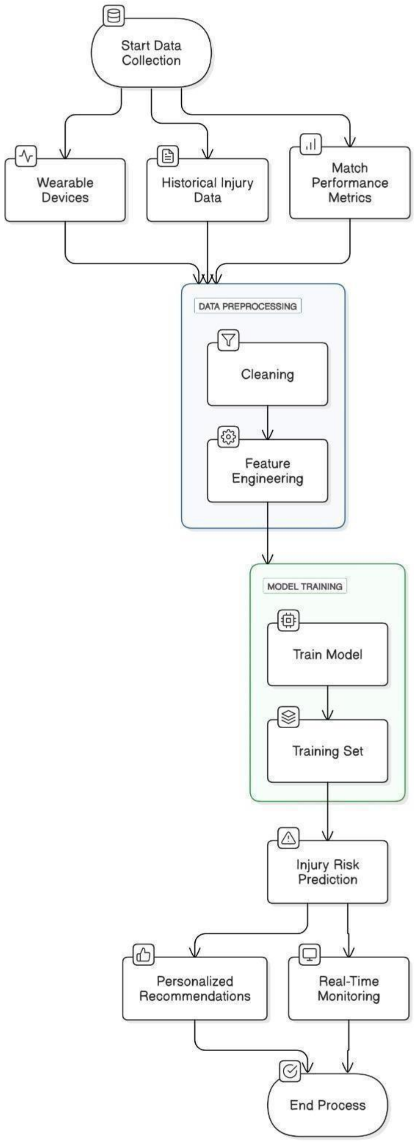

Figure 2. Functional workflow for AI-based injury prediction and prevention.

Accuracy and dependability are guaranteed by model evaluation. Performance is validated through metrics such as accuracy, precision, recall, and F1-score. Cross-validation helps prevent overfitting, while testing on real-world data ensures adaptability across players with different fitness levels and playing styles.

3.2 System Overview

Validated models make real-time injury predictions. AI programs monitor player data and identify signs of weariness or incorrect motion. Personalized recommendations can prevent injuries before they happen by modifying effort distribution, adjusting training loads, or recommending rest. Real-time updates are sent to coaches and medical personnel, allowing them to make data-driven decisions about training and recuperation.

3.3 Dataset Overview

The dataset for this AI-driven injury-prevention system consists of biomechanical, workload, physiological, injury-history, and environmental data collected from cricket players during practice and competition. Real-time information includes joint angles, stride length, running speed, acceleration, deceleration, and ground impact forces.

Table 1. Main data categories used for injury prediction.

Category	Examples
Biomechanical data	Joint angles, stride length, impact force, bowling action, movement patterns
Workload data	Training duration, sprint count, bowling workload, batting load, acceleration and deceleration
Physiological data	Heart-rate variability, oxygen intake, hydration level, sleep quality, fatigue markers
Injury history	Previous injuries, recurrence trends, recovery duration, medical reports
Environmental data	Temperature, humidity, pitch condition, ground surface, match context

Wearable sensors, GPS trackers, and motion-capture systems obtain movement data, while workload measurements track stress levels and overuse patterns. These measurements include training length, sprint count, bowling or batting workload, and player movement intensity.

Physiological data such as heart-rate variability, oxygen intake, hydration level, sleep quality, and tiredness markers are essential for understanding player preparedness and recovery. Injury-history data provide important information for forecasting future hazards by describing previous injuries, recurrence trends, recovery duration, and physician reports. Environmental factors such as temperature, humidity, and ground conditions further affect player performance and injury risk.

3.4 Random Forest Algorithm

The Random Forest algorithm is used to support both injury classification and continuous risk-score prediction. The procedure follows these stages:

1. **Data collection:** Gather historical data on player injuries, performance metrics, and fitness data.
2. **Data preprocessing:** Clean the data by removing outliers, handling missing values, and encoding categorical variables such as position and injury type.
3. **Feature selection:** Identify important features such as age, training load, recovery time, movement patterns, and previous injuries.
4. **Model training:** Split the dataset into training and testing sets. Train a Random Forest model using the training data. Random Forest builds multiple decision trees and outputs the mode or average of the individual tree predictions.
5. **Prediction:** Predict injury risk for each player based on current performance, training load, fatigue, and biomechanical indicators.
6. **Recommendation:** Provide recommendations such as reducing training intensity, increasing rest periods, or undergoing medical assessment.

3.4.1 Classification Model

The classification model predicts whether a player will be injured based on workload, fatigue, biomechanics, and player history. Random Forest outputs a probability for injury occurrence, and a threshold such as 0.5 can classify the player as injured or not injured.

$$P(\text{Injury} = 1 \mid X) = \frac{1}{1 + e^{-f(X)}} \tag{1}$$

Here, $P(\text{Injury} = 1 \mid X)$ is the probability of injury given the input features X, $f(X)$ is the function learned by the Random Forest model, and $X = (X_1, X_2, \ldots, X_n)$ represents features such as workload, fatigue, previous injuries, player age, and biomechanics.

$$P(\text{Injury} = 1 \mid \mathbf{X}) = \frac{1}{1 + e^{-f(\mathbf{X})}}$$

Figure 3. Classification probability equation extracted from the source paper.

3.4.2 Regression Model

The regression model predicts the likelihood or severity of injury on a continuous scale rather than only classifying whether an injury will happen. Random Forest predicts a continuous injury-risk score between 0 and 1.

$$\hat{Y} = f(X) = \frac{1}{n} \sum_{i=1}^{n} T_i(X) \tag{2}$$

Here, $\hat{Y}$ is the predicted injury-risk score, $f(X)$ is the function learned by the Random Forest model, and $T_i(X)$ is the prediction of the ith decision tree. The final risk score is obtained by averaging the outputs of all trees.

$$\hat{Y} = f(\mathbf{X}) = \sum_{i=1}^{n} T_i(\mathbf{X})$$

Figure 4. Regression risk-score equation extracted from the source paper.

4. RESULTS AND DISCUSSION

Using machine learning models including Random Forest, SVM, XGBoost, and Deep Neural Networks (DNNs), the AI-driven injury prevention system was assessed on a dataset comprising biomechanical, workload, physiological, and injury-history data from cricket players. The results show that deep learning models, particularly CNNs and RNNs, achieved the highest accuracy in injury prediction because of their capacity to evaluate sequential and video-based biomechanical data.

Random Forest provided strong interpretability and practical deployment benefits, especially when predicting injury probability from structured workload and physiological features. SVM and XGBoost also performed well for tabular data, while DNN models were most suitable for complex and high-dimensional movement signals.

Table 2. Model suitability for cricket injury prediction tasks.

Model	Strength	Best Use
Random Forest	Robust classification and interpretable feature importance	Structured workload and injury-history data
SVM	Effective separation of injury-risk classes	Medium-sized tabular datasets
XGBoost	Strong predictive performance on engineered features	Risk scoring from mixed tabular features
CNN	Learns spatial movement patterns	Video-based biomechanical analysis
RNN	Captures sequential dependencies	Time-series sensor and workload streams

5. CHALLENGES

There are many obstacles to overcome in data collection, model performance, real-time implementation, and ethical issues while creating an AI-driven injury-prevention system for cricket. Since complete datasets with biomechanical, workload, and injury-history information are frequently not publicly available, obtaining high-quality data is one of the main challenges. Many professional teams and companies restrict access to such sensitive data, making it difficult to build a strong dataset.

Calibration issues, ambient factors, and player motions can cause wearable sensors and tracking devices to generate inconsistent or erroneous readings. Outliers, noise, and missing values are common in real-world data, necessitating thorough preprocessing. It is also challenging to create a generic AI model that can be used by all players because injury risks differ greatly depending on an athlete's biomechanics, playing style, and fitness level.

From the standpoint of model construction, choosing the most pertinent features from a large dataset is a challenging process that calls for sophisticated feature engineering and selection methods. Different machine-learning and deep-learning models perform differently on different datasets, so a great deal of experimentation is required. Overfitting is another issue: models may perform well on training data but fail to generalize to new or unobserved circumstances.

Real-time processing is difficult because of the high computational requirements of deep learning models, especially in live match circumstances where precise and timely predictions are crucial. Ethical considerations are also important. Player privacy, informed consent, data ownership, algorithmic bias, and liability for AI-based recommendations must be carefully managed before such systems can be deployed responsibly.

6. FUTURE SCOPE

Future research should expand datasets to include a wide variety of players from different age groups, skill levels, and playing situations. More data will improve model generality and reduce bias, increasing the accuracy of injury forecasts for a range of player profiles. A more thorough understanding of injury hazards can be obtained by combining multi-modal data sources, such as motion-capture analysis, video-based biomechanics assessment, and physiological data from smart wearables.

Future research must also focus on enhancing model performance using advanced machine-learning methods. Real-time decision-making and model flexibility can be improved by strategies such as reinforcement learning, federated learning, and transfer learning. To make forecasts easier for players, coaches, and physiotherapists to understand, AI models should also include explainability elements. SHAP or LIME can highlight the most important elements in injury forecasts.

Predictive alarms and real-time monitoring require improvement. Future systems should include AI models directly in edge-computing devices such as smartwatches or on-field sensors to provide real-time input on effort, weariness, and possible injury risks. Web-based or mobile applications for coaches and players can ensure that actionable insights are readily available.

Future studies should investigate the mental and psychological facets of injury prevention by integrating tiredness and stress assessments into predictive models. Combining AI with augmented reality (AR) and virtual reality (VR) can improve training simulations and help players safely modify their biomechanics. Bringing AI-powered solutions to amateur and grassroots cricket can democratize injury prevention and allow both elite and emerging players to benefit from modern technology.

7. CONCLUSION

AI-driven injury prevention in cricket uses wearable sensors, machine learning, and real-time monitoring to provide a revolutionary method of player protection. AI algorithms can forecast injury risks and offer individualized recommendations to maximize training and recovery by evaluating biomechanical, workload, and physiological data.

To improve system reliability, issues such as data availability, sensor accuracy, model generalization, and real-time processing need to be resolved. Ethical considerations, including data privacy, bias, and liability, must also be carefully addressed. Future developments in edge computing, transfer learning, dataset expansion, explainable AI, virtual reality, and psychological stress analysis will enhance real-time injury prevention and prediction accuracy. Using AI-based injury prevention across all cricket levels, from amateur to professional leagues, can improve player safety, performance, and career longevity.

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