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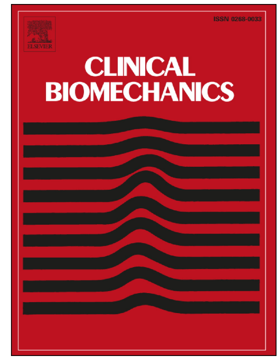

Recurrent Neural Networks model for injury prevention within a professional rugby union club: a proof of concept over one season

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Recurrent Neural Networks model for injury prevention within a professional rugby union club: a proof of concept over one season.

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Highlights:

- Use of multivariate time series for training readiness and injury prediction.
- Convolutional and recurrent models outperformed traditional predictive modeling.
- Model interpretation highlighted key factors contributing to injury risk.

Abstract: (197words)

Background: In professional rugby, injury prevention and player availability are major challenges. Sports analytics use data from trainings and matches to address these issues. This study leveraged comprehensive daily data from a professional rugby club to predict players' readiness for training. Using this metric helped assess its effectiveness in predicting intrinsic injuries and improving injury prevention strategies.

Methods: Models including logistic regression, decision trees, and Long Short-Term Memory-based neural networks, were evaluated for their predictive accuracy and ability to discern patterns indicative of injury risks or readiness for physical activities.

Findings: The study demonstrated that long-short term memory and convolutional one-dimension models outperform traditional machine learning methods in analyzing players' physical conditions. This approach may support earlier identification of injury risks and inform workload management. Using model evaluation and interpretability techniques, including Local Interpretable Model-Agnostic Explanations (LIME) module, the study provided a framework for sports scientists, coaches, and medical staff to mitigate injury risks and optimize training sessions.

Interpretation: As a preliminary exploration, this study paves the way for further research into the integration of machine learning and neural networks in sports science, promising transformative impacts on injury prevention strategies in rugby.

Keywords: rugby union; injury prevention; supervised learning; recurrent neural network.

(4164 words).

1. **Introduction**

In sports, injuries play a fundamental role in shaping both individual athletic development and the overall performance of teams, highlighting their profound impact on the optimization of training strategies and competitive outcomes.

The development of data now allows medical and technical staffs to have a complete follow-up of the player, ranging from their injury history to their daily workload. The prevention of injuries and the understanding of their occurrence is a major issue for professional sports structures.

Many studies have focused their emphasis on the development of predictive models for injury prediction across different sports. Numerous works have utilized screening tests and neuromuscular tests as predictive factors. The works of Wagemans et al. [1] showed that more lesions occurred when the balance values in abduction and the muscular strength in adduction of the leg were lower than the baseline values recorded. Rossi et al. [2], within a professional football team, decided to use GPS data, representing the physical activity of the players, combined with the players' injury history to develop a model which were able to predict 80% of the injuries that occurred during the year. Their study also highlighted the importance of model interpretation in injury prediction. Hecksteden et al. [3] also developed a predictive injury model by combining screening data with player monitoring data. Within a German third division football club, they developed a gradient-boosted model and studied the most important predictive parameters (feature importances) of their model. They concluded that machine learning-based injury forecasting founded on the integration of screening and monitoring data was promising.

Rugby is a sport characterized by frequent and intense physical contact, factors that complicate injury prediction. Injuries stem from various risk factors categorized as intrinsic or extrinsic. Intrinsic risk factors relate to the individual player’s characteristics, such as physical fitness, flexibility, injury history, biomechanics, and technical skills. Extrinsic risk factors, on the other hand, include external elements like playing conditions (e.g., field quality or weather), equipment, and interactions with other players. Poorly maintained fields or inappropriate equipment can heighten the injury risk. Exposure to contact in rugby is especially complex and unpredictable. The game’s inherently uncertain and chaotic nature involves intense, sudden collisions and tackles that vary in intensity and frequency, making injury risk management challenging. As described by A. Gardner et al. in their study [4], research conducted in English rugby has shown that head injuries (concussions, lacerations, contusions, etc.) are common and account for about 25% of injuries occurring during a match.

Various studies have begun to use predictive models for injury prevention and monitoring the health status of players after an injury. On one hand, numerous studies have utilized logistic regression and multiple logistic regression to predict and correlate physiological and psychological events[5][6][7]. On the other hand, some studies have decided to employ different machine learning methods to enhance injury prevention and physical load management, as well as identifying relevant information for selecting young players. S. Tedesco et al. [8] used supervised methods to learn and identify anterior cruciate ligament (ACL) injuries several years post-injury based on change of direction (COD) data. H. Thornton et al. [9] identified the period of increased risk of illness using different decision tree methods (random forest, gradient boosting) whereas J. Owen et al. [10] employed Bayesian machine learning models to identify psychological and physiological factors that could differentiate talented young players from others. However, to the authors knowledge, no study has yet investigated the use of multivariate time series modeling in rugby union. Furthermore, a tool based on predictive injury modeling would be a real daily advantage for the performance staff members of a club.

In our work, we sought to compare several models, including multivariate time series models composed of LSTM layers, as well as those combined with a Conv1D convolutional layer, in order to best predict a player's physical readiness for training using various data sources collected daily within a professional rugby club over one season.

2. Methods

The entire study, including the data used and the models developed, was conducted under the supervision and expertise of the medical staff of Racing 92.

The intent of the study was to utilize multiple data sources available in the daily routine of the team to prevent the occurrence of injuries among the players. The timing of data collection varies according to the type of data: while some, such as physical activity data, are collected several times a week, others, like screening data, come from periodic collections that occur at key moments of the season: pre-season, mid-season, injury if it occured.

The data from both the professional squad and the academy were used in our study, totaling an initial pool of 72 players. The 2022-2023 season was examined, with data covering 48 weeks, ranging from July 5th, 2022 to June 9th, 2023.

Based on availability of complete GPS, screening, contextual, and medical status data, 42 players met the inclusion criteria and were retained for analysis. For each of these players, multivariate data was collected, leading to a dataset of over 1,200 player-day sequences.

Figure 1. Flowchart representing the inclusion criteria of our methodology.

In total, 28 parameters were analyzed in our study, and they were divided into five categories: data from Global Positioning Systems (GPS), screening data, contextual data, environmental data, and status data, which in this case corresponded to the output of our models. We also had access to the players' injury data, allowing our approach to have a comprehensive analysis.

2.1 Workload data

GPS data allows the transcription of a player's physical activity during a rugby session (games or trainings). The GPS devices used were the Vector V7 from Catapult, which provide information at frequencies of 10 and 100 Hz. Thus, for each physical activity, 10 parameters were extracted:

- The duration of the session, in minutes.
- The total distance made by the player, in meters.
- The total distance over 7 km.h^{-1} which represents the distance run by the player, in meters.
- The total distance over 13 km.h^{-1}, in meters.
- The total distance over 18 km.h^{-1}, in meters.
- The total distance over 21 km.h^{-1}, in meters.

- The total number of accelerations over 2 m.s^{-2}.
- The total number of decelerations over 2 m.s^{-2}.
- The total number of efforts above 70% of the player's maximum speed, meaning the number of times they exceeded 70% of their maximal speed.
- The total number of accelerations over 5G received by the player.

2.2 Screening data

Screening data refers to tests carried out by medical staff and physical trainers to assess a player's condition at specific points in the season. These tests included physical tests, mobility tests, or neurological tests.

The 1.2 km shuttle run test (Bronco test) [11] is a field-based fitness test very popular in rugby. The protocol consists of a continuous 20, 40, and 60 m shuttle run, completed five times at a maximal intensity (i.e., 20 m and back, 40 m and back, 60 m and back). The performance, in minutes, achieved by the player in completing this test provides data reflecting their physical performance.

Three additional tests, conducted by physiotherapists, allowed us to evaluate the mobility of the players in the squad:

- the Dorsiflexion Lunge Test (DFT) is used to assess the dorsiflexion range of movement (DROM) at the ankle joint [12]. Three parameters are extracted: the average left score, the average right score, and the differential between the average left and right scores.
- The Active Knee Extension (AKE) test [13] is used to assess hamstring muscle length and the range of active knee extension in the position of hip flexion. Thus, three parameters were extracted: the average left score, the average right score, and the differential between the average left and right scores.
- The Schober test (finger-to-floor distance) allows for the measurement of the flexion of the spinal column segment located at the lumbar vertebrae [14].

The neurological aspect was also considered in this study. Indeed, using a Neurotracker® [15], a popular perceptual-cognitive training tool in sports, the players performed tests to examine cognitive abilities, utilizing a 3D multiple object-tracking (MOT) task. The data obtained from these tests were:

- The average time taken to complete the exercise.
- The neurological profile based on the time differential of the player when performing three exercises in a row (ex: Increase, Peak, ...).

2.3 Contextual data

A professional rugby season is also characterized by the sequence of matches and competition weeks. These pieces of information seem crucial for monitoring the evolution of the players' physical condition and the possible occurrence of injuries. Four parameters were thus extracted from the professional team's schedule:

- The competition of the match taking place at the end of the training week (Championship, European Cups (Challenge Cup or Champions Cup), or a week without a match).
- The location of the match taking place at the end of the training week (home or away)

- The number of days before the next match.
- The number of days after the previous one.
- The average time taken to complete the exercise.

2.4 Environmental data

Environmental conditions also seem to be factors that can lead to the occurrence of injuries. Therefore, meteorological data seemed relevant, and we were able to extract daily temperatures (in degree Celsius) from Le Plessis-Robinson (location of the Racing 92 training center) from OpenWeatherMap.

2.5 Status data

Almost daily, each player is assigned a status by clubs' doctors, reflecting their ability or inability to participate in the day's training sessions. These different statuses indicate whether the players are fit to train (status="T"), adapted (status="A"), receiving treatment (status="M"), or in rehabilitation (status="R"). In our modeling approach, the statuses were grouped into two options:

Table 1: Grouping of statuses into two classes: fit and unfit to training.

Aptitude to train	Status
Fit to train	T, A
Unfit to train	M, R

2.6 Injury data

Injury data are not used for modeling but will be used to study the model's results and associated predictions.

The medical staff of the club keeps a record of all injuries occurring during a season. Several parameters supplement the information about the injury: its location, the player's downtime, whether the injury mechanism is intrinsic or extrinsic, etc. Intrinsic injuries, which occured without external trauma, appear to be the most predictably injuries and will be the ones we use for interpreting our model.

2.7 Data standardisation

Data standardization was a critical step in our preprocessing to ensure that the numerical values of different scales were brought to a common scale without distorting differences in the ranges of values. We applied two distinct standardization approaches for our dataset: one for GPS data and another for the screening test data.

For parameters derived from GPS tracking, we performed an individual-based standardization. This method involved scaling the data for each player separately.

The formula used for standardization is as follows: $z_{i,j} = \frac{x_{i,j} - \mu_{i,j}}{\sigma_j}$.

where $z_{i,j}$ is the standardized score for the ith observation of the jth player, $x_{i,j}$ is the original value, $\mu_{i,j}$ is the mean of the player, and σ_j is the standard deviation for the jth player's dataset. This approach allowed us to account for individual variability and to compare each player's data relative to their own performance benchmarks.

For the screening test data, we adopted a team-based standardization method. Here, the standardization process was conducted across the entire team's dataset. This means that for each screening parameter, we calculated a single mean and standard deviation for the whole team and used those values to standardize individual player scores. The intention behind this approach was to maintain consistency and comparability of the data across the team.

2.8 Multivariate time series

Our methodology addressed the intricate structure of multivariate time series, which are composed of synchronized observations from multiple interrelated variables over time. The focus is on capturing the complex interdependencies and temporal relationships that exist among these variables, as they collectively contribute to the system's behavior.

Figure 2. Representation of our multivariate time series structure.

The figure 2 here illustrates the concept of multivariate time series as described in the accompanying text. It visualizes how individual time series, which represent univariate data collected over time, are synchronized to form a multivariate time series. Each row in the diagram corresponds to a univariate time series, and when combined, they constitute a multivariate time series that encapsulates multiple dimensions of data.

The vertical axis labeled "Number of dimensions" denotes the different variables that are being observed, each providing a unique data stream that contributes to the whole. Meanwhile, the horizontal axis represents the length of the time series, with T denoting specific time intervals at which the data are collected.

2.9 Predictive modeling

The aim of our study is to model a player's ability or inability to train based on the various parameters previously enumerated. To achieve this, we utilized various machine and deep learning algorithms to construct the most effective models possible.

Table 2: Explanations of the algorithms used.

Algorithms	References	Principles
Logistic Regression	[16]	Predicts the probability of a binary outcome using a sigmoid function and logit transformation, outputting values between 0 and 1.

<u>Decision Trees</u> a) Random Forest b) XGBoost (eXtreme Gradient Boosting)	[17], [18]	a) Constructs multiple decision trees during training and outputs the majority class. Handles non-linear relationships. b) Sequentially improves predictions by correcting errors of previous trees using boosting.
<u>Reccurent Neural Networks (RNN)</u> a) Long Short-Term Memory (LSTM) b) Convolutional Layers with RNN	[19], [20]	a) LSTM, a specialized type of RNN, is designed to process sequential data and manage long-term dependencies. The overall operation of an LSTM, can be summarized in three steps: • Detect relevant information from the past, drawn from the cell state through the forget gate. • Select, from the current input, the information that will be relevant in the long term, via the input gate. This information will be added to the cell state, which serves as long-term memory. • Extract from the new cell state the short-term important information to generate the subsequent hidden state through the output gate. b) Conv1D layers serve as an initial preprocessing step, applying convolutional operations to capture local temporal patterns in the input time series. By summarizing and reducing data dimensionality, these layers can extract key features. Conv1D layers can be associated to LSTM layers to build more effective models, as shown in Figure 3.

Figure 3. Example of the architecture of the model Conv1D + LSTM-2.

2.10 Model overfitting and regularization

To limit overfitting, especially given the complexity of deep learning models and the number of input features, several regularization strategies were implemented.

First, dropout layers were added to the architecture of recurrent neural networks. These layers randomly deactivate a fraction of neurons during each training iteration, reducing reliance on specific activations and improving model generalization.

Second, early stopping was employed during training: model performance on a validation set was monitored, and training was halted automatically if no improvement was observed after a predefined number of epochs.

These techniques, combined with a sufficiently large number of input sequences (>1,200 player-day samples), helped mitigate overfitting and improve robustness in predictions.

2.11 Model evaluation metrics

In the study of multivariate time series for binary outcomes within imbalanced datasets, it is important to consider different metrics for model evaluation. Traditional accuracy measures can be misleading due to the disproportionate class distribution. In our case, we address this challenge by utilizing three key metrics: the accuracy, the F1-Score and the Brier Score.

Table 3: Explanations of the different metrics used to evaluate models.

Metric	Definition (Formula)	For Imbalanced Datasets
Accuracy	Ratio of correctly predicted observations to total observations. $\left(\frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}\right)$	Fundamental metric but overestimates performance on the majority class.
F1-Score	Harmonic mean of precision and recall, balancing false positives and false negatives. $\left(2 \cdot \frac{Precision\ \cdot Recall}{Precision + Recall}\right)$	Reflects ability to predict minority class and penalizes false classifications.
Brier Score	Mean squared difference between predicted probabilities (f_t) and actual outcomes (o_t). $\left(\frac{1}{N} \cdot \sum_{t=1}^{N} (f_t - o_t)^2\right)$	Pertinent for binary outcomes in imbalanced datasets, as it accounts for the probability calibration of the predictions, offering a more nuanced understanding of model performance.

2.12 Model interpretability

We also emphasize the critical importance of understanding the decision-making process of our predictive models, especially when dealing with complex multivariate time series data. We employed the Local Interpretable Model-agnostic Explanations (LIME) technique which facilitates the interpretation of our model's behavior by approximating it locally using an interpretable model [21].

The LIME method works by perturbing the input data and observing the changes in the model's predictions. By fitting a simple model, such as a linear regression, to these perturbations, LIME highlights which features significantly influence the output for individual predictions. This local approximation approach allows us to glean insights into the contributing factors behind the model's decision for a particular instance, even if the global model is highly complex and nonlinear.

In the case of multivariate time series analysis, it also provides a substantial benefit by not only discerning features importance but also by highlighting the specific temporal segments that influence the prediction.

3. Results

3.1 Results of models

Seven models were developed, and we can observe their reliability in the following table:

Table 4: Results of the different models on three metrics: accuracy, F1-score, and Brier score.

Models	Accuracy	F1-Score (S = Unfit to train)	Brier Score
Logistic Regression	81.8	0.49	0.131
Random Forest	90.6	0.73	0.071
XGBoost	91.6	0.78	0.066
LSTM-2*	79.9	0.22	0.152
LSTM-3	89.1	0.70	0.086
Conv1D + LSTM-2	92.5	0.81	0.059
Conv1D + LSTM-3	92.9	0.83	0.054

* LSTM-x indicates that the model contains x LSTM layers.

For the following results, we have decided to use model Conv1D + LSTM-3, made of one Conv1D layer and three LSTM layers, which proved to be the most efficient model following the training based on the three metrics previously analyzed.

3.2 Model interpretation

As previously presented, rugby is a sport where contacts can be numerous and significant. Many injuries are related to this aspect of the game, making them difficult to predict, and thus models may not be able to detect them. In our results analysis, we therefore focused on the analysis of the occurrence of intrinsic injuries, injuries caused without direct trauma. The use of our model's output allows us to address various cases of interpretations.

Figure 4. Comparison of the model output probability and the status of the player X.

As we can see on the figure 5, the model appears to detect the appearance of a symptom or injury in the player that will manifest itself a few days later.

The interest in this type of work and models goes beyond mere prediction. It is important for members of the technical staff to understand the model's outputs. Taking the case of the previous injury to player X, the LIME module allowed us to understand the significant increase in the probability of unfitness.

Figure 5. Interpretations of the model's predictions regarding player X, using the LIME module.

On the figure 6, we can observe red bars (representing the parameters that influence the model to predict that the player is at risk of injury) and green bars (representing the parameters influencing the model to predict that the player is in good shape). In our case, the red bars are therefore of interest for us. For the injury of player X, we can notice that the distance run at high intensity (distance above 18 km/h) on the preceding days (t-2, t-4, then t-3, t-5) appears to be the factor that most influenced the prediction of the player's injury.

We also observe other use cases of our predictive model:

- Cases where instability appears in the days preceding the injury, as shown by the example of player Y in the figure 7.
- Other cases where the model fails to predict the onset of the injury and only "notices" it after a few days such as the example of player Z in the figure 8.

Figure 6. Comparison of the model output probability and the status of the player Y.

Figure 7. Comparison of the model output probability and the status of the player Z.

In the context of player Y (figure 7), we used again the LIME module to visualize which parameters were determined as influential by the model in predicting that the player was at risk of injury. We focused on the two highest prediction peaks before the injury occurred.

Figure 8. Interpretations of the model's predictions regarding player Y, using the LIME module.

On the figure 9, we take a close look to the red bars which are our parameters of interest. For the injury of player Y, we can notice that the distance run at high intensity (distance above 18 km/h) on the preceding days but also the age of the player (player Y was 34.5 years old at this time) appears to be the factor that most influenced the prediction of the player's injury.

4. Discussion

Our study demonstrated that combining Conv1D and LSTM models improves the prediction of injury risks in a professional rugby club compared to traditional machine learning methods like logistic regression and decision trees. Conv1D layers, optimized for one-dimensional data, are particularly suitable for time-series analysis as they capture local temporal patterns. LSTMs complement this by modeling long-term dependencies in multivariate time-series data. This hybrid approach effectively handles the complex and evolving dynamics of players' physical states, offering a nuanced understanding of injury predictive factors.

Comparative analysis with existing literature reveals that our findings corroborate the growing consensus on the efficacy of machine learning and deep learning approaches in sports injury prediction. Studies such as Rossi et al. [2] and Hecksteden et al. [3] have previously emphasized the promise of machine learning models in predicting injuries using workload data in soccer.

However, there are certain limitations to this study. Firstly, the study is based on data from a single rugby club, which might limit the generalization of the results. While the results are encouraging, they must be interpreted within the context of a single-season, single-team dataset. Further studies are needed to confirm these findings across other settings and populations. Certain additional data in this work could have provided important elements to our models to facilitate their predictions. Data on injury history (how long since the last injury, the number of injuries in the last x months, x last years, ...) seem to be relevant in the model's ability to predict the occurrence of a new injury. Similarly, the addition of monitoring data seems interesting. These data are daily questionnaires that players respond to regarding their physical condition, sleep, stress, ... For the following seasons and the development of new models, data collection has been improved, and these data will be considered. It is also possible that unmeasured factors, such as players' psychological conditions or specific environmental variables, influenced the model performance. Future exploration of these variables could offer additional insights into injury prediction.

Secondly, some information would benefit from being more detailed, especially in the case of environmental data. Indeed, the Racing 92 club has the unique feature of playing its matches in an indoor stadium with synthetic turf, alternating with an outdoor training center that has natural grass. This alternation of environmental conditions could potentially have an influence on the physical condition of the players. Weather condition data such as the presence of rain, snow, or ice can also add relevance to our predictions.

In the application of the model, we initially focused on understanding the occurrence of intrinsic injuries. Indeed, extrinsic injuries, that is, those related to external trauma, seem unpredictable, and the model will therefore have difficulty recognizing them. However, the use of our models could provide information for the study of concussions, a major issue in contact sports like rugby. Some assumptions suggest that, with equal impacts endured, a player who is more fatigued due to excessive workload or having a high injury history may be more likely to suffer a concussion.

Finally, an extension of our study to provide more accuracy and relevance would be to develop a metric that calculates the model's ability to predict the occurrence of an injury (its D-day) without requiring manual verification. Indeed, the metrics used so far are based on predicting the player's status, making the prediction of D+2, D+3, ... easier knowing that the player had an injured status on D+1.

5. Conclusions

The results of this study highlighted the potential of multivariate time series models to significantly enhance injury prediction capabilities within a professional rugby union club. This finding is consistent with emerging research in the field of sports analytics, where deep learning techniques, particularly those capable of processing sequential and time-series data, are growing. Our study extends this body of knowledge by demonstrating that models combining convolutional layers with LSTM layers can effectively discern complex patterns in players' physical conditions and activities. In our context, these models showed improved predictive performance compared to traditional approaches such as logistic regression and decision trees, although further validation is required to confirm these findings in broader settings. Our research contributes by applying Conv1D + LSTM models specifically to the context of rugby using various data sources such as workload, screening or contextual data. Furthermore, our approach emphasizes model interpretability via LIME, providing actionable insights for injury prevention.

The practical implications of this research are significant for sports scientists, coaches, and medical staff in rugby. By adopting these models, they can better anticipate injury risks and manage player workloads more effectively, thus potentially reducing the incidence of injuries. Furthermore, the interpretability of the model, enhanced by LIME, provides actionable insights, allowing staff to understand the factors contributing most significantly to injury risks.

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Conflicts of Interest: The authors declare no conflicts of interest.

Use of generative AI in scientific writing: The authors declare having used generative AI in the writing process for this manuscript.

Figure 1. Flow chart representing the inclusion criteria of our methodology.

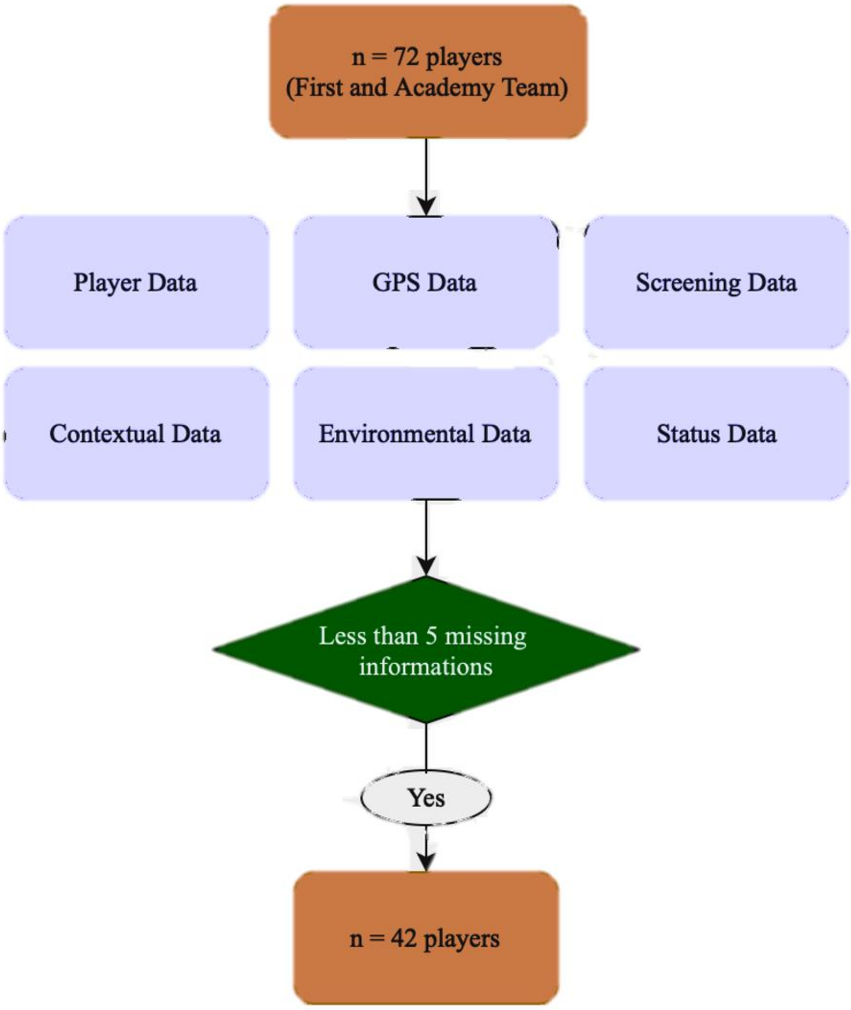


Figure 2. Representation of our multivariate time series structure.

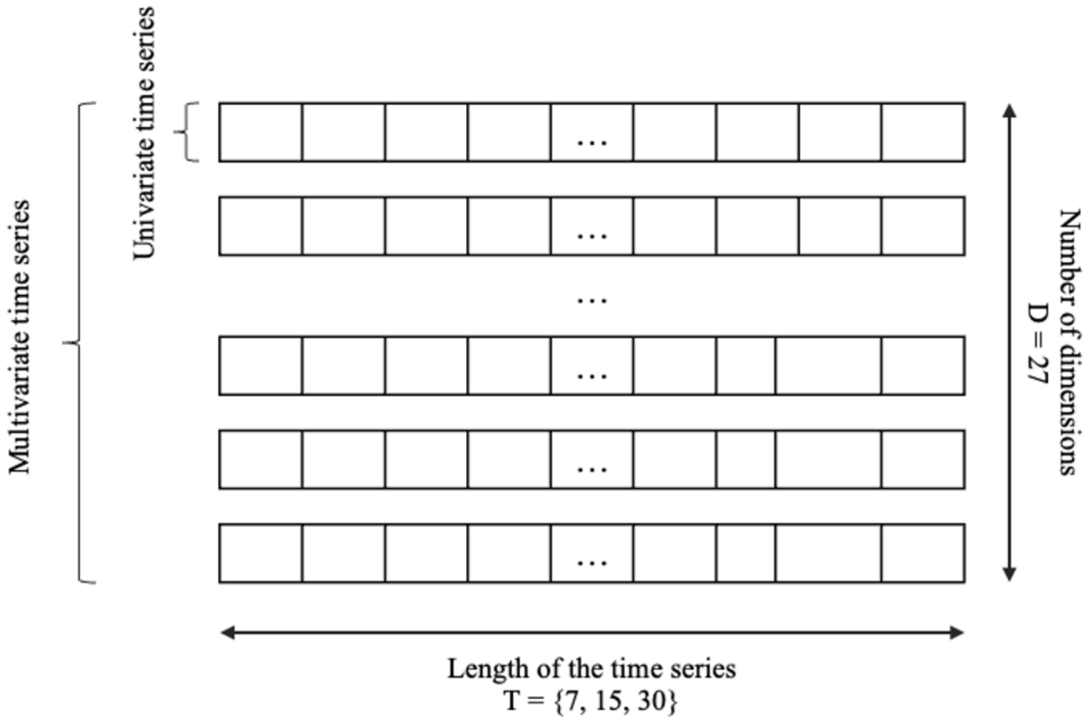


Figure 3. LSTM cells representation.

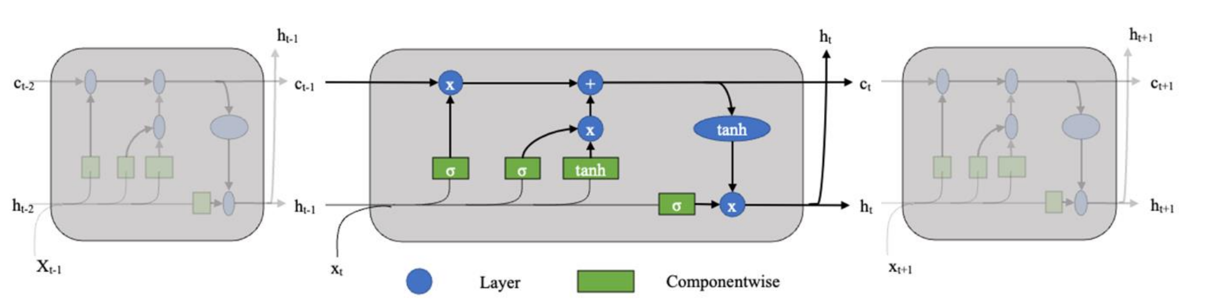


Figure 4. Example of the architecture of the model Conv1D + LSTM-2.

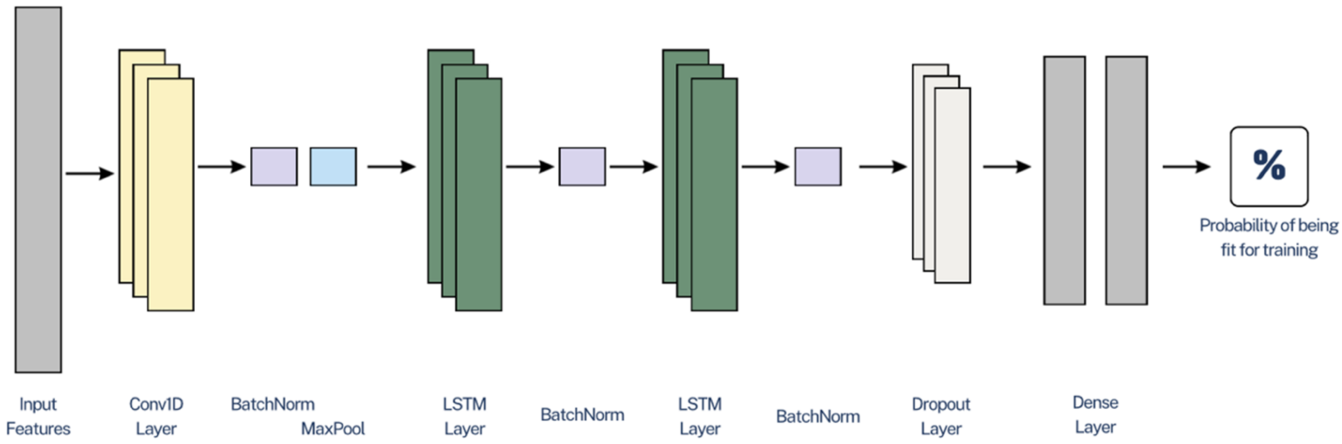


Figure 5. Comparison of the model output probability and the status of the player X.

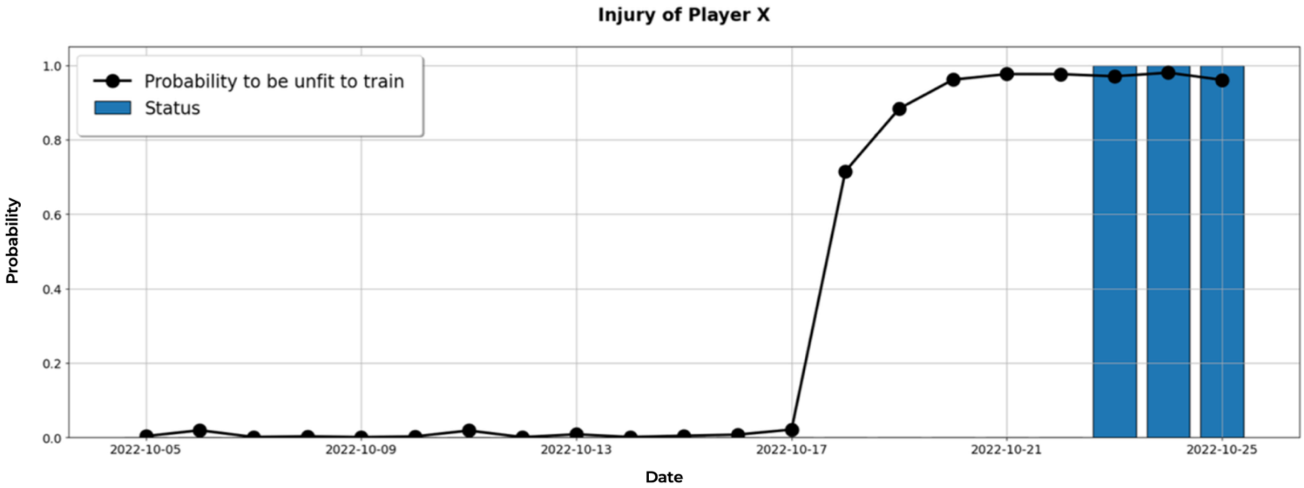


Figure 6. Interpretations of the model's predictions regarding player X, using the LIME module.

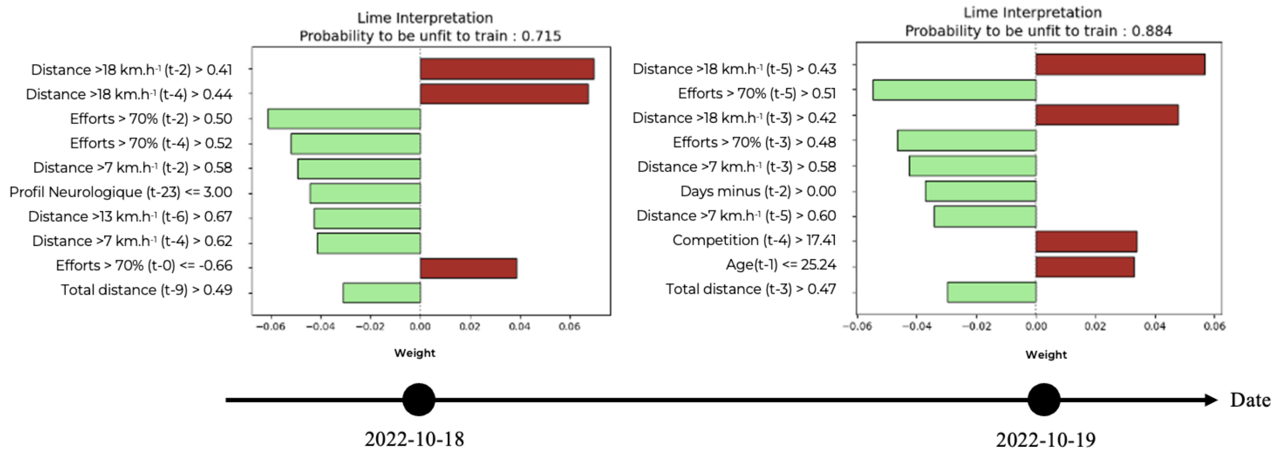


Figure 7. Comparison of the model output probability and the status of the player Y.

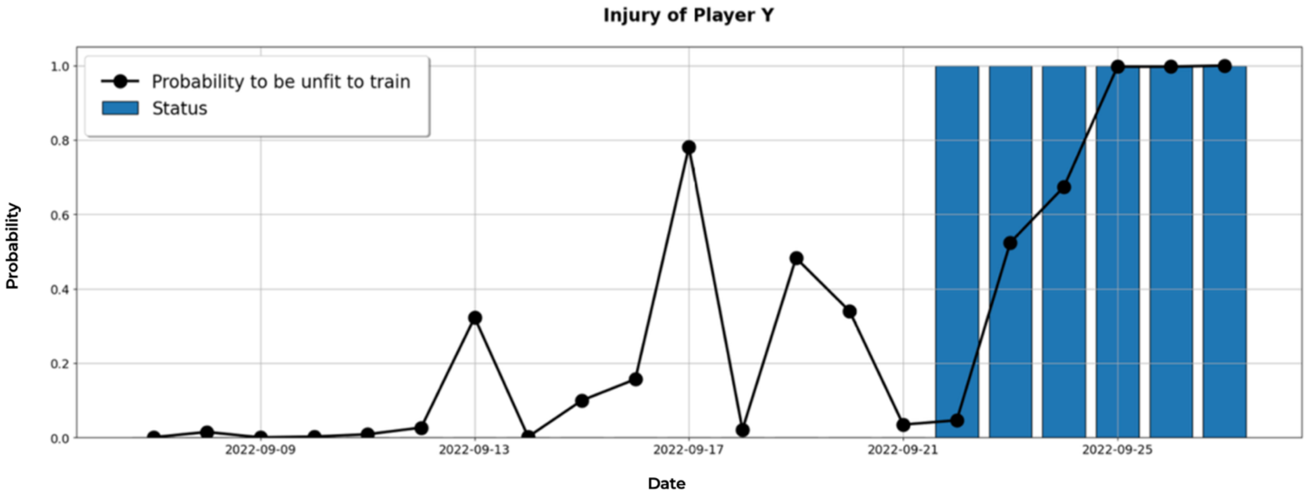


Figure 8. Comparison of the model output probability and the status of the player Z.

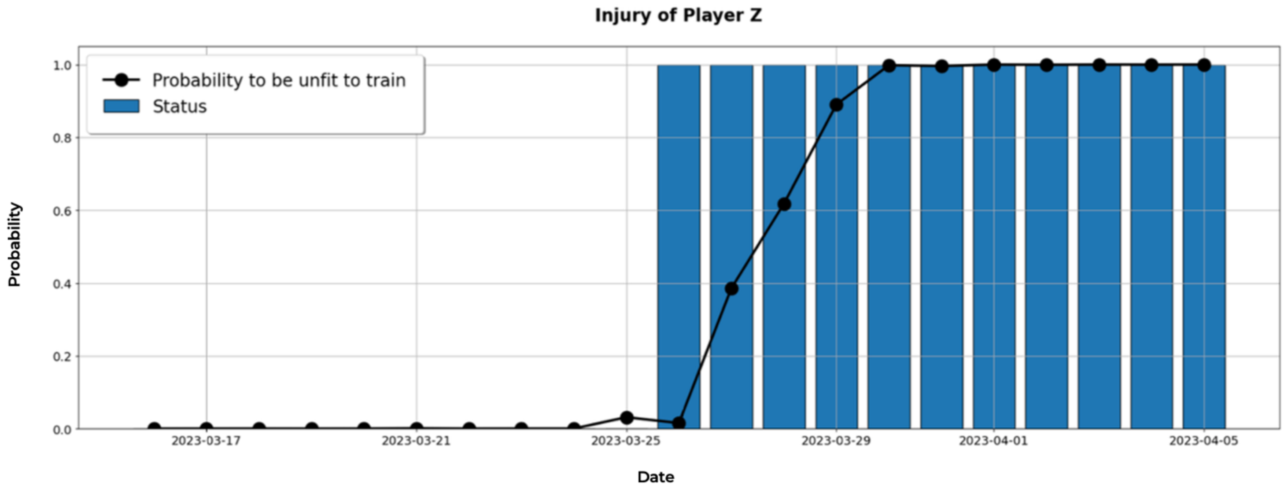
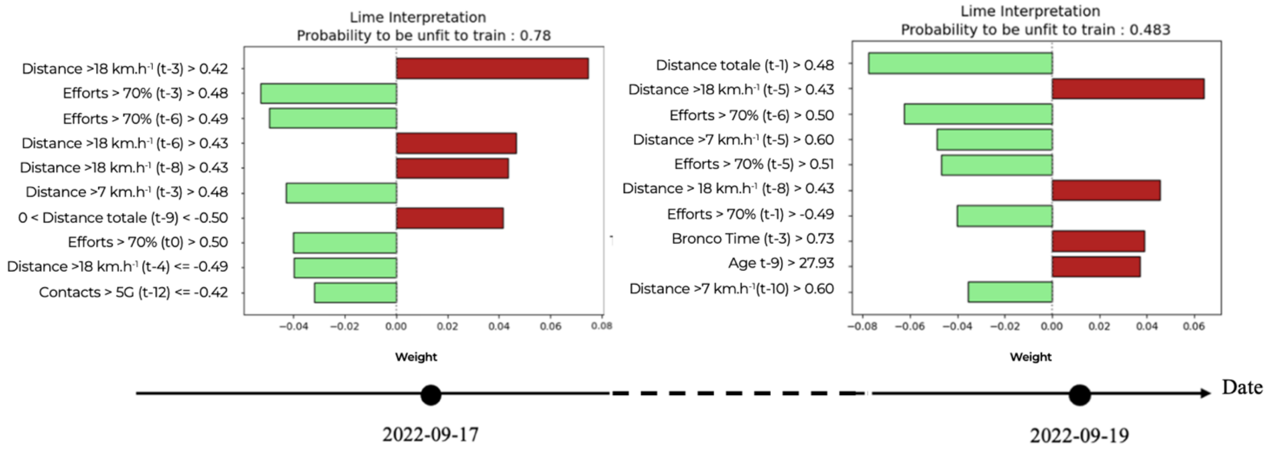


Figure 9. Interpretations of the model's predictions regarding player Y, using the LIME module



Declaration of interests

☐ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☒ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Maxence Duffuler reports financial support was provided by Arts et Métiers Institute of Technology. Maxence Duffuler reports a relationship with Arts et Métiers Institute of Technology that includes: funding grants and non-financial support. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Highlights:

- Use of multivariate time series for training readiness and injury prediction.
- Convolutional and recurrent models outperformed traditional predictive modeling.
- Model interpretation highlighted key factors contributing to injury risk.