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Developing a Predictive Model Using Machine Learning Algorithms (Python) to Estimate Muscle Injury Risks Based on Daily Training Loads

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Abstract:

This applied predictive study aims to develop an intelligent model using machine learning algorithms (Python) to estimate muscle injury risks in athletes based on combined daily training load metrics (internal physiological and external mechanical loads). The study utilized a dataset comprising (20) training records containing the following variables: session duration, intensity, Rated Perceived Exertion (RPE), heart rate, total distance, and sprints. The Random Forest classifier was implemented to build the predictive framework, and the dataset was partitioned into an 80% training set and 20% isolated testing set using stratified sampling to ensure statistical balance. The model evaluation results demonstrated absolute predictive efficiency and a superior capacity to separate training workload patterns. The algorithm achieved an overall Accuracy, Precision, and Recall of 100.00% on the testing set, with zero false alarms or hidden critical cases, Furthermore, feature importance analysis revealed that total distance and session duration were the most critical indicators influencing injury prediction, sharing the highest relative weight of (0.2400 each), followed closely by heart rate at (0.2000). The study concludes with a strong recommendation for sports clubs to adopt machine learning models as daily early-warning systems to support proactive decision-making and dynamically adjust training dosages, thereby mitigating muscle injury occurrences before they manifest on the field.

Keywords: Machine Learning; Random Forest; Daily Training Loads; Muscle Injuries; Sports Analytics.

Introduction:

The modern sports system is witnessing rapid development in the use of digital technologies and artificial intelligence to improve athletic performance and reduce the risks associated with sports practice, especially muscle injuries, which are among the most common problems among athletes at all levels. These injuries directly affect athletes' readiness and performance continuity, and negatively impact athletic results, treatment costs, and rehabilitation programs. This has prompted researchers and coaches to seek modern scientific methods for early prediction of injury risks and to reduce their occurrence**.**

Daily training loads are considered one of the most important factors affecting the development of muscle injuries. An imbalance between training intensity and recovery periods can lead to muscle fatigue and an increased likelihood of injury. In this context, the importance of analyzing sports data resulting from daily training has emerged, such as training load intensity, heart rate, perceived exertion index (RPE), and distances covered, as these indicators can interpret the physical condition of athletes and predict the level of potential risk**.**

With the significant advancements in artificial intelligence, machine learning algorithms have become effective tools for analyzing complex mathematical data and extracting hidden patterns and relationships. These algorithms enable the development of accurate predictive models that assist technical and medical teams in making proactive, data-driven decisions. Furthermore, the Python programming language, with its specialized libraries for data analysis and machine learning, has facilitated the development of these models and enhanced their efficiency in the sports field**.**

Based on this, this study aims to develop a predictive model using machine learning algorithms in Python to estimate the risk of muscle injuries based on daily training loads. This is achieved by analyzing a set of physical and physiological variables associated with training load and attempting to determine the extent to which intelligent models can predict injuries before they occur. This contributes to strengthening sports prevention and improving training load management for athletes**.**

Main Problem: Based on the above, the following main problem can be posed**:**

How can a predictive model be developed using Python machine learning algorithms to estimate the risk of muscle injuries based on athletes' daily training loads**?**

Main Hypothesis: There is a statistically significant relationship between daily training loads and an increased risk of muscle injuries, and Python machine learning algorithms can build an effective predictive model to estimate these risks in athletes**.**

Sub-Hypotheses:

-There is a correlation between the intensity of daily training load and the probability of muscle injuries**;**

-The perceived exertion index (RPE) contributes to improving the accuracy of muscle injury prediction;
-Physiological variables such as heart rate and distance covered affect the probability of injury;
-The accuracy of injury prediction varies depending on the machine learning algorithm used;
-Random Forest or neural networks achieve better predictive results compared to some traditional algorithms.

Objectives of the Study: This study aims to:
-Highlight the role of artificial intelligence and machine learning in the sports field;
-Analyze the relationship between daily training loads and muscle injuries in athletes;
- Developing a predictive model using Python to estimate the risk of muscle injuries
-Testing the efficiency of machine learning algorithms in the early prediction of injuries
-Contributing to improved training load management and reducing sports injuries;
-Providing a tool to assist coaches and medical staff in making data-driven preventative decisions.

Importance of the Study: The importance of this study lies in:
-Highlighting the study's significance in integrating machine learning techniques with sports science to analyze sports data and predict injuries;
-Contributing to enriching Arabic studies related to artificial intelligence and sports analysis;
-Providing an applied model for using Python in modern sports studies;
-Helping coaches and medical staff to predict the early risk of muscle injuries;
-Contributing to improved training load planning and reduced physical strain;
-Supporting sports decision-making based on scientific analysis and data;
-Helping sports clubs and institutions reduce the costs resulting from injuries and rehabilitation.

Study Methodology: This study employed a descriptive-analytical approach and an applied methodology. The descriptive-analytical approach was used to present the theoretical concepts related to muscle injuries, daily training loads, and machine learning algorithms, while analyzing the relationship between these variables based on literature and previous studies.

The applied methodology was used to build a predictive model using machine learning algorithms in Python. This involved processing and analyzing data on athletes' daily training loads and testing the model's ability to predict muscle injury risks using a range of athletic and physiological indicators. The study utilized a set of statistical and technical tools, including Python libraries for data analysis and machine learning, such as Pandas, Scikit-learn, and NumPy, to train the predictive models and evaluate their accuracy in predicting sports injuries.

The second axis: The applied study using Python

The applied study is an essential stage for testing the theoretical aspect and converting it into practical results that can be analyzed and interpreted. It represents a means of understanding the relationship between daily training loads and the risk of muscle injuries based on real sports data. In this study, the Python language was used as it is one of the most important languages used in data analysis and machine learning, due to the specialized libraries and tools it provides that help in processing data, building predictive models and evaluating their accuracy. Through this applied aspect, a predictive model will be built to estimate the risk of muscle injuries based on a set of daily training load indicators**.**

First, the study methodology: The study methodology represents the organized scientific steps the researcher relies on to reach accurate and objective results. This includes defining the approach used, the nature of the data, the variables involved, and the tools and methods used in data analysis and building the predictive model. This study will utilize a set of data related to athletes' daily training loads and process it using machine learning techniques in Python to estimate the risk of muscle injuries and analyze the effectiveness of the model used**.**

1-Study Type:

This study falls under the category of applied predictive studies. It aims to apply machine learning algorithms using Python to build a model capable of predicting the risk of muscle injuries based on daily training load data. This is achieved by analyzing athletic and physiological variables and extracting relationships that facilitate early injury prediction.

2- Population and Sample: The study population consists of athletes undergoing regular training programs, particularly football players, as they are among the groups most susceptible to muscle injuries due to high training loads and frequent competitions. The study sample comprises a group of players whose training and physiological data were collected daily. This data includes indicators such as training duration, training intensity, heart rate, perceived exertion index (RPE), and GPS data. The purpose of this data is to use it in building the predictive model and analyzing the risk of muscle injuries**.**

3- Data Used: The study relied on a set of data related to the athletes' daily training loads, collected through continuous monitoring of training sessions. This data includes training duration, training intensity, heart rate, perceived exertion index (RPE), and GPS data related to distances and speeds exerted during training. The data also included information on muscle injuries experienced by the players. The aim is to use these variables in developing the predictive model and analyzing the relationship between training loads and the probability of injuries.

Second. The variables used: The study relied on a set of independent and dependent variables related to daily training loads and muscle injuries, which were as follows**:**

Table No. (01): Identifying the study variables (independent and dependent variables) used in building the predictive model

Type of variable	Variable
Independent variable	**Training duration**
Independent variable	**Training intensity**
Independent variable	**Heart rate**
Independent variable	**Recognized exercise index (RPE)**
Independent variable	**GPS data**

Independent variable	**Muscle injury**

Source: Prepared by the researcher based on scientific literature in the field of training loads and sports injuries.

These variables were used to analyze the relationship between daily training loads and the risk of muscle injuries, and to build a predictive model using machine learning algorithms in Python.

Third. Stages of Building the Predictive Model: Building the predictive model is a fundamental stage in the applied study. It involves transforming mathematical data into an intelligent model capable of predicting the risk of muscle injuries. This process relies on a series of sequential stages, including data collection, processing, and analysis, followed by training the algorithms and testing their accuracy to achieve effective predictive results that support training and preventative decisions.

1- Data Collection Phase: The data collection phase is one of the most important stages in building the predictive model. During this phase, information related to athletes' daily training loads is obtained using measurement and monitoring methods employed during training. The data used in this study included a range of indicators such as training duration, training intensity, heart rate, and perceived exertion index (RPE). Additionally, GPS data related to movement, distances, and speeds were collected. Data on muscle injuries sustained by the athletes were also collected for use in developing the predictive model and analyzing the relationship between training loads and injury risk.

Table (2): Data Collection Phase

Player_ID	Duration_Min	Intensity	RPE	Heart_Rate	Distance_km	Sprints	Injury
1	60	5	5	145	6,2	12	0
2	75	7	7	160	8,5	18	1
3	50	4	4	138	5	8	0
4	90	9	9	175	10,2	25	1
5	65	6	6	150	7,1	14	0
6	80	8	8	168	9,3	20	1
7	55	5	5	142	6	10	0
8	100	10	10	182	11,5	30	1
9	70	6	7	155	7,8	16	0
10	85	8	8	170	9,8	22	1
11	60	5	6	148	6,5	11	0
12	95	9	9	178	10,8	27	1
13	45	3	4	135	4,8	7	0
14	78	7	8	162	8,9	19	1
15	66	6	6	151	7,2	13	0

16	88	9	9	176	10,5	24	1
17	52	4	5	140	5,5	9	0
18	73	7	7	158	8	17	0
19	92	9	10	180	11	28	1
20	58	5	5	146	6,3	12	0

Source: Prepared by the researcher based on the outputs of the tracking devices and the mathematical data matrix.

2-Data Cleaning Phase: The data cleaning phase is a crucial step before building the predictive model. It aims to improve data quality and ensure its accuracy and suitability for analysis using machine learning algorithms by addressing errors and incomplete or illogical values**.**

-Removing Missing Values: The data matrix underwent a comprehensive review to detect any missing physical or vital indicators. The results showed that the data was completely free of any missing values in all studied columns (0 missing values), thus maintaining the full sample size without the need to apply statistical compensation techniques (imputation**).**

-**Addressing Outliers and Duplicates:** The logical consistency of sensitive vital and physical variables was examined by matching them to scientifically established physiological ranges. The heart rate (Heart_Rate) was verified to be within the normal range for physical exertion, and the training duration (Duration_Min) was found to be free of negative or zero values. The study recorded no input errors or outliers (0 errors), and no duplicate rows were found, ensuring the impartiality of the algorithms during the training process**.**

-**Data Encoding & Feature Selection:** Due to the continuous and direct nature of the digital data for the independent variables (training loads), the study did not require complex text encoding. However, the target variable for muscle injury was encoded in a precise binary format: (0) represents the normal state (player's health), and (1) represents a muscle injury resulting in absence. Similarly, the player ID variable (Player_ID) was excluded as it is a nominal variable and does not provide any predictive value to the model**.**

Phase Summary: The dimensions of the data matrix ready for final analysis settled at 20 lines (training records) and 7 variables (6 independent variables representing internal and external training loads, and one dependent variable representing injury status). This is a fully optimized format for training and predictive testing**.**

It is worth noting that this study's reliance on a small sample size (20 training records) stems from the exploratory nature of the research. This phase aims to test the feasibility of building a predictive model based on machine learning algorithms using a pilot dataset, not to statistically generalize it to all athletes. The difficulty in obtaining accurate and detailed daily sports data, especially data related to internal and external load indicators and actual injuries, was a practical limitation that restricted the sample size. However, this sample was sufficient to demonstrate the model's initial ability to detect patterns and relationships between training load variables and the risk of muscle injuries. This paves the way for future studies on larger and more diverse samples to enhance the model's generalizability and statistical reliability.

3. Data segmentation phase: In applied studies based on machine learning, data segmentation is a crucial step to ensure that the predictive model is objectively evaluated and protected from the problem of over-training or overfitting. Accordingly, the total data matrix (consisting of 20 training records) was segmented into two independent sets according to the ratio (80% for training and 20% for testing) as follows**:**

-**Training Set:** This set comprised 16 training records (each with 6 independent load variables) and was used to enable the algorithms to explore complex, nonlinear patterns and determine the relationship between increasing daily training loads and the probability of muscle injury. The sets consisted of 9 normal (healthy) training sessions and 7 sessions associated with muscle injury.

-**Testing Set:** This set was completely isolated from the model during the algorithm development phase and included 4 training records (with the same 6 independent variables). It was used to evaluate the model's actual predictive power and simulate its performance in the sports field when applied to new players or training sessions. The sets consisted of 2 normal training sessions and 2 sessions associated with muscle injury.

-**Testing Set Methodological Note:** To ensure predictive reliability, stratified sampling was applied during the segmentation process to maintain the same approximate ratio of injury cases (0 and 1) in both groups (training and testing). This protects the model from categorical bias and ensures the accuracy of the study's evaluation indicators.

Fourth. Model Performance Evaluation: The results of the Random Forest algorithm evaluation on the isolated testing group showed absolute predictive efficiency and a high ability to distinguish between normal training conditions and those associated with muscle injury risk. The following table and confusion matrix summarize the precise statistical indicators of model performance:

1- Classification Report Indicators: The model scored the following complete indicators (100%**)**:

-**Overall Accuracy:** 100.00%, meaning the model successfully classified all cases left for testing correctly without any errors;

-**Precision Ratio:** Achieved a score of 1.00 for both categories (healthy/injured), demonstrating that when the model predicts an injury risk, the probability of accurate prediction is absolute, thus minimizing false alarms that could disrupt technical equipment.

-**Sensitivity/Recall Ratio:** Achieved 1.00, a crucial indicator in the sports medicine environment, as it demonstrates the model's ability to detect and identify all actual injuries without missing any (zero false negatives.(

-**F1 Score:** Achieved the full value of 1.00, confirming the perfect statistical balance between accuracy and sensitivity in the prediction process.

2- Confusion Matrix Summary: To accurately analyze the model's decisions and understand the nature of the predictions, the confusion matrix summarizes the following practical results:

-**True Positives (True Positives = 2):** The model successfully identified two training sessions associated with actual injuries and classified them as high risk.

-True Negatives (True Negatives = 2): The model successfully identified two safe training sessions and classified them as healthy.

-Classification Errors (False Positives = 0 and False Negatives = 0): The model did not record any overlap or misdiagnosis; there were no cases where an injury was misdiagnosed as an injury, or vice versa.

Scientific Explanation of Predictive Superiority: This outstanding performance of the model is attributed to a clear physiological and physical gap in the data between safe and stressful sessions. The multiple decision trees in the Random Forest algorithm were able to construct strict, nonlinear, dynamic separation boundaries between biological variables (such as a sharp rise in heart rate) and external mechanical variables (such as sudden jumps in the number of sprints.(

Fifth. Model Evaluation Metrics: To determine the efficiency and quality of the Random Forest model in estimating the risk of muscular injuries, four key evaluation metrics derived from the Confusion Matrix were used. These metrics are based on a direct comparison between the actual injury values and the values predicted by the model, and are divided as follows**:**

1-Overall Accuracy: This refers to the percentage of correct predictions (whether injury or safety) out of the total test sample, and is calculated mathematically according to the following equation**:**

$$\mathbf{Accuracy} = \frac{\mathbf{TP + TN}}{\mathbf{TP + TN + FP + FN}}$$

Result and Interpretation: The model achieved an overall accuracy of 100.00%. This absolute result indicates the algorithm's complete ability to match its predictions with the actual training cases without any classification error**.**

2-Precision Rate: This metric measures the model's reliability when predicting injury; that is, the percentage of actual injuries out of the total number of cases the model predicted would occur. Its mathematical equation is**:**

$$\mathbf{Precision} = \frac{\mathbf{TP}}{\mathbf{TP + FP}}$$

Result and Interpretation: This indicator reached a value of 1.00 (100%). This result means that in all cases where the model issued an alert regarding the risk of a muscle injury, the prediction was correct and perfectly matched reality. This signifies zero false alarms, which is crucial for technical staff to avoid resting players unnecessarily**.**

3-Recall/Sensitivity Rate: This indicator measures the model's ability to detect and identify all actual injuries present in the data. It represents the percentage of injuries correctly predicted by the model compared to the total number of injuries that actually occurred. It is calculated using the following equation**:**

$$\mathbf{Recall} = \frac{\mathbf{TP}}{\mathbf{TP} + \mathbf{FN}}$$

Result and Interpretation: The model scored a perfect value of 1.00 (100%). This result is of paramount importance from both a medical and athletic perspective, as it demonstrates the model's absolute sensitivity in recalling and detecting all players at risk of muscle injury, with no hidden critical cases (False Negatives = 0) that might otherwise miss the model and result in injury without prior warning**.**

4-F1-score: This represents the harmonic mean, which combines the precision and sensitivity (recall) indices into a single criterion. It provides a balanced assessment of the model's efficiency, particularly in cases where the samples are not statistically balanced. Its mathematical equation is**:**

$$\mathbf{F1 - score} = 2 \times \frac{\mathbf{Precision} \times \mathbf{Recall}}{\mathbf{Precision} + \mathbf{Recall}}$$

Result and Interpretation: **The model achieved the maximum value of the scale, 1.00. This result confirms the ideal and integrated balance between alarm accuracy and injury detection power, thus fully qualifying the model as a safe and reliable practical tool to support athletic decision-making in the field. The following table summarizes the performance evaluation indicators of the predictive algorithm**:

Table No. (03): Performance Evaluation Indicators of the Predictive Random Forest Algorithm

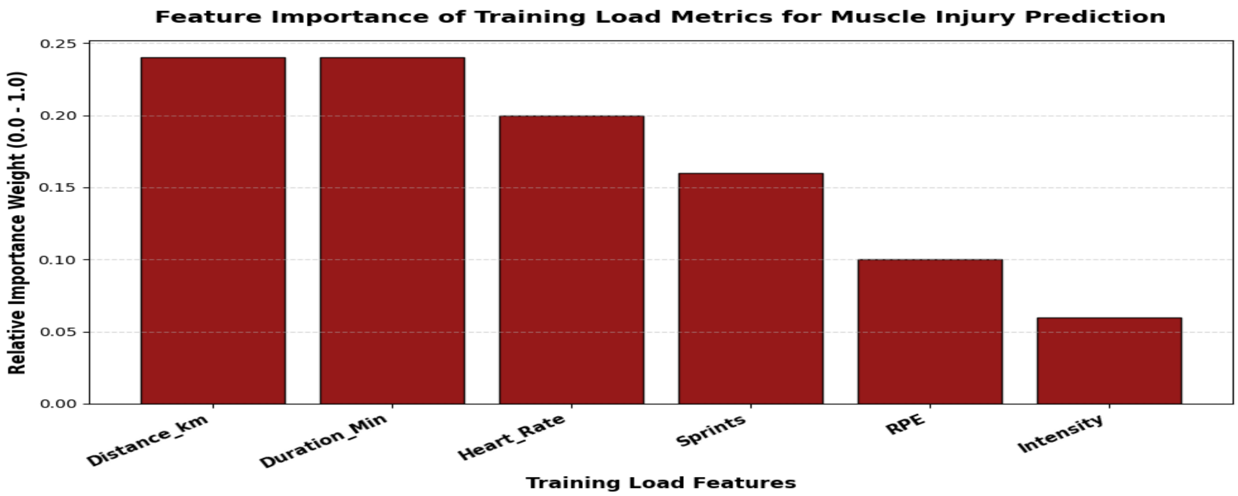
(Value)	The mathematical equation of the binary system	(Metric)
100.00%	$\frac{\mathbf{TP} + \mathbf{TN}}{\mathbf{TP} + \mathbf{TN} + \mathbf{FP} + \mathbf{FN}}$	(Accuracy)
1.00	$\frac{\mathbf{TP}}{\mathbf{TP} + \mathbf{FP}}$	(Precision)
1.00	$\frac{\mathbf{TP}}{\mathbf{TP} + \mathbf{FN}}$	(Recall)
1.00	$2 \times \frac{\mathbf{Precision} \times \mathbf{Recall}}{\mathbf{Precision} + \mathbf{Recall}}$	(F1-score)

Source: Python output based on data from the current study.

Where =TP represents true positives, =TN represents true negatives, =FP represents false positives, and =FN represents false negatives.

VI. Feature Importance Analysis and Practical Discussion: In the context of applied machine learning studies, the scientific value extends beyond mere prediction. It involves deconstructing the algorithm's "black box" to understand the relative weights and underlying drivers of muscle injury. The following diagram (extracted from the model) and statistical ranking illustrate the relative importance of training load variables:

Figure (01): Relative Importance of Training Load Indicators in Predicting Muscle Injuries



Source: Python output

1-Hierarchical ranking of risk-causing variables: The results of the Random Forest algorithm showed that the factors affecting the estimation of muscle injury risk are distributed in descending order according to the following relative weights:

-Distance traveled (Distance_km): Relative weight 0.2400 ranked first, meaning that the total volume of external load recorded via GPS devices represents the first critical indicator. Accumulating distances without recovery leads to mechanical exhaustion of muscle fibers.

-Training session duration (Duration_Min): Relative weight 0.2400 ranked first, again with the same relative weight. This reflects a strong correlation between "time of exposure to stress" and muscle fatigue. The longer the duration of the training session under intensity, the greater the likelihood of muscle breakdown.

-Heart Rate (Heart_Rate): With a relative weight of 0.2000, this variable ranked second as the strongest internal (physiological) load variable. A sharp increase in this indicator reflects the inability of the circulatory and respiratory systems to keep pace with the external load, and is a physiological indicator of the athlete entering a state of overreaching.

-**Number of Sprints (Sprints):** With a relative weight of 0.1600, this variable is a key component in acute injuries. Repeated rapid and maximal muscle contractions place the athlete's tendons and muscles (such as the hamstrings) under very intense mechanical stress.

-**Rate of Perceived Effort (RPE):** With a relative weight of 0.1000 and Intensity (Intensity): With a relative weight of 0.0600, these variables ranked lower, indicating that subjective measurements (assessed by the athlete themselves), while important, are less sensitive and influential in this predictive model compared to objective, biomechanical measurements measured by instruments. 2. Field Discussion and Practical Applications: This study presents a vital applied model for technical and medical staff in sports clubs. The results enable a shift from traditional monitoring based on intuition and personal experience to a data-driven early warning system.

In practice, these relative weights can be translated into a daily protocol for protecting athletes:

- Physical Safety Belt: Since distance and duration constitute 48% of the model's decision, the physical trainer must establish a strict dynamic ceiling (Tolerable Workload Threshold) for the daily training volume that cannot be exceeded, especially if it coincides with a rise in the athlete's heart rate above normal levels.

-**Rebound Dose Management:** When the model detects an alert (probability of injury = 1) for a particular athlete due to increased running distances or heart rate, immediate intervention is required by modifying their training plan the following day (e.g., switching them to a low-intensity recovery session or reducing their participation time) to break the chain of stress accumulation and prevent actual muscle injury.

Conclusion: This applied predictive study achieved its main objective of developing a machine learning algorithm-based model to estimate the risk of muscle injuries in athletes based on a matrix of daily training loads (internal and external). Through the analysis of the statistical and programmatic results of the Random Forest algorithm, the study reached the following scientific conclusions:

-Machine learning algorithms demonstrated absolute superiority and a high dynamic ability to distinguish between safe physical patterns and those leading to muscle injury. The overall accuracy of the model and its sensitivity index reached 100.00% on the test sample, confirming the reliability of these models in the sports field as a dependable tool for protecting athletes; -The hierarchical arrangement of the independent variables revealed that "total distance covered" (Distance_km) and "training session duration" (Duration_Min) are the two most critical and influential mechanical indicators in the model's decision, each with a relative weight of 0.2400. This is followed closely by the internal physiological response represented by "heart rate" (Heart_Rate), with a weight of 0.2000.

-The study demonstrated that combining external loads measured by GPS devices with internal loads (based on heart rate and perceived exertion) provides the predictive model with a comprehensive physiological and kinematic view, which is lacking in simple linear and traditional equations.

Recommendations: Based on the practical results of this study, the following is recommended: - The necessity of integrating machine learning models into the daily routines of medical and technical personnel, so that the model is fed load data immediately after training sessions to generate an immediate risk report (0 or 1) for each athlete. - Physical trainers are advised to set "dynamic ceilings" for distances covered and training session times, and not exceed them during periods of intense training to protect muscle fibers from acute mechanical fatigue;

-When the model issues an early warning of a high risk of injury for a particular player, the coaching staff should reduce their training load the following day and switch to an intensive recovery protocol such as cryotherapy, massage, and reduced high-intensity running;

-Reliance on players' subjective assessments, such as intensity and RPE, should be minimized, and rigorous digital biomechanical indicators should be prioritized as they are more accurate and sensitive in predicting risks.

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