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The authors declare that the results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation. The results of this study do not constitute endorsement by ACSM. AS and DO are listed as co-inventors on a patent filed for a field testing device of eccentric hamstring strength (PCT/AU2012/001041.2012) as well as being minority shareholders in Vald Performance Pty Ltd, the company responsible for commercializing the device. The remaining authors declare no competing interests. No funding was received.

Abstract:

Purpose: Three of the most commonly identified hamstring strain injury (HSI) risk factors are age, previous HSI and low levels of eccentric hamstring strength. However, no study has investigated the ability of these risk factors to predict the incidence of HSI in elite Australian footballers. Accordingly, the purpose of this prospective cohort study was to investigate the predictive ability of HSI risk factors using machine learning techniques. **Methods:** Eccentric hamstring strength, demographic and injury history data were collected at the start of pre-season for 186 and 176 elite Australian footballers in 2013 and 2015 respectively. Any prospectively occurring HSIs were reported to the research team. Using various machine learning techniques, predictive models were built for 2013 and 2015 within-year HSI prediction and between-year HSI prediction (2013 to 2015). The calculated probabilities of HSI were compared to the injury outcomes and area under the curve (AUC) was determined and used to assess the predictive performance of each model. **Results:** The minimum, maximum and median AUC values for the 2013 models were 0.26, 0.91 and 0.58 respectively. For the 2015 models, the minimum, maximum and median AUC values were, correspondingly, 0.24, 0.92 and 0.57. For the between-year predictive models the minimum, maximum and median AUC values were 0.37, 0.73 and 0.52 respectively. **Conclusion:** While some iterations of the models achieved near perfect prediction, the large ranges in AUC highlight the fragility of the data. The 2013 models performed slightly better than the 2015 models. The predictive performance of between-year HSI models was poor however. In conclusion, risk factor data cannot be used to identify athletes at an increased risk of HSI with any consistency.

Key words: Injury prediction, machine learning, eccentric hamstring strength, hamstring injury risk.

INTRODUCTION

Hamstring strain injuries (HSIs) are the most common injury in elite Australian football (1) and can have significant physical (2-4) and financial consequences for an athlete and their sporting organization (5). As such, risk factors for HSI have received much attention (6-12). The most common risk factors identified in Australian footballers are a history of HSI and increasing age (9). More recently, work has focused on factors that can be targeted through intervention to potentially reduce the risk of HSI. Previous work reported that elite Australia footballers with levels of eccentric hamstring strength (assessed during the Nordic hamstring exercise) below 256 N at the start of pre-season were 2.7 times more likely to sustain a HSI that season (10). However, this cutoff was determined retrospectively from the data it was applied to and while deductive methodologies such as this are able to establish a link between a factor such as eccentric hamstring strength and injury risk, they cannot be used to predict injury (13). Recent commentary has highlighted the need to estimate the predictive ability of risk factors by applying a predetermined cutoff to different samples (13). Injuries such as HSI, however, are typically the result of the interactions between multiple factors and univariate cutoff values are likely to display poor predictive capacity (14, 15).

While multivariate relationships between HSI risk factors have been examined previously, these investigations typically employ a linear approach to identifying the interactions between these variables (15, 16). These interactions, however, are more likely to be non-linear (14-16). It has been suggested that moving away from the identification of univariate risk factor cutoffs and instead towards injury pattern recognition will improve the ability to predict and ultimately prevent injury (14). Supervised learning techniques, which are a type of machine learning, have been proposed as appropriate methodologies to account for the complex, non-linear interactions between risk factors and to recognise patterns that lead to injury (14). Supervised learning is the process by which a data set with a known outcome variable (i.e. injured or uninjured), referred to

as training data, is used to identify patterns and predict the unknown outcome variable of an independent data set, referred to as testing data (17). No study has developed supervised learning models, using data from multiple teams measured across multiple seasons, to predict the occurrence of HSI. Studies identifying risk factors and their associated cutoffs can provide important information regarding the aetiology of injuries (18). Research of this nature can ultimately help to inform injury prevention practices and guide risk mitigation strategies (19). However, investigations employing supervised learning techniques are needed to determine the predictive ability of previously reported HSI risk factors such as eccentric hamstring strength, age and previous HSI.

Therefore, the aim of the current study was to investigate whether supervised learning techniques could be used to predict the occurrence of HSI, using risk factor and demographic data measured across multiple seasons as predictor variables.

METHODS

Study design

Data for this prospective cohort study was collected during the 2013 and 2015 Australian Football League (AFL) seasons. The 2013 study period was conducted from November 2012 to September 2013 and the 2015 study period was conducted from November 2014 to September 2015. The authors would like to note that data collected during the 2013 study period has been previously published (10). Demographic and lower limb injury history data for each athlete were provided to the research team at the beginning of the 2013 and 2015 study periods. Eccentric hamstring strength was assessed at start of pre-season training for 2013 (November 2012) and 2015 (November 2014). Throughout the study periods, any prospectively occurring HSIs were reported to the research team. This study was approved by the Queensland University of Technology Human Research Ethics Committee (approval number: 1100001116).

Participants

Seven teams (39% of the total competition) competing in the AFL participated in at least one of the study periods. Three of these teams participated in both the 2013 and 2015 study periods. Four teams only participated in either the 2013 or 2015 study period. Each athlete was provided with a plain language statement outlining the study and provided informed written consent. In total, 186 and 176 elite Australian footballers agreed to participate in the 2013 and 2015 study periods respectively. Although data for 210 athletes were previously reported (10), eccentric hamstring strength was only assessed at the start of pre-season for 186 athletes during the 2013 study period. Due to de-identification of the data, it was not possible to determine which athletes provided data for both study periods.

Demographic and injury history data

Demographic data for each athlete were provided to the research team at the beginning of each study period. This included age (years), stature (cm), mass (kg) and primary playing position (forward, back, midfield or ruck (11)). The medical staff for each of the participating teams also completed a questionnaire detailing the lower limb injury history of each athlete prior to the 2013 and 2015 seasons. This included history of HSI within the preceding 12 months and history of anterior cruciate ligament (ACL) injury at any stage during the athlete's career.

Eccentric hamstring strength assessment

The assessment of eccentric knee flexor strength during the Nordic hamstring exercise has been previously reported (10, 20, 21). The participants knelt on a padded board with their ankles secured superior to the lateral malleolus by ankle straps. These straps were attached to custom made uniaxial load cells (Delphi Force Measurement, Gold Coast, Australia) with wireless data acquisition capabilities (Mantracourt, Devon, United Kingdom). Following a warm up set of

three submaximal repetitions, participants were asked to perform three maximal repetitions of the Nordic hamstring exercise. The participants were instructed to lean forwards as slowly as possible whilst maximally resisting this movement with both limbs, keeping the trunk and hips neutral throughout. The athletes were encouraged to perform maximally on every repetition. The assessment took place within a week of each individual athlete's return to pre-season training for the 2013 and 2015 seasons. Data were transferred to a computer at a 100 Hz through a wireless USB base station (Mantracourt, Devon, United Kingdom). The peak forces (measured in N) from each limb and repetition were averaged to determine athletes' eccentric hamstring strength. The absolute difference in the average force (N) between limbs was determined to be the between-limb imbalance.

Reporting of prospective HSIs

A prospectively occurring HSI was defined as acute pain in the posterior thigh that resulted in disruption of the hamstring fibres, as confirmed by magnetic resonance imaging (MRI) (10). For all injuries that fulfilled these criteria, the relevant team doctor or physiotherapist completed a standard injury report form which detailed the limb that was injured, the location of the injury (i.e. proximal muscle-tendon junction, mid muscle belly etc.), mechanism of injury (i.e. high-speed running, jumping etc.), severity of the injury determined from MRI and the number of days taken to return to full training (10).

Modelling approaches

Two approaches were taken when selecting variables to include as input data for the predictive models. The first approach only included eccentric hamstring strength, age and previous HSI as predictors for future HSI. The second approach included eccentric hamstring strength, age, previous HSI, between-limb imbalance, previous ACL injury, stature, mass and primary playing

position. Both years (2013 and 2015) were first analysed individually to predict within-year HSI. The modelling approach taken for within-year HSI prediction can be found in Figure 1A. Between-year HSI prediction was then explored by allocating the 2013 data as training data and the 2015 data as testing data (Figure 1B). To account for any variance caused by random sampling, data pre-processing and cross-validation, 10,000 iterations of each modelling approach were performed. All analyses were performed using the R statistical programming language (22).

Algorithms

Five different supervised learning techniques were used to build predictive models (see table, Supplemental Digital Content 1, A brief description of each machine learning algorithm and all relevant parameters, <http://links.lww.com/MSS/B163>). These were:

- Naïve Bayes.
- Logistic regression.
- Random forest.
- Support vector machine.
- Neural network.

Explaining the mathematical functions of each of these models is beyond the scope of this paper. However, naïve Bayes and logistic regression algorithms were chosen for their simple probabilistic classification, whereas random forest, support vector machine and neural network algorithms were chosen for their ability to model complex, non-linear interactions amongst multiple predictor variables.

Data pre-processing

All continuous data (age, eccentric hamstring strength, stature and mass) were standardised prior to building the predictive models. Standardisation is common practice when implementing

supervised learning techniques as some models may be sensitive to the vastly different ranges and magnitudes of predictor variables (17). This involves transforming the data so that the mean is equal to zero and the standard deviation is equal to one. Data were standardised using the following equation:

$$x^1 = \frac{x - \bar{x}}{s}$$

Where x equals the original value, x^1 equals the standardised value, \bar{x} equals the mean and s equals the standard deviation.

The input data for within-year HSI prediction were standardised to the relevant year (i.e. 2013 or 2015). The training data (2013) and the testing data (2015) for between-year HSI prediction were standardised independently. Another challenge when using statistical learning techniques, particularly to predict injury, is class imbalance (23). Although HSI is the most common injury in elite Australian football (1), uninjured athletes still outnumber athletes who sustain a HSI. In cases of class imbalance, supervised learning algorithms can achieve high accuracy by always predicting the more frequently occurring class (24). However, this high accuracy is only reflective of the underlying class distribution. Synthetic minority over-sampling techniques (SMOTE) were developed to address the problem of having imbalanced classes (24). SMOTE is a combination of under-sampling and synthetic over-sampling techniques (24). Under-sampling is the process by which observations from the over-represented class are randomly removed, whereas synthetic over-sampling creates observations of the under-represented class that have similar features to already existing observations (24). In the current study, the uninjured observations were randomly under-sampled by 50% and the injured observations were synthetically over-sampled by 100%. Predictive models were built using SMOTE and no SMOTE to compare performance.

Cross-validation and parameter tuning

Supervised learning algorithms have a number of parameters (see table, Supplemental Digital Content 1, A brief description of each machine learning algorithm and all relevant parameters, <http://links.lww.com/MSS/B163>) which can be tuned to determine how an algorithm interacts with the training data (25). The aim of supervised learning is to select the parameters that optimise an algorithm's ability to perform on the testing data (25). The most common method of finding the optimal parameter combination is by performing a grid search that considers all parameter combinations (25). One potential issue with this method however, is overfitting, which occurs when the parameters selected are too closely fit to the training data from which they were derived (26). This reduces generalisability and the ability of an algorithm to perform on the testing data (26). A solution to overfitting is cross-validation (25). Ten-fold cross-validation splits the training data into 10 equal subsets. One of the subsets is withheld and the remaining nine subsets are used to perform a grid search for the optimal parameter combination. The selected parameters are then validated using the withheld subset. This process is repeated 10-fold, with each subset being withheld once as the validation subset. The parameter combination that performs the best across each fold is then selected for the final model. Ten-fold cross validation was used in the current study to select the optimal parameter combination for each algorithm.

Performance outcomes

Accuracy can be a poor indicator of performance when attempting to predict injury incidence (24). Cohen's kappa coefficient is an alternative to accuracy that accounts for the base rate of expected accuracy due to random chance. However, both accuracy and kappa are calculated based on the number of correct and incorrect binary classifications and do not take into account the estimated probability of an observation belonging to one class or the other. For example, if

Athlete A has a 49% probability of HSI and Athlete B has 1% probability of HSI, both these athletes are predicted to remain uninjured. Accuracy and kappa do account for the fact that Athlete A was 48% more likely to sustain a HSI than Athlete B. Area under the curve (AUC) of a receiver operator characteristic (ROC) curve measures the probability that a positive case will be ranked higher than a negative case. An AUC of 0.5 indicates prediction no better than random chance, with a value of 1.0 indicating perfect prediction (13). In the current study, predicted injury probabilities were used to construct a ROC curve, and AUC was used to measure the likelihood that the observations with a higher probability of injury were actually the injured observations. As AUC is calculated using predicted injury probabilities and not the number of correct and incorrect binary classifications, it can be a more sensitive measure of performance than accuracy or kappa (27). Accordingly, the AUC of each algorithm was calculated and was used to compare predictive performance as well as to select the optimal parameter combination for each model.

RESULTS

Cohort and prospective injury details

2013

One-hundred and eighty six athletes (age 23.2 ± 3.6 years, stature 188.0 ± 7.1 cm, mass 87.6 ± 7.5 kg) participated in the 2013 study period. Of these, 27 sustained a prospective HSI (age 23.8 ± 3.6 years, stature 185.3 ± 6.3 cm, mass 84.4 ± 5.6 kg) and 159 did not (age 23.1 ± 3.6 years, stature 188.4 ± 7.2 cm, mass 88.1 ± 7.7 kg). High-speed running was the most common mechanism of injury (59%) and biceps femoris long head was the most commonly injured muscle (78%). Five injuries occurred during the pre-season period and 22 occurred during the in-season period. The average eccentric hamstring strength and between-limb imbalance of the injured athletes was 260 ± 79 N and 45 ± 46 N respectively. For the uninjured athletes, the

average eccentric hamstring strength and between-limb imbalance was 301 ± 84 N and 49 ± 56 N respectively.

2015

During the 2015 study period, 176 athletes participated (age 25.0 ± 3.4 years, stature 187.6 ± 7.5 cm, mass 87.0 ± 8.6 kg). Twenty six athletes sustained a HSI (age 25.2 ± 3.4 years, stature 187.8 ± 7.3 cm, mass 87.1 ± 8.3 kg) and 150 did not (age 25.1 ± 3.5 years, stature 187.7 ± 7.8 cm, mass 87.0 ± 8.9 kg). The most common mechanism of HSI was high-speed running (50%) and the most commonly injured muscle was biceps femoris (92%). Nine injuries occurred during the pre-season period and 17 occurred during the in-season period. The average eccentric hamstring strength and between-limb imbalance of the injured athletes was 341 ± 80 N and 30 ± 21 N respectively. For the uninjured athletes, the average eccentric hamstring strength and between-limb imbalance was 341 ± 78 N and 34 ± 30 N respectively.

Within-year predictive performance

2013

The median AUC for all 2013 within-year predictive models was 0.58. There were no large differences between the predictive performance of models built using all variables as predictors (median AUC of 0.57) and models built using only the three variables as predictors (median AUC of 0.59). Using SMOTE and no SMOTE input data did not improve predictive performance, with both sets of models resulting in a median AUC of 0.58 and 0.59 respectively. For all 2013 within-year predictive models, AUC ranged from 0.26 to 0.91. Naïve Bayes was the best performing algorithm, with a median AUC of 0.60. The performance of each individual algorithm for 2013 within-year predictive models built using three variables and all variables can be found in Figure 2A and 2B respectively.

2015

For all 2015 within-year predictive models, the median AUC was 0.57. Similar to 2013, there was no difference in the predictive performance of models built using all variables as predictors and only the three variables as predictors, with both sets of models resulting in a median AUC of 0.57. The case was the same for models using SMOTE and no SMOTE input data (median AUC of 0.57). The range in AUC for the 2015 models was slightly larger than the 2013 models (0.24 to 0.92). The equal best performing algorithms were random forest and support vector machine, with a median AUC of 0.58. The performance of each individual algorithm for 2015 within-year predictive models built using three variables and all variables can be found in Figure 3A and 3B respectively.

Between-year predictive performance

The performance of the between-year predictive models was poorer than the within-year predictive models, with a median AUC of 0.52. The median AUC was 0.52 and 0.53 for models built using all variables and three variables respectively. Similar to the within-year predictive models, using SMOTE input data did not significantly improve performance, with these models resulting a median AUC of 0.53 compared to a median AUC 0.52 for models built using no SMOTE input data. There was little variation in AUC for the independent algorithms as each iteration was performed using the same training and testing data. Across all the between-year predictive models, AUC ranged from 0.37 to 0.73. Naïve Bayes was the best performing algorithm, with a median AUC of 0.54. The performance of each individual algorithm for between-year predictive models built using three variables and all variables can be found in Table 1.

DISCUSSION

The aim of the current study was to investigate whether the application of various supervised learning techniques, using risk factor and demographic data collected over two seasons, could be

used to predict the occurrence of HSI. The main finding of this study was that eccentric hamstring strength, age and previous hamstring strain injury data cannot be used to identify athletes at an increased risk of HSI with any consistency. While some iterations of the within-year predictive models achieved near perfect performance (maximum AUC of 0.92), others performed worse than random chance (minimum AUC of 0.24).

The large discrepancy in AUC is indicative of the fragility of the data. Although each iteration was performed using the same data, small changes in the randomly sampled training and testing data vastly influenced the performance of the within-year predictive models. This not only demonstrates the sensitivity of AUC to sampling, but also suggests that larger datasets are needed when investigating the predictive ability of injury risk factors. Collecting more data will likely result in an increase in the number of observed injuries and consequently a more robust dataset. This will in turn improve the ability of supervised learning techniques to identify patterns with more consistency, should such patterns exist. In addition to within-year predictive performance, this study also investigated the performance of between-year predictive models. As the training data (2013 data) and testing data (2015 data) were the same for every iteration, the resulting AUC ranges were much smaller than within-year predictive models, with any variability in AUC only caused by cross-validation and SMOTE. Despite less discrepancy, the performance of between-year predictive models was poor, with a median AUC of 0.52.

The etiology of HSI is multifactorial and injuries typically occur as a result of the interactions between numerous variables (28, 29). The poor predictive performance displayed by between-year predictive models may be due to differing contributing factors between the 2013 and 2015 injuries, specifically the role of eccentric hamstring strength. In 2013, the injured athletes were, on average, 42 N weaker than the uninjured athletes. In 2015 however, there was no difference in the average eccentric hamstring strength between the injured and uninjured athletes. Overall, the 2015 cohort was stronger than the 2013 cohort. Despite this, the percentage of players that

sustained a HSI was identical in both seasons (15%), which suggests that eccentric hamstring strength was less of an influencing factor in the HSIs that occurred in 2015, as opposed to 2013. Previous work, which investigated eccentric hamstring strength and HSI risk, found that weaker rugby union players were no more likely to sustain a HSI than stronger players (20). The authors of this study (20) suggest that the conflicting results with previously published work (10) may be due to the rugby union players investigated (20) being considerably stronger than the previously investigated Australian footballers (10). It is also suggested that athletes with high levels of eccentric hamstring strength may not see any additional protective benefit from further increases in strength (10, 20). This hypothesis aligns with the current findings that eccentric hamstring strength may not play as large a role in HSI risk in a stronger cohort (2015) compared to a weaker cohort (2013).

The current study investigated whether the inclusion of data that have not been directly linked to HSI risk in Australian footballers, in addition to previously reported HSI risk factors, improved predictive performance. The inclusion of between-limb imbalance, previous ACL injury, stature, mass and playing position, in addition to eccentric hamstring strength, age and previous HSI, did not improve predictive performance (Figures 2 and 3). In some cases these data may have confounded predictive performance, with the majority of the 2013 within-year predictive models performing better when built using only previously reported HSI risk factors (Figure 2). The results of the current study are comparable to the findings of prior work, which attempted to predict all injuries using workload data from a single AFL team (30). This study observed a mean AUC of 0.65 when predicting all non-contact injuries. Hamstring related injuries were predicted with a mean AUC of 0.72, however these injuries were not specifically HSIs (30). Earlier work has observed an association between high-speed running distances and HSI risk (8, 11), however it was concluded that these measures examined in isolation are poor predictors of HSI and should be examined in concert with other variables (11). The results of previous work

(8, 11, 30) suggest that the inclusion of workload data, in addition to other HSI risk factors, may improve the ability to predict HSI occurrence, however this is yet to be examined.

Imbalanced classes have previously been highlighted as a limitation of injury prediction research (30). This study compared the performance of predictive models built using SMOTE and no SMOTE. Using SMOTE to under-sample the uninjured observations and over-sample the injured observation did not improve predictive performance for within-year predictive models (Figures 2 and 3) or between-year predictive models (Table 1). These results are in contrast to prior work, which observed increases in predictive performance when SMOTE were used to build support vector machine models (30). It is possible that SMOTE is only beneficial when used to synthetically reproduce predictor variables from a complex data set, such as workload derived from global position systems data. In the current study, the uninjured observations were randomly under-sampled by 50% and the injured observations were synthetically over-sampled by 100%. However, these values were chosen arbitrarily and it is unknown whether a different percentage of under- and over-sampling would impact predictive performance.

The current study has a number of limitations that may have influenced predictive performance. The data used as predictor variables in the current study were only collected at the beginning of pre-season training for each study period. It is unknown whether more frequent measures of variables such as eccentric hamstring strength would have improved predictive performance. It is also unknown whether the magnitude of change in eccentric hamstring strength across a season may be a more sensitive measure than absolute strength. While eccentric hamstring strength, age and previous HSI are purported as HSI risk factors (9, 10, 12, 29, 31), there are a number of other factors not included in this study which have been linked to the risk of HSI. The inclusion of further HSI risk factors, such as workload (8, 11) and biceps femoris fascicle length (21), may improve the ability to predict HSI.

Furthermore, there is a lack of literature regarding the application of supervised learning techniques in injury prediction research. The proportions of data used as training and testing data, as well as the proportions of data under- and over-sampled, were chosen arbitrarily and it is unknown whether different proportions would have influenced predictive performance. There are a number of different supervised learning techniques and while some of the techniques applied in the current study have been applied in previous work (30), it is unknown how different techniques would have impacted predictive performance. Lastly, the current findings relate to HSIs that fulfilled the criteria of acute pain in the posterior thigh that resulted in disruption of the hamstring fibres, as confirmed by MRI (10). Cases that were MRI negative but clinically positive were not included in this study and it is difficult to determine how the inclusion of these injuries would have impacted the findings. In addition to this, other injury types are certain to occur and these should be accounted for by including them as competing risks in the modelling approach (32).

In conclusion, eccentric hamstring strength, age and previous HSI data cannot be used to identify Australian footballers at an increased risk of HSI with any consistency. Despite suggestions that the ability to predict injury with prospectively collected data is limited, the application of supervised learning techniques in elite sport still warrants further investigation. It is unclear whether injury probabilities calculated by predictive models can be used to identify at risk athletes and guide risk mitigation strategies to ultimately reduce injury incidence. With the previously discussed considerations in mind, future research is needed to determine what, if any improvements can be made in injury prediction performance.

Declaration:

The authors declare that the results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation. The results of this study do not constitute endorsement by ACSM.

Competing interests:

AS and DO are listed as co-inventors on a patent filed for a field testing device of eccentric hamstring strength (PCT/AU2012/001041.2012) as well as being minority shareholders in Vald Performance Pty Ltd, the company responsible for commercialising the device. The remaining authors declare no competing interests.

Contributorship:

JR and NM contributed to the design of the study. JR, AS, MW, SD, RT, JH, MB and DO contributed to the collection of the data. JR, AS, MW, SD, RT, JH and DO performed the data analysis. JR and NM performed the statistical analysis. JR and DO drafted the manuscript. AS, NM, MW, SD, RT, JH and MB contributed to the manuscript.

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Ethical approval:

This study was approved by the Queensland University of Technology Human Research Ethics Committees (approval number: 1100001116).

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Figure captions:

Figure 1. The modelling approaches for A) within-year hamstring strain injury prediction (used to analyse 2013 data and 2015 data independently), and B) between-year hamstring strain injury predictions (used to analyse 2013 data and 2015 data collectively). The performance outcome used was area under the curve. Ten thousand iterations of each modelling approach were performed. SMOTE, synthetic minority over-sampling techniques.

Figure 2. The individual performance of 2013 within-year hamstring strain injury prediction models built using A) eccentric hamstring strength, age and previous hamstring strain injury as input data, and B) eccentric hamstring strength, age, previous hamstring strain injury, between-limb imbalance, previous anterior cruciate ligament injury, stature, mass and primary playing position as input data. The solid horizontal line indicates the expected performance due to random chance and the dotted horizontal line represents the median area under the curve of all models. SMOTE, synthetic minority over-sampling techniques.

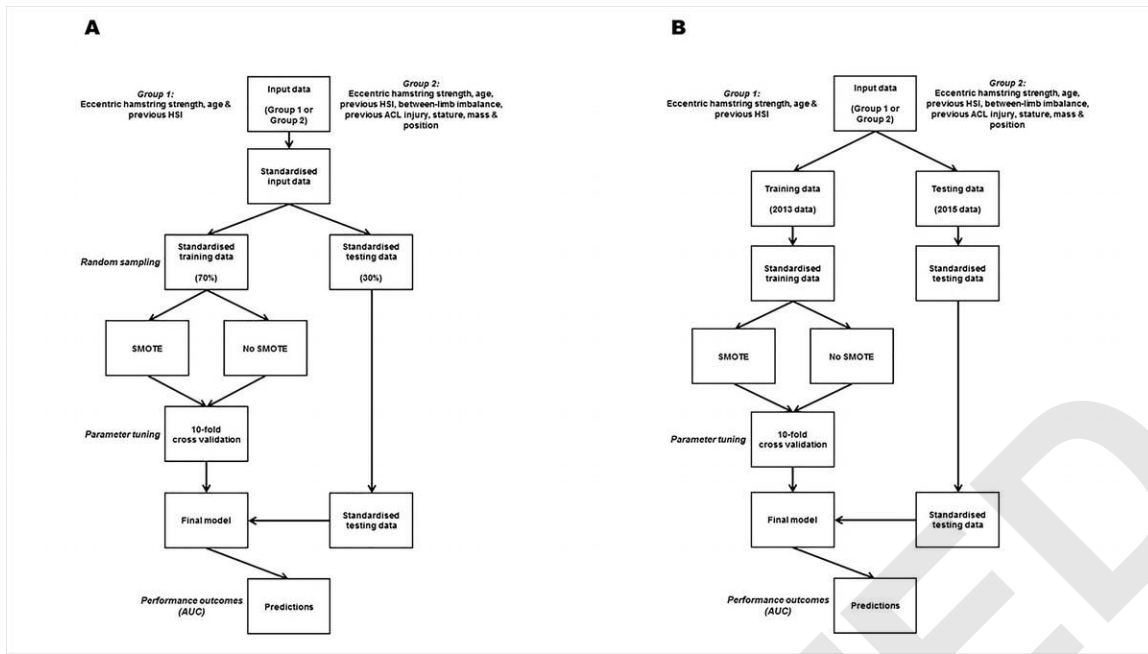
Figure 3. The individual performance of 2015 within-year hamstring strain injury prediction models built using A) eccentric hamstring strength, age and previous hamstring strain injury as input data, and B) eccentric hamstring strength, age, previous hamstring strain injury, between-limb imbalance, previous anterior cruciate ligament injury, stature, mass and primary playing position as input data. The solid horizontal line indicates the expected performance due to random chance and the dotted horizontal line represents the median area under the curve of all models. SMOTE, synthetic minority over-sampling techniques.

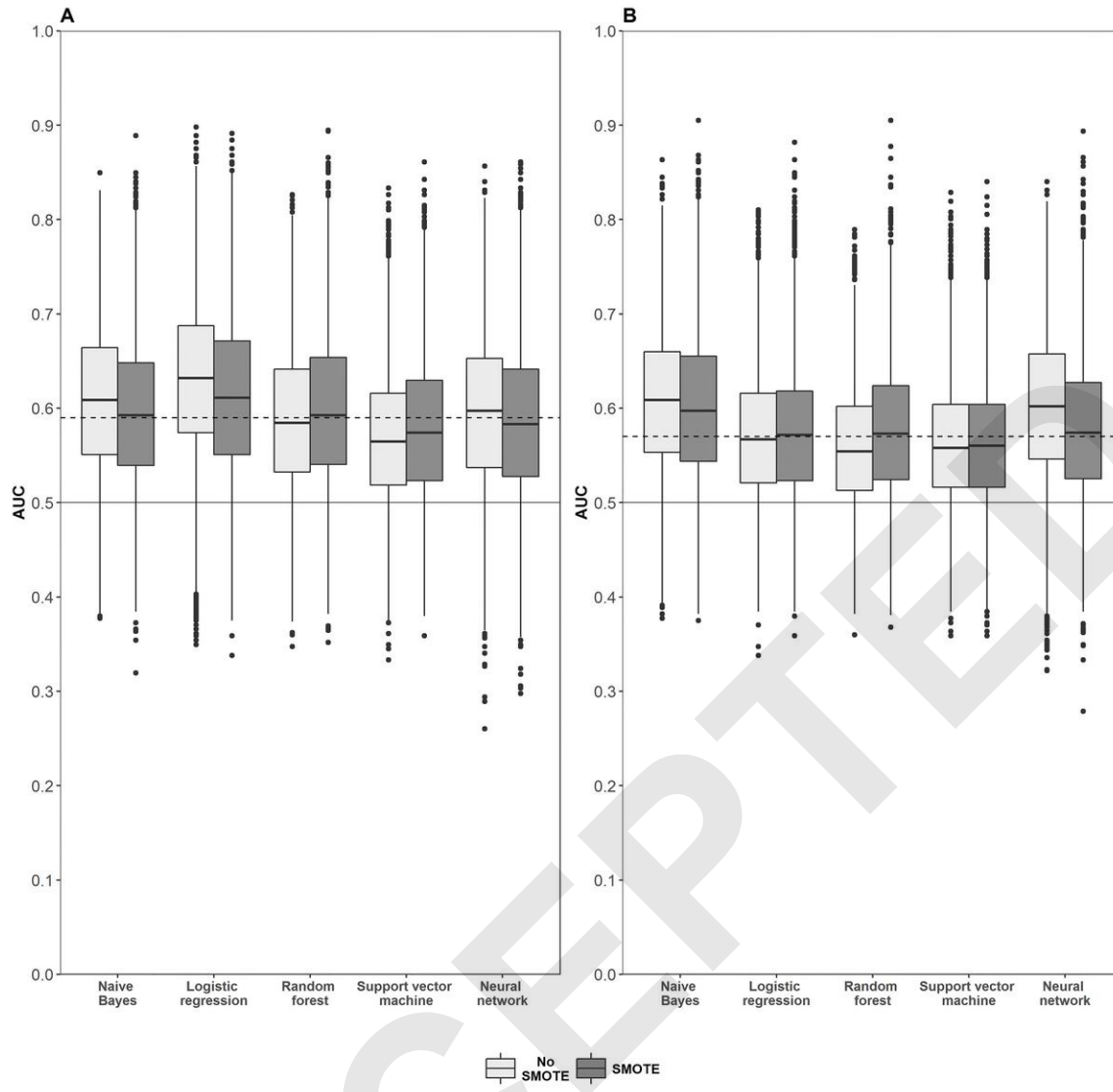
Supplemental digital content

Supplemental Digital Content 1.docx

A brief description of each machine learning algorithm and the parameters that can be tuned for each algorithm using the R statistical programming language.

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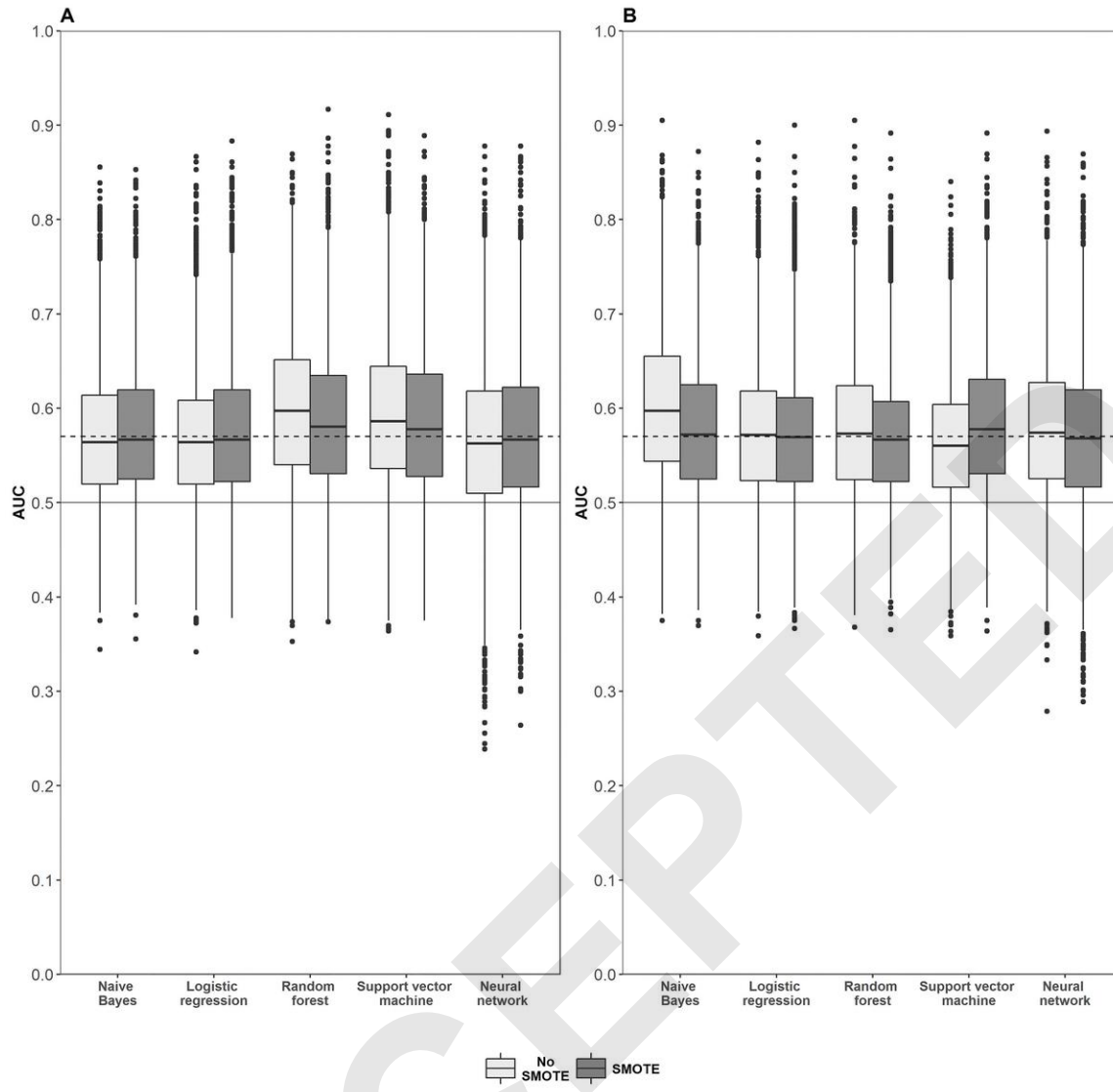


Table 1. Descriptive statistics summarising the individual performance of between-year HSI prediction models built using 2013 data for training and 2015 data for testing. Performance is measured as area under the curve.

Algorithm		Area under the curve			
		Group 1 [*]		Group 2 [#]	
		No SMOTE	SMOTE	No SMOTE	SMOTE
Naïve Bayes	Minimum	0.49	0.41	0.47	0.42
	Lower quartile	0.54	0.53	0.47	0.52
	Median	0.54	0.55	0.47	0.55
	Upper quartile	0.54	0.56	0.47	0.57
	Maximum	0.54	0.65	0.57	0.65
Logistic regression	Minimum	0.54	0.45	0.53	0.43
	Lower quartile	0.54	0.48	0.53	0.50
	Median	0.54	0.54	0.53	0.52
	Upper quartile	0.54	0.54	0.53	0.54
	Maximum	0.54	0.58	0.53	0.62
Random forest	Minimum	0.48	0.42	0.45	0.41
	Lower quartile	0.51	0.50	0.52	0.51
	Median	0.51	0.52	0.53	0.53
	Upper quartile	0.52	0.54	0.54	0.55
	Maximum	0.54	0.65	0.57	0.65
Support vector machine	Minimum	0.43	0.41	0.45	0.41
	Lower quartile	0.49	0.51	0.48	0.50
	Median	0.51	0.53	0.52	0.52
	Upper quartile	0.52	0.55	0.52	0.55
	Maximum	0.61	0.68	0.54	0.66
Neural network	Minimum	0.44	0.37	0.45	0.40
	Lower quartile	0.50	0.50	0.50	0.50
	Median	0.51	0.52	0.50	0.52
	Upper quartile	0.54	0.54	0.51	0.54
	Maximum	0.65	0.65	0.57	0.73

^{*}Group 1; models built using eccentric hamstring strength, age and previous hamstring strain injury as input data.

#Group 2; models built using eccentric hamstring strength, age, previous hamstring strain injury, between-limb imbalance, previous anterior cruciate ligament injury, stature, mass and primary playing position as input data.

SMOTE, synthetic minority over-sampling techniques.

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Supplementary Digital Content 1. A brief description of each machine learning algorithm and the parameters that can be tuned for each algorithm using the R statistical programming language.

Algorithm	Description	Parameters	Parameter description
Naïve Bayes	A probabilistic classifier based on Bayes' theorem and conditional probabilities	Laplace correction	A technique used to smooth categorical data and prevent the high influence of zero probabilities
		Distribution type	Specifies whether a kernel density estimator is used or not
		Bandwidth adjustment	Specifies the bandwidth size. Only relevant when a kernel density estimator is used
Logistic regression	Used to develop a regression equation from the log odds	No tuning parameters	
Random forest	An ensemble learning method that operates by constructing multiple decision trees	Number of randomly selected predictors	Specifies the number of variables available to be used to split the data at each tree node
Support vector machine	Used to construct a non-linear, multidimensional separating hyperplane for classifying observations	Sigma	Specifies the flexibility of the decision boundary
		Cost	Specifies the cost of incorrect classification
		Weight	Allocates a weighting to a preferential class
Neural network	A network of connected artificial neurons which transmit information and learn from correct or incorrect classifications	Number of hidden units	Number of hidden units used to apply functions to the input data
		Weight decay	Specifies the cost of allocating large weights to input units