# A Machine Learning Approach to Assess Injury Risk in Elite Youth Football Players

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**ABSTRACT**

ROMMERS, N., R. RÖSSLER, E. VERHAGEN, F. VANDECASTEELE, S. VERSTOCKT, R. VAEYENS, M. LENOIR, E. D'HONDT, and E. WITVROUW. A Machine Learning Approach to Assess Injury Risk in Elite Youth Football Players. *Med. Sci. Sports Exerc.*, Vol. 52, No. 8, pp. 1745–1751, 2020. **Purpose:** To assess injury risk in elite-level youth football (soccer) players based on anthropometric, motor coordination and physical performance measures with a machine learning model. **Methods:** A total of 734 players in the U10 to U15 age categories (mean age, 11.7 ± 1.7 yr) from seven Belgian youth academies were prospectively followed during one season. Football exposure and occurring injuries were monitored continuously by the academies' coaching and medical staff, respectively. Preseason anthropometric measurements (height, weight, and sitting height) were taken and test batteries to assess motor coordination and physical fitness (strength, flexibility, speed, agility, and endurance) were performed. Extreme gradient boosting algorithms (XGBoost) were used to predict injury based on the preseason test results. Subsequently, the same approach was used to classify injuries as either overuse or acute. **Results:** During the season, half of the players ($n$ = 368) sustained at least one injury. Of the first occurring injuries, 173 were identified as overuse and 195 as acute injuries. The machine learning algorithm was able to identify the injured players in the hold-out test sample with 85% precision, 85% recall (sensitivity) and 85% accuracy (f1 score). Furthermore, injuries could be classified as overuse or acute with 78% precision, 78% recall, and 78% accuracy. **Conclusions:** Our machine learning algorithm was able to predict injury and to distinguish overuse from acute injuries with reasonably high accuracy based on preseason measures. Hence, it is a promising approach to assess injury risk among elite-level youth football players. This new knowledge could be applied in the development and improvement of injury risk management strategies to identify youth players with the highest injury risk. **Key Words:** INJURY PREVENTION, ADOLESCENT, CHILD, SOCCER

EPIDEMIOLOGY

Elite-level youth football is known to entail a high injury risk (1,2), which is often attributed to early specialization, high training loads, and high training and game intensities (3,4). To specifically target injury risk mitigation strategies in this group, knowledge of both modifiable and nonmodifiable risk factors is crucial. The few existing studies in elite-level youth football mainly focus on anthropometric factors, landing strategies, and a limited number of functional tasks (5–9). In practice, however, it is often not feasible for clubs and coaches to perform thorough player screening for injury risk management purposes due to limited time and financial means. Therefore, there is a strong interest to assess injury risk based on field-specific and relatively easy screening tests, such as motor performance tests already taken by many clubs to monitor player development.

Previous studies did not show an association between motor performance measures and injury risk in different cohorts of youth football players (8,10). Due to the complex nature of injuries, a single variable is usually insufficient to provide a meaningful estimate of the injury risk of a player (11). Hence, considering the multifactorial nature of injuries, it is key to incorporate a multitude of risk factors in any injury risk analysis (11). More advanced data science approaches, including machine learning, often better integrate the complexity of injury events compared with traditional statistics (12), and these approaches can take many variables and interactions between these into account (13). To date, this kind of approach has mainly been used in relatively small samples of elite athletes,

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mostly considering training load variables, but already demonstrated promising results (14–18).

To extend this knowledge from data science, the aim of this study was to use a machine learning approach to evaluate the risk of injury in youth elite-level football players, based on anthropometric, motor performance, and demographic measures. The first aim was to use preseason test results to assess the accuracy of a machine learning model predicting injury during the season. The second aim was to apply a similar model to correctly classify different types of injuries, namely overuse and acute injuries.

## METHODS

### Participants and Design

The present prospective study followed 734 male youth football players during the 2017 to 2018 competitive season (August 2017 until May 2018). Players of the under 10 yr (U10) up to the under 15 yr (U15) age categories were recruited from the youth academies of seven Belgian premier league football clubs. All players being medically cleared to play at the start of the season were eligible to participate. Verbal and written information about the study design and potential risks and benefits upon participation was provided to the players and their parents or legal caretakers. The parents provided written informed consent and the youth player provided his written assent. The study protocol was approved by the medical ethical committee of the Vrije Universiteit Brussel (B.U.N. 143201628616), and all measurements were performed according to the ethical standards of the Helsinki Declaration.

### Procedures

At the start of the competitive season (August 2017), a test battery of anthropometric, motor coordination and physical fitness measures was taken by a group of trained assessors, coordinated by the principal investigator (N.R.) to guarantee standardization of all tests. At the same time, demographic information regarding the football experience (in years) and date of birth were collected through a questionnaire.

**Anthropometry, growth, and maturity status.** Body height (Seca 213 Portable Stadiometer, Seca, Germany) and sitting height (Harpenden sitting height table, Holtain, UK) were measured to the nearest 0.1 cm. We calculated the players' leg length as the difference between their recorded body height and sitting height. Body weight was determined to the nearest 0.1 kg using a digital scale (Tanita BC-420SMA, Tanita, Japan). The years from peak height velocity (PHV), an indicator for maturational timing, was estimated using the prediction equation of Mirwald and colleagues (19).

**Motor coordination.** We determined players' level of generic motor coordination using the three subtest short version of the Körperkoordinationstest für Kinder (KTK3) (20,21), consisting of 1) jumping sideways (JS), 2) moving sideways (MS), and 3) balancing backwards (BB). These three subtests were conducted as described by Kiphard and Schilling (22). All individual subtest scores as well as the total sum score were included in the analysis.

Football-specific motor coordination was tested using the Ghent University dribbling test (23). The players completed a prescribed circuit as fast as possible in two conditions: first without the ball (agility), and subsequently with the ball (dribbling skills). The time of both attempts was measured to the nearest 0.01 s with a handheld stopwatch.

**Physical performance.** Flexibility of the lower back and posterior chain was measured using the sit and reach test to the nearest 0.5 cm (24). To test the players' endurance, the YoYo Intermittent Recovery Test Level 1 was conducted on artificial turf in dry weather conditions according to the guidelines of Krustrup and colleagues (25). In addition, three strength measures were included in our test battery: the standing broad jump (SBJ), countermovement jump (CMJ), and curl-ups. The SBJ was executed as described in the Eurofit test battery's manual (26). The CMJ performance was tested in two conditions, using the Optojump system (OptoJump System, Microgate, Italy): first the player performed three jumps with the hands on the hips, followed by three jumps with an arm swing (27). The best attempt in each of the conditions of the SBJ and CMJ was used for analysis. We tested abdominal strength by the number of correctly executed curl-ups in 30 s (26). Speed and agility were tested by a repeated sprint test (28) and a *t* test, respectively. The players performed four maximal sprints of 30 m, with 25 s of rest in between. Fastest split times at 5, 10, 20, and 30 m as well as maximum decline over 30 m were used for analysis. Agility was assessed by the *t* test that was executed twice: first with all turns performed left, and subsequently with all turns performed right (23). Both tests were performed on artificial turf with time registered to the nearest 0.001 s (MicroGate Racetime2; Microgate, Italy).

**Football exposure.** Individual match and training exposure were recorded by the team coaches according to the consensus statement of Fuller and colleagues (29) to calculate the injury incidence. Attendance at training and individual playing time during matches were registered in the player monitoring system, or by the use of Excel sheets designed by the research team.

**Injury registration.** Injuries were registered by the medical staff of each youth academy using a prespecified injury registration form. On this form, the date of occurrence, type, and location of injury were registered. The date of return to full participation was later added. An injury was defined as a medical attention injury (i.e., injury that required an assessment of medical or paramedical staff) (29). All participating youth academies had medical staff available at every training and match, and all players experiencing any physical complaint, had to seek assessment from the medical staff. The injuries were classified as either overuse or acute injuries. An overuse injury was defined as an injury without a single identifiable event responsible for the injury, whereas an acute injury resulted from a specific identifiable event (29). The first occurring injury for each player was taken into account in our analysis.

### Statistical Analysis

Baseline characteristics of the players are presented as means and standard deviations for all variables. We used a machine learning approach to predict injury based on the preseason screening test results. In a second model, we aimed to correctly classify acute and overuse injuries. All analyses were performed in Python using the XGBoost application (version 0.81), an optimized distributed gradient boosting library. XGBoost is a highly flexible and versatile tool that was built for the purpose of model performance and computational speed. It supports fine tuning of the model and addition of regularization parameters to control overfitting (13). Therefore, it is a suitable application for the purpose of our study. We built a model using our training data consisting of a random sample of 80% of all collected data. During the boosting process, a set of weak learners is combined to improve prediction accuracy. Gradient descent was used to minimize the cost function parameterized by a specific model parameter. Finally, to optimize the cost function, hinge loss was used. Hinge loss penalizes predictions both when they are incorrect and when they are correct but not confident. After the model was built, it was evaluated using cross-validation. Also, grid search was performed for hyperparameter optimization. Finally, the best-performing model was tested on our test data, consisting of the remaining 20% of all collected data.

To interpret and visualize the output of each model, we used the SHapley Additive exPlanations (SHAP) approach (SHAP summary plot) (30). This approach visualizes every single player or injury case and gives an overview of the variables in the model by order of importance (vertically listed features), with the top ones having a higher global impact on the model than bottom ones. The SHAP values represent the impact of a variable in the decision making process. Dots representing the SHAP values for each feature value of a player in the dataset are plotted horizontally next to the feature. Positive SHAP values represent a higher probability of a positive prediction (i.e., being injured). Each dot is colored by the value (i.e., measured value) of the feature for an individual, where blue represents the lower values (e.g., lower body height), and red the higher values (e.g., higher body height). To assess the value of the models, precision (ratio of the number of true positive observations over the total number of predicted positive observations), recall or sensitivity (ratio of the correctly predicted positive observations to all observations that were actually positive), and f1 score (harmonic mean of precision and recall) were calculated for both the training data set (80%) and the test data set (20%).

## RESULTS

Data from 734 players of the U10 to U15 age categories were used in the analysis. During the 2017 to 2018 season, 368 of them sustained at least one injury during 129.209 h of football exposure in total (112.745 h of training and 16.464 h of match exposure). An overview of the player characteristics for the total sample, the injured, and the noninjured players can be found in Table 1. A detailed overview of the injuries by mechanism, type, location, and severity is presented in Table 2.

TABLE 1. Preseason test results for the total sample and for injured and noninjured players separately, as well as for the players who sustained an overuse injury and the players who sustained an acute injury.

| | Total Sample (*N* = 734) | Injured (*n* = 368) | Noninjured (*n* = 366) | Overuse Injury (*n* = 172) | Acute Injury (*n* = 196) |
|---|---|---|---|---|---|
| | Mean (SD) | Mean (SD) | Mean (SD) | Mean (SD) | Mean (SD) |
| Age (yr) | 11.7 (1.7) | 12.2 (1.7) | 11.2 (1.5) | 12.1 (1.7) | 12.2 (1.7) |
| Height (cm) | 149.4 (12.4) | 152.8 (13.4) | 146.5 (10.7) | 153.0 (13.1) | 152.5 (13.7) |
| Weight (kg) | 39.3 (10.1) | 41.9 (11.2) | 37.0 (8.3) | 42.3 (11.2) | 41.6 (11.2) |
| Fat percentage (%) | 17.3 (1.9) | 12.4 (3.6) | 13.5 (3.3) | 12.7 (3.7) | 12.2 (3.6) |
| BMI (kg·m$^{-2}$) | 13.0 (3.5) | 17.6 (2.0) | 17.0 (1.6) | 17.7 (2.1) | 17.5 (1.9) |
| Sitting height (cm) | 77.5 (5.8) | 78.8 (6.3) | 76.4 (5.2) | 78.9 (6.3) | 78.7 (6.4) |
| Leg length (cm) | 71.8 (7.4) | 74.0 (7.9) | 70.0 (6.4) | 74.0 (7.6) | 73.9 (8.2) |
| Maturity offset (yr) | −2.0 (1.4) | −1.6 (1.5) | −2.3 (1.2) | −1.6 (1.5) | −1.6 (1.5) |
| Age at PHV (yr) | 13.7 (0.6) | 13.8 (0.6) | 13.6 (0.5) | 13.7 (0.6) | 13.8 (0.6) |
| SBJ (cm) | 170.2 (21.5) | 174.2 (23.3) | 166.7 (19.2) | 173.6 (23.3) | 174.8 (23.3) |
| CMJ (cm) | 24.9 (5.2) | 26.0 (5.6) | 23.9 (4.6) | 26.0 (5.7) | 26.1 (5.5) |
| CMJ with arm swing (cm) | 29.7 (5.9) | 31.1 (6.4) | 28.5 (5.2) | 30.9 (6.4) | 31.3 (6.4) |
| Curl-ups (n) | 33.9 (6.8) | 35.4 (6.9) | 32.6 (6.4) | 35.6 (6.7) | 35.2 (7.0) |
| Sit and reach (cm) | 19.4 (5.8) | 20.2 (5.5) | 18.8 (6.0) | 20.2 (5.2) | 20.2 (5.7) |
| Jumping sideways (n) | 94.6 (12.7) | 96.0 (12.7) | 93.5 (12.5) | 95.3 (12.5) | 96.6 (12.9) |
| Moving sideways (n) | 57.9 (10.2) | 59.3 (10.6) | 56.7 (9.6) | 58.7 (10.3) | 59.8 (10.9) |
| Balancing backwards (n) | 55.5 (11.5) | 56.7 (11.2) | 54.4 (11.7) | 56.0 (10.9) | 57.4 (11.4) |
| KTK3 sum score | 207.9 (29.3) | 211.9 (29.5) | 204.3 (28.6) | 210.0 (28.4) | 213.7 (30.5) |
| *t* Test left (s) | 8.7 (0.5) | 8.7 (0.5) | 8.8 (0.5) | 8.7 (0.5) | 8.6 (0.5) |
| *t* Test right (s) | 8.8 (0.5) | 8.8 (0.5) | 8.9 (0.5) | 8.8 (0.5) | 8.7 (0.5) |
| Dribbling without ball (s) | 12.3 (1.2) | 12.1 (1.1) | 12.4 (1.2) | 12.1 (1.1) | 12.0 (1.1) |
| Dribbling with ball (s) | 20.4 (2.3) | 20.2 (2.3) | 20.5 (2.2) | 20.2 (2.3) | 20.2 (2.3) |
| Sprint 5 m (s) | 1.19 (0.09) | 1.18 (0.09) | 1.21 (0.09) | 1.2 (0.1) | 1.2 (0.1) |
| Sprint 10 m (s) | 2.1 (0.1) | 2.0 (0.1) | 2.1 (0.1) | 2.0 (0.1) | 2.0 (0.1) |
| Sprint 20 m (s) | 3.6 (0.3) | 3.6 0.3 | 3.7 0.2 | 3.6 (0.3) | 3.6 (0.3) |
| Sprint 30 m (s) | 5.2 (0.4) | 5.1 0.4 | 5.2 0.4 | 5.1 (0.4) | 5.0 (0.4) |
| Decay 30 m (s) | 0.4 (0.2) | 0.4 0.2 | 0.4 0.2 | 0.4 (0.2) | 0.4 (0.2) |
| YoYo IR test (m) | 944.4 (534.6) | 1030.5 589.7 | 871.8 472.1 | 973.5 (559.7) | 1082.6 (613.0) |
| Years of football experience (yr) | 5.1 (3.8) | 5.0 (4.0) | 5.2 (3.6) | 6.9 (2.0) | 7.3 (2.0) |

n: number of; BMI, body mass index; KTK3, 3 subtest short version of the Körperkoordinationstest für Kinder.

EPIDEMIOLOGY

TABLE 2. Injury characteristics.

| | *n* (%) |
|---|---|
| Total injuries | 368 (100) |
| Mechanism | |
| Overuse injuries | 173 (47.0) |
| Acute injuries | 195 (53.0) |
| Injury type | |
| Fracture | 24 (6.5) |
| Other bone and joint injuries | 14 (3.8) |
| Meniscus/cartilage | 1 (0.3) |
| Sprain/ligament injury | 39 (10.6) |
| Muscle rupture/tear/strain/cramps | 116 (31.5) |
| Tendon injury/rupture/tendinosis/bursitis | 100 (27.2) |
| Hematoma/contusion/bruise | 65 (17.7) |
| Wound | 1 (0.3) |
| Concussion | 1 (0.3) |
| Injury location | |
| Head/face | 1 (0.3) |
| Shoulder/clavicular | 8 (2.2) |
| Upper arm | 1 (0.3) |
| Forearm | 3 (0.8) |
| Wrist | 13 (3.5) |
| Hand/finger/thumb | 12 (3.3) |
| Sternum/ribs/upper back | 2 (0.5) |
| Lower back/pelvis/sacrum | 12 (3.3) |
| Hip/groin | 72 (19.6) |
| Thigh | 63 (17.1) |
| Knee | 81 (22.0) |
| Lower leg/Achilles tendon | 45 (12.2) |
| Ankle | 36 (9.8) |
| Foot/toe | 19 (5.2) |
| Injury severity, d | |
| 0 | 7 (1.9) |
| 1–3 | 62 (16.8) |
| 4–7 | 95 (25.8) |
| 8–28 | 136 (37.0) |
| >28 | 68 (18.5) |



**Predicting injury.** The extreme gradient boosting model was able to predict injury with a precision of 84% in the training dataset supported by 587 players. This means that only 16% of players indicated by the model as injured actually remained uninjured. This model had a recall of 83%, and an f1 score of 83%. When the model was run on the test data supported by 147 players, the precision, recall and f1 scores were all 85%, showing a reasonable accuracy and sensitivity of the model. The most important variables related to injury risk, are shown using a SHAP approach (Fig. 1A). A higher predicted age at PHV, higher body height and leg length, lower fat percentage and average performance on the SBJ were identified as the five most important predictors for injury. A better sit-and-reach performance, average *t* test and lower 10-m sprint performance affected the prediction for a smaller amount.

**Classifying overuse and acute injuries.** Player characteristics by injury mechanism are displayed in Table 1. All 368 injuries were either classified as overuse ($n = 173$) or acute ($n = 195$) injuries. The extreme gradient boosting model supported by 294 injuries in the training data set, reached a precision and recall score of 82% in classifying injuries, and f1 score of 81%. In the test data set, supported by 74 injuries, a precision, recall and f1 score of 78% was reached. This shows that the model is reasonably accurate in classifying injuries correctly by mechanism. The most influential variables in the decision making process are visualized by the SHAP approach (Fig. 1B). Most variables only affected the decision making for a limited amount with SHAP values not exceeding 0.4. A lower predicted age at PHV, higher sitting height, slower *t* test performance, and lower MS score were related to overuse injuries.

## DISCUSSION

The results of this prospective study show that it is possible to predict injury over the season with 85% accuracy in the unseen test data. Only 15% false positives were observed and 15% injured players misclassified as uninjured based on preseason anthropometric, motor performance, and demographic measures. Moreover, overuse injuries could be distinguished from acute injuries with a slightly lower accuracy using the same preseason test results.

Two previous studies did not find an association between preseason performance tests and injury risk using traditional statistics (8,10). In contrast to traditional approaches, boosted regression tree models, which are designed to maximize the precision and accuracy in classification, allow us to include many more variables than often used multivariate models. This different approach aiming for the highest classification accuracy, could explain the contradictory findings of our study compared with previous ones identifying associations between certain variables and injury risk. The added clinical value of a machine learning model is the interpretation of the classification based on all variables, next to the interpretation of individual variables as risk factors. Based on the SHAP values, we can indicate which variables and corresponding values of these variables played the largest role in the classification decisions.

**Predicting injury.** The five most important variables that predict injury are anthropometric measures. Interpreting the SHAP values, we notice that a higher predicted age at PHV, longer legs, higher body height, and lower body fat percentage increased injury risk. These finding can be explained by the large increase in injury incidence with age (31–33). Our study confirms the findings of previous studies, identifying higher body height and weight (7), and higher predicted age at PHV (34) as risk factors for injuries. Interestingly, we see that a worse performance on the sit and reach test was protective against injuries, whereas a good performance increased the risk of injury classification to a small extent. This is not in line with previous research showing that a lack of muscle flexibility is a risk factor for muscle injuries in adult players (35). In our sample of youth players, however, only few noncontact muscle strain injuries have been reported. The other motor performance measures that appear among the 20 most important variables, influence many classifications, but only affected the classification of being injured or not for a small amount.

**Overuse and acute injuries.** Our model aimed to distinguish injured players whose first injury was an acute one, from players who sustained an overuse injury. To our knowledge, no previous study aimed to distinguish between types of injuries. Our model showed that performance measures appear among the five most influential variables. After age at PHV, the most important variable is performance on the moving

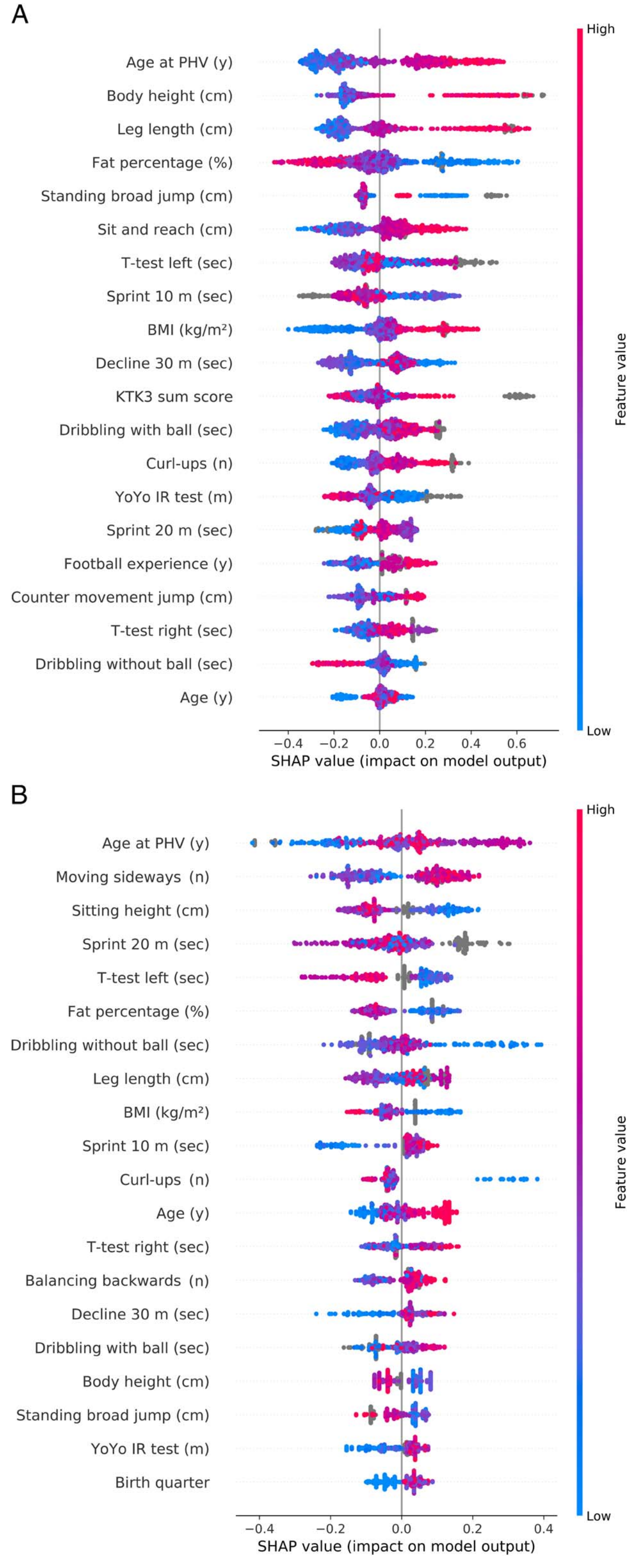


**FIGURE 1—SHAP. The features in the model are listed from the relatively most (top) to least (bottom) important by their global impact on the model. *Dots* representing the SHAP values for each feature value of an individual in the dataset are plotted horizontally next to the feature. Overlapping points are jittered in *y*-axis direction, so we get a sense of the distribution of the Shapley values per variable. The higher the absolute value (either positive or negative), the higher the importance in the classification decision-making process. Positive SHAP values represent a higher probability of a positive prediction (i.e., being injured). Each dot is colored by the value (i.e., measured value) of the feature for an individual, where blue represents the lower values (e.g., worse SBJ score), and red the higher values (e.g., better SBJ score). A *gray dot* represents a missing value. (A) SHAP values of the variables in the model predicting injury. Positive SHAP values represent a higher chance of injury. (B) SHAP values of the variables in the model classifying overuse and acute injuries. Positive SHAP values represent the risk of acute injuries, whereas negative values correspond to overuse injury risk. BMI, body mass index, n, number of; KTK3, 3 subtest short version of the Körperkoordinationstest für Kinder; YoYo IR1, YoYo Intermittent Recovery Test Level 1.**

sideways task, followed by the 20-m sprint time and the *t* test performed with left turns. None of these individual variables have previously been associated with overuse or acute injuries specifically (5,10). Future research should focus on risk factors for specific types of injuries, to get a more conclusive view of risk profiles.

**Perspectives and practical applications.** With the models built in this study, a practitioner could screen the players before the start of the season and determine the probability of injury for each player with reasonably high precision and accuracy. Subsequently, a prediction of the most likely type of injury (i.e., overuse or acute) could be made for players likely to get injured, by entering their test data in the other model. The outcomes of the models give the practitioner an estimation of the players who are most in need of injury risk management initiatives. The additional knowledge coming from our machine learning model could help clubs to spend their available time and funds for extensive screening and injury risk management more effectively.

The possibility to reach a high accuracy in classifying injured and noninjured players and types of injuries based on a combination of anthropometric, motor performance, and demographic measures suggests that risk profiles for certain types of injuries exist, in which none of the risk factors shows a high individual association with injury occurrence. We therefore suggest that future research continues to look for risk profiles. Furthermore, our models could be validated with unknown data from a different cohort to investigate the generalizability in a larger, potentially international population of elite-level youth football players.

**Strengths and limitations.** This is the largest prospective study to date closely monitoring youth football players over an entire season and collecting standardized test data. The proposed combined test battery is simple to use in the field and also has its value in talent identification and development purposes (36), which increases the practical relevance of our study protocol. A major limitation of our study is that only the first occurring injury of every player was considered in our analyses, because the motor performance measures potentially change after return from an injury. Consequently, because players can sustain multiple injuries over one season, the analysis does not reflect the complete picture. Furthermore, we only tested the players at the start of the competitive seasons and then monitored injuries over the entire season. Anthropometric and motor performance measures change over the course of the season due to training and natural development. We, therefore, suggest that future studies take the proposed test battery every few months to have assessments closer to the time of injury.

## CONCLUSIONS

In this unique study, we observed that a machine learning model was reasonably accurate in the prediction of injury in elite-level youth football players based on preseason test results. It is also possible to classify players sustaining overuse or acute injuries with a slightly lower accuracy based on the same measures. Practitioners could use this information to assess the risk of particular types of injuries before the start of the competitive season. This information would allow academies to focus the available (financial) resources for injury risk management on those players with a higher injury risk.

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