Journal of Sports Sciences

ISSN: 0264-0414 (Print) 1466-447X (Online) Journal homepage: www.tandfonline.com/journals/rjsp20

Finding the needle in the haystack of isokinetic knee data: Random Forest modelling improves information about ACLR-related deficiencies

Kevin Nolte, Alexander Gerharz, Thomas Jaitner, Axel J. Knicker & Tobias Alt

JOURNAL OF SPORTS SCIENCES
2025, VOL. 43, NO. 2, 173–181
https://doi.org/10.1080/02640414.2024.2435729

SPORTS MEDICINE AND BIOMECHANICS

OPEN ACCESS Check for updates

Finding the needle in the haystack of isokinetic knee data: Random Forest modelling improves information about ACLR-related deficiencies

Kevin Nolte [a], Alexander Gerharz [b], Thomas Jaitner [a], Axel J. Knicker [c] and Tobias Alt [d]

[a]Institute for Sports and Sport Science, TU Dortmund University, Dortmund, Germany; [b]Department of Statistics, TU Dortmund University, Dortmund, Germany; [c]Institute of Movement and Neuroscience, German Sport University Cologne, Cologne, Germany; [d]Department of Biomechanics, Performance Analysis and Strength & Conditioning, Olympic Training & Testing Centre Westphalia, Dortmund, Germany

ABSTRACT

The difficulties of rehabilitation after anterior cruciate ligament (ACL) injuries, subsequent return-to-sport (RTS) let alone achieving pre-injury performance, are well known. Isokinetic testing is often used to assess strength capacities during that process. The aim of the present machine learning (ML) approach was to examine which isokinetic data differentiates athletes post ACL reconstruction (ACLR) and healthy controls. Two Random Forest models were trained from data of unilateral concentric and eccentric knee flexor and extensor tests (30°/s, 150°/s) of 366 male (63 post ACLR) as well as 183 female (72 post ACLR) athletes. Via a cross-validation predictive performance was evaluated and the Random Forest showed outstanding results for male (AUC = 0.90, sensitivity = 0.76, specificity = 0.88) and female (AUC = 0.92, sensitivity = 0.85, specificity = 0.89) athletes. The Accumulated Local Effects plot was used to determine the impact of single features on the predictive likelihood. For both male and female athletes, the ten most impactful features either referred to the disadvantageous (injured, non-dominant in control group) leg or to lateral differences. The eccentric hamstring work at 150°/s was identified as the most impactful single parameter. We see potential for improving the RTS process by incorporating and combining measures, which focus on hamstring strength, leg symmetry and contractional work.

ARTICLE HISTORY
Received 9 March 2024
Accepted 21 November 2024

KEYWORDS
Anterior cruciate ligament reconstruction; rehabilitation; hamstring; interpretable machine learning; random forest

1. Introduction

Return-to-sport (RTS) after anterior cruciate ligament (ACL) injuries let alone achieving pre-injury performance is a very difficult task. Systematic reviews and meta-analyses showed that only 65% of athletes return to their pre-injury level of sports and only 55% to a competitive level after surgery (Ardern et al., 2014). In addition, re-injuries occur in 23% of athletes under 25 years old, who do come back to sports (Wiggins et al., 2016).

One key element in RTS scenarios is assessing strength capacities, e.g., of the knee extensor and flexor muscles and isokinetic dynamometry, is considered to be the "gold standard" for that (Dvir et al., 1989), because it provides highly reliable measures of associated parameters (Alt et al., 2014; Ayala et al., 2012). With the peak moment described as the most relevant parameter (Dvir, 2014). Strength tests in general are frequently implemented in ACL injury prevention, prediction as well as rehabilitation and RTS decision making (Petersen et al., 2014; Undheim et al., 2015; van Melick et al., 2016). Even simple decision rules based on leg symmetry in performance tests, including isokinetic quadriceps strength and hop tests, can considerably reduce re-injury risk (Grindem et al., 2016) and asymmetry in quadriceps strength is also an important indicator for asymmetry in landing mechanics (Palmieri-Smith & Lepley, 2015; Schmitt et al., 2015). Achieving this symmetry in quadriceps strength has been identified as the most difficult criterion within a return-to-sport test battery including isokinetic strength, isometric strength and single-leg hop tests after ACL injury (Norte et al., 2021). Therefore, current consensus suggests that athletes should achieve quadriceps and hamstring strength greater than 90% of the uninvolved leg before their RTS (Lynch et al., 2015). However, it was also demonstrated that muscle strength of hamstrings and quadriceps is impaired after ACLR compared to a control group in the injured as well as the uninvolved leg (Alt, Breitenmoser, et al., 2022; Larsen et al., 2015) and that leg symmetry can overestimate knee function after an ACL injury (Wellsandt et al., 2017). This evidence suggests a criteria purely based on symmetry is not sufficient for making a RTS decision. Overall, a lack of validity of RTS criteria after ACLR still remains (Gokeler et al., 2022).

Apart from RTS, predicting injuries by physical tests or screening test batteries is considered virtually impossible (Bahr, 2016). Despite that, the ability to incorporate multiple factors in a model is promising and machine learning (ML) approaches displayed the ability to identify athletes at high risk of injury when performing sports (Van Eetvelde et al., 2021).

The application of more complex ML approaches like neural networks is sometimes considered problematic for being "black box" (Bullock et al., 2022), meaning that it is not possible to derive an understanding of the prediction process from the model. However, new advances in ML research help analysing

CONTACT Kevin Nolte kevin.nolte@tu-dortmund.de Institute for Sports and Sport Science, TU Dortmund University, Otto-Hahn-Straße 3, Dortmund 44227, Germany

models and give further information on why a model produces a certain prediction as effort is put forth to accommodate the importance of interpretability (Molnar, 2020).

The present study aims to facilitate and elucidate information about differences and potential deficiencies related to ACLR with a two-stage approach. The first objective is to train a Random Forest model to distinguish between athletes within 6 to 24 months after ACLR and healthy controls based on isokinetic data of the knee flexor and extensor muscles and analyse its predictive performance. While predicting a past injury is not necessary, ML models are optimised based on the input data and simply classify between injury and no injury. Therefore, we investigate whether athletes post ACLR and healthy controls can be distinguished with high accuracy in a multifactorial approach using multiple parameters from isokinetic testing.

In addition, differences between male and female athletes are analysed as the described procedure is conducted separately for both sexes. That approach prevents sex from becoming an underlying factor for the ML models due to the differences in isokinetic strength (Alt, Breitenmoser, et al., 2022; El-Ashker et al., 2017; Hewett et al., 2008) and relative number of injuries within the data.

The second objective encompasses further investigating the two models and analysing how single features impact the prediction. We are confident this will provide further insight into which strength characteristics are most prevalent in distinguishing athletes post ACLR and healthy controls and should therefore be focused on in research and rehabilitation.

2. Materials and methods

2.1. Participants

A total of 366 male (age: 22.2 ± 4.9 years, height: 183.6 ± 8.5 cm, mass: 80.8 ± 11.9 kg) and 183 female (age: 23.0 ± 4.7 years, height: 171.3 ± 6.6 cm, mass: 66.2 ± 10.4 kg) athletes gave their written informed consent to voluntarily join the study. These included 135 athletes 6 to 24 months post ACLR, 63 male (age: 24.5 ± 6.5 years, height: 184.9 ± 8.0 cm, mass: 84.4 ± 12.7 kg) and 72 female (age: 23.9 ± 5.1 years, height: 171.9 ± 6.5 cm, mass: 69.4 ± 12.3 kg). At the time of testing, all participants executed regular training for fitness or in different sports up to a professional level (35% track and field, 16% soccer, 11% handball, 10% basketball, and 28% other sports). Exclusion criteria encompassed acute pain of the knee joint and/or thigh muscle as well as injuries (hamstring strain injury within the last two years, contralateral or recurrent ACL injury). During the testing period, all participants maintained their normal physical activity level except for resistance training.

2.2. Instruments

The isokinetic dynamometer IsoMed 2000 (D&R Ferstl GmbH, Hemau, Germany) was used for all tests. A double shin pad for unilateral knee flexion and extension was attached to the dynamometer axis. The shin pad's distal part was fixed by a strap ~ 2–3 cm proximal to the medial malleolus of the participants. A calibration of the device was performed before and after each testing session.

2.3. Procedures

The unilateral knee tests of the left and the right leg followed a protocol with proven reliability (Alt et al., 2014, 2017) in a single testing session. It started with a randomised test condition followed by a stratified testing order (e.g., left extensor, right flexor, left flexor and right extensor) (Figure 1). Each participant completed the protocol in a separate familiarisation session preceding the testing session by 48–168 hours (Petersen et al., 2014). After determining their body mass, the participants underwent a 10-minute warm-up period (relaxed jogging and dynamic stretching of the lower extremity muscles). As recommended,

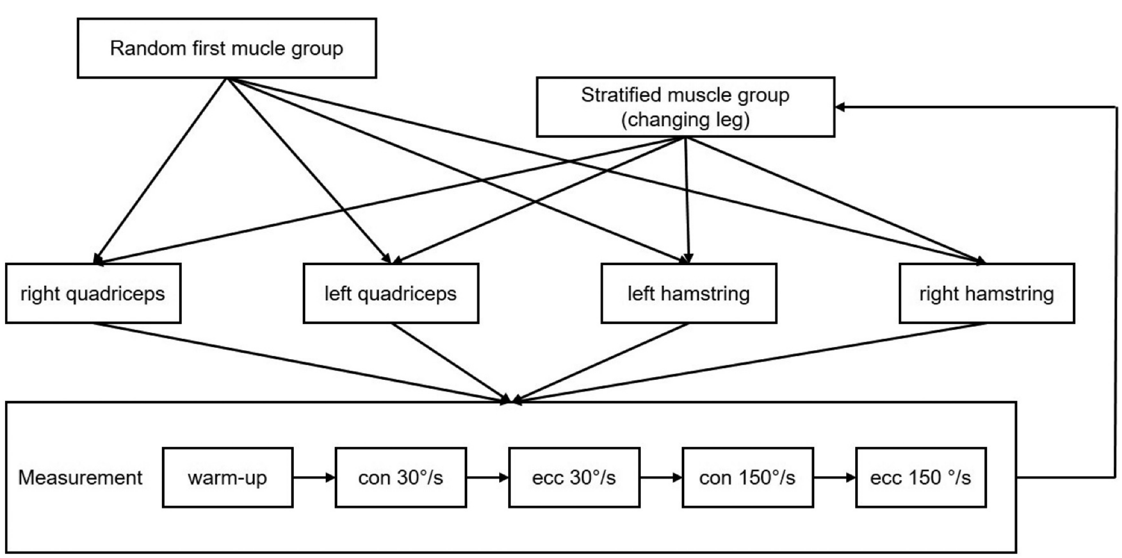

Figure 1. Flowchart isokinetic testing. Flowchart depicting the isokinetic testing of unilateral concentric (con) and eccentric (ecc) measurements at different velocities for knee flexors and extensors.

discrete movements in a single direction (uni-directional) were executed throughout the largest possible range of motion (ROM) to maximise the duration of voluntary activation (Alt et al., 2014; Rothstein et al., 1987). For knee flexion (0–110° ROM_{knee}), participants laid prone (extended hip) by pulling their trunk with the hands to the lounger (Alt et al., 2019). Knee extensions (90–0° ROM_{knee}) were performed in supine position (extended hip) with handgrips providing sufficient stability (Alt et al., 2016). To minimise accelerative inaccuracies the subjects were asked to take off their shoes (Alt et al., 2017; Petersen et al., 2014). The dynamometer axis was aligned with the participants' lateral femoral epicondyle with the assistance of a laser pointer in a pre-activated muscular state at 0° knee flexion (Alt et al., 2018). After a static gravity correction measurement, the participants performed six submaximal (~50–80%) concentric (con) and eccentric (ecc) repetitions of the respective muscle group. The return into starting position occurred passively at 120°/s. Each set consisted of five repetitions (two ~75%, three 100%). The last three repetitions were selected for further analysis. A 1-min-interset rest ensured sufficient recovery. For both muscle groups, concentric movements were executed at 30°/s prior to eccentric ones followed by those at 150°/s (Alt et al., 2014, 2017, 2020). The slower angular velocities ensured a measurement close to the isometric maximum with a time under tension of 3s for one repetition. The 150°/s allow measuring a faster movement while keeping over 80% of the ROM within the isokinetic phase. Strong verbal encouragement was provided throughout to facilitate maximum effort by the participants.

2.4. Data processing

Raw data (200 hz) were recorded by the manufacturer's software (IsoMed analyse V.2.0) and stored as ASCII files. A custom-made software (C++) isolated the isokinetic ROM (±1% deviation of angular velocity) and filtered the data (5^{th} order Butterworth low-pass filter, 6 hz cut-off frequency). For each testing condition, the trial with the highest gravity-corrected peak moment (PM) and contractional work (CW) was selected. Conventional (PM_{Hcon}/PM_{Qcon}) and functional (PM_{Hecc}/PM_{Qcon}) hamstring-quadriceps ratios (H:Q ratios) as well as lateral differences were calculated for each angular velocity. The dynamic control ratio at the equilibrium point (DCRe) with the highest moment out of nine intersection points (each combination of the three flexor and extensor movements) was identified (Alt et al., 2017). Normalisation to body mass enabled inter-individual comparison.

2.5. Statistical analysis

2.5.1. The Random Forest

For the ML approach, the Random Forest has been chosen as it can deal with collinearity as well as non-linear relationships between features and outcome. The collinearity had to be considered as multiple measurements of the same muscle group are performed. Consequently, high correlation between some features is expected and plausible. The features also include ratios, which inherently tend to have a sweet spot so not assuming a purely linear relationship to the outcome within the model is preferable.

The Random Forest is based on multiple decision trees, which are evaluated independently of each other. The relative frequency of trees, which predict a specific outcome, can be interpreted as the estimated likelihood for that outcome. The final binary classification is done due to a threshold for that likelihood. Each tree is computed using the CART (classification and regression tree) algorithm on a bootstrap sample of the data (Breiman, 2001).

In the present study a total of 62 features were available (see Appendix). These included the PM and CW for each leg as well as the lateral differences for each test condition. In addition, the conventional and functional H:Q ratios and the DCRe were calculated. For incorporating single leg features in the model the self-proclaimed dominant leg in the control group and the unaffected leg in the ACL group were categorised as the advantageous (adv) leg. Respectively, the non-dominant leg and the injured leg were categorised as the disadvantageous (dis) leg. For the computation of the Random Forest R and the R package "random Forest" were used and Random Forest models with 200 trees were created.

2.5.2. Assessing predictive performance

The predictive performance of the model is evaluated with a 10-fold cross validation (Refaeilzadeh et al., 2009). To account for the unbalanced data the cross validation was stratified so each fold contains a similar amount of injured subjects. The threshold in the likelihood for classification was optimised due to the Youden-Index (Fawcett, 2004). For the performance assessment the measures' sensitivity and specificity as well as the Receiver Operating Characteristic (ROC)-curve and corresponding Area Under the Curve (AUC) were used (Youden, 1950). For its general interpretation, we referred to the rule of thumb introduced by Hosmer et al (Hosmer et al., 2013): AUC = 0.5 no discrimination, 0.5<AUC <0.7 poor, 0.7≤AUC <0.8 acceptable, 0.8≤AUC <0.9 excellent and 0.9≤AUC outstanding.

As leg symmetry > 90% in isokinetic PM has been shown to reduce re-injury risk (Grindem et al., 2016), we use it as a reference. For the comparison, the association between the lateral difference in concentric quadriceps strengths, measured as the difference in PM at 30°/s, and the injury status was analysed with the aforementioned performance measures.

2.5.3. The ALE plot

For further investigation of the model and its features the Accumulated Local Effects (ALE) plot is used. The ALE plot describes how features influence the prediction on average. The main idea is to observe changes in prediction when altering a feature. The ALE plot for a single feature is derived from dividing the values of the feature into intervals. For each observation within the respective interval the predicted likelihood is calculated from using the upper bound of the interval as well as the lower bound of the interval as the value for the feature. Then the differences of these likelihoods are averaged across all observations within the interval to compute the slope for a straight line in this interval, the local effect. These straight lines are later accumulated and centred for visualisation. The division into small windows prevents the creation of unrealistic combinations of values in the process. The range and direction of the ALE plot can be used to quantify a features influence on the prediction of an ML model (Apley & Zhu, 2020). For the calculation the R package "ALEPlot" was utilised and 30 was chosen for the number of intervals.

3. Results

The predictive performance of the Random Forest models (Table 1) revealed outstanding discrimination for both male (AUC = 0.90) and female (AUC = 0.92) athletes. This is further illustrated in the ROC-curves in Figure 2. At the optimal threshold, specificity is similar in both models with 0.88 for males and 0.89 for females, but sensitivity is higher for females (0.85 to 0.76). A discrimination solely founded on the leg symmetry of PM_{Qcon} at 30°/s is acceptable in males (AUC = 0.71) and females (AUC = 0.79).

Analysing the ALE plots enables the possibility to order the features by their influence on the prediction likelihood (Table 2). For both male and female athletes, the top ten features either refer to the disadvantageous leg or to lateral differences. CW_{Hecc} of the disadvantageous leg at 150°/s revealed the highest ALE range for both sexes. Furthermore, the top five features in male athletes also appeared in the top 10 for female athletes. These included four referring to the CW of the hamstrings of the disadvantageous leg. For male athletes the other six features in the top ten describe lateral imbalances, with three describing hamstring strength and three describing quadriceps strength. Five out of those six also referred to CW. For female athletes, only three out of the ten most impactful features describe lateral imbalances. Eight out of the ten features used CW and seven are derived from the tests at 150°/s dynamometer speed.

The ALE plot for CW_{Hecc} of the disadvantageous leg at 150°/s dynamometer speed (Figure 3) demonstrated an almost steady decrease for the prediction in both males and females. Therefore, the higher the value of the parameter, the less likely the model will predict an ACLR. In both sexes a steep slope can be observed at values of 16 to 18 mJ/(kg°).

Table 1. Predictive performance.

Model		Sensitivity	Specificity	AUC
Random Forest	♀	0.85	0.89	0.92
	♂	0.76	0.88	0.90
leg symmetry PM_{Qcon} 30°/s	♀	0.76	0.70	0.79
	♂	0.60	0.79	0.71

Predictive performance measures of Random Forest models and association of symmetry in quadriceps peak moments (PM_{Qcon} at 30°/s) in males (♂) and females (♀). Sensitivity and specificity were calculated at the optimal threshold regarding Youden-Index.

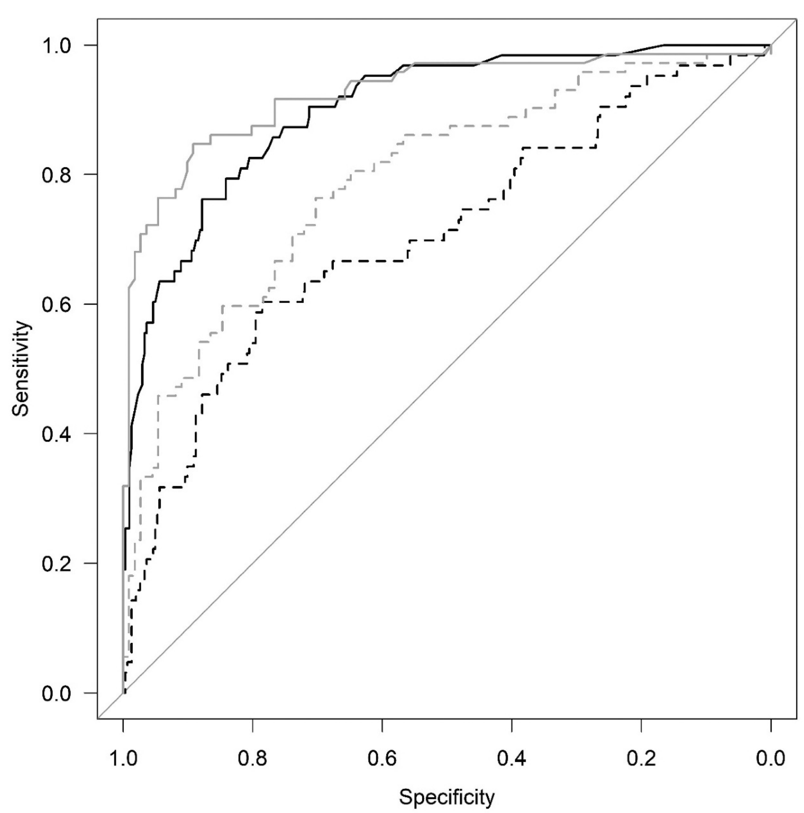

Figure 2. ROC-curves. Receiver Operating Characteristic-curves of the Random Forest models (solid) and symmetry in PM_{Qcon} 30°/s (dashed) in male (black) and female (grey) athletes.

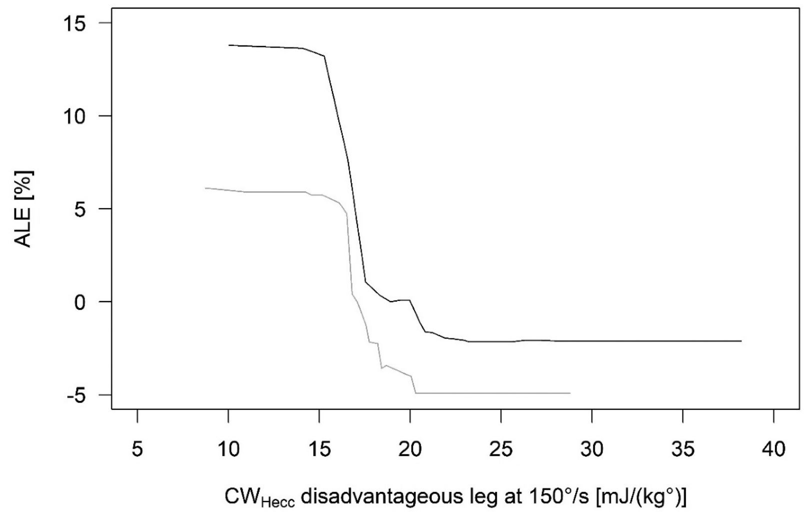

Figure 3. ALE plot. Accumulated Local Effects plot for the maximum eccentric work of the Hamstrings of the disadvantageous leg at 150°/s dynamometer speed in male (black) and female (grey) athletes. The slope of the curve indicates whether the predicted likelihood increases or decreases when altering the value of the feature.

Table 2. Top ten features.

♂ feature	ALE range [%]	♀ feature	ALE range [%]
CW_{Hecc} at 150°/s	16.0	CW_{Hecc} at 150°/s	11.0
Δ CW_{Hecc} at 30°/s	14.6	CW_{Hcon} at 30°/s	9.4
CW_{Hcon} at 30°/s	11.4	Δ CW_{Qecc} at 150°/s	9.4
CW_{Hcon} at 150°/s	11.2	PM_{Qcon} at 150°/s	8.5
CW_{Hecc} at 30°/s	10.3	CW_{Hcon} at 150°/s	8.5
Δ PM_{Qecc} at 150°/s	9.3	Δ CW_{Hecc} at 30°/s	7.7
Δ CW_{Hcon} at 30°/s	9.0	Δ PM_{Qcon} at 150°/s	7.2
Δ CW_{Hecc} at 150°/s	8.7	CW_{Qcon} at 150°/s	7.0
Δ CW_{Qcon} at 30°/s	8.3	CW_{Hecc} at 30°/s	6.3
Δ CW_{Qcon} at 150°/s	7.8	CW_{Qecc} at 150°/s	6.1

Features with the largest ALE range for the Random Forest models. Features referred to lateral differences (Δ) or the disadvantageous leg. Grey background highlights features appearing for both sexes.

4. Discussion

4.1. Return-to-sport decision rules

The first main objective was to answer the question if an ML model based on isokinetic knee data can distinguish between athletes post ACLR and healthy controls. The Random Forest enabled a multifactorial approach using multiple features derived from isokinetic testing even if they are correlated. The Random Forest models displayed outstanding predictive performance with an AUC of 0.92 for female athletes and 0.90 for male athletes. This makes the subsequent analysis more viable, and it underlines that muscle strength is markedly impaired after ACLR (Larsen et al., 2015). In contrast, the commonly applied RTS criteria of quadriceps leg symmetry measured as concentric peak moment demonstrated acceptable discrimination for both sexes with AUC of 0.79 and 0.71. It is expected for the ML model to outperform a classification based on one feature but these results do suggest that even for just assessing thigh muscle strength it is beneficial to evaluate more than just one criterion.

The ALE plots allowed us to identify the features that have the highest impact on the likelihood prediction of the Random Forest model. To our knowledge this is the first study to utilise this method in a post injury context. For male and female athletes, CW_{Hecc} at 150°/s of the disadvantageous leg was identified as the most impactful feature on the Random Forest prediction. Adding CW_{Hcon} at 30°/s and 150°/s, male and female athletes share three out of the top five features in regards to the ALE plot analysis that all refer to the hamstring strength in the disadvantageous leg. We therefore conclude that deficient strength capacities of the knee flexors in the injured leg is a major characteristic that distinguishes athletes post ACLR and healthy controls. Thus, a focus should be put on improving hamstring strength in the rehabilitation process post ACLR which is in line with current approaches (Buckthorpe et al., 2021). In addition, hamstring muscle loading has been demonstrated to reduce loading of the ACL (Li et al., 1999; Shelburne & Pandy, 1998; Shoemaker et al., 1993). Furthermore, CW assesses the strength capacity across the full range of motion (Alt et al., 2020). Therefore practitioners should choose exercises that train hamstring strength in different positions or through a full range of motion.

For the male athletes, six out of the ten most impactful features are differences between advantageous and disadvantageous leg including both quadriceps and hamstrings. This applies for three features in female athletes. Overall, it still indicates that leg symmetry is another important characteristic that distinguishes between athletes post ACLR and healthy controls. This is in line with the consensus of using leg symmetry as an important RTS criterion (Alt, Breitenmoser, et al., 2022; Lynch et al., 2015).

In contrast to current literature about isokinetic dynamometry (van Melick et al., 2016), features of CW were more relevant for the models in both sexes (Table 2). Peak moment has not been indicative of peak anterior tibial shear force (Bennett et al., 2008) and CW might provide insights into the strength capacities across the full range of motion (Alt et al., 2020). Furthermore, eccentric tests proved to be beneficial. In contrast, current consensus recommends concentric isokinetic tests (Urhausen et al., 2022). These findings also suggest to incorporate eccentric exercises as part of the strength and conditioning regime following ACLR, which has been shown to improve lower limb strength after ACLR (Lepley et al., 2015; Stojanovic et al., 2023). Also, features measured at 150°/s were more prevalent especially for females (Table 2). Therefore, including eccentric movement and higher speeds in isokinetic testing as well as analysing CW instead of solely focusing on the PM as a parameter could potentially improve the assessment of athletes by practitioners or researchers for example in a RTS scenario. Overall, this calls for more comprehensive isokinetic testing and analysis to optimise RTS decision making but we acknowledge that this is not usually possible in a clinical setting.

4.2. Application of ML statistical methodology

The main goal of the ML approach was to utilise the ALE plots to identify the most important features within a multifactorial model. Therefore, other aspects of model optimisation like variable selection have not been conducted. The lists of parameters with the highest impact on the model contained some highly correlated parameters. This is unusual because typically it is not beneficial for an ML model to incorporate highly correlated features since most of the information is already included with one of them. It is however explainable due to the specific optimisation of the Random Forest which uses random subsets of variables in each iteration. So in any given iteration the potentially best variable might not be available and a highly correlated variable is chosen as it provides similar information.

We think ML can be a powerful tool to deal with multifactorial problems, because newer methods are developed that help decipher the complex and uninterpretable underlying architecture, the so-called black box, of ML approaches like the Random Forest. It is still to note that our findings inherit a level of uncertainty as they result from analysing a model that tries to describe the real world and not from analysing the real world itself. However, this approach should help practitioners and sport scientists to make more nuanced and quantitative assessments and decisions as well as allow the investigation of even more complex data.

4.3. Limitations & perspectives

The main limitation of the present study is the sole focus on data derived from isokinetic dynamometry. Even though 62 features were incorporated in the methodology, we did not meet the demand that is put forth in RTS research to incorporate multiple aspects such as range of motion/flexibility, neuromuscular control, agility and psychological readiness, cutting tasks, landing tasks (McPherson et al., 2019; Paterno et al., 2017; Unverzagt et al., 2021). Another limitation of the present study is that the participants' rehabilitation was neither supervised nor guided following standardised procedures like previous studies did (Czamara et al., 2011; Ebert et al., 2018; Hohmann et al., 2011; Królikowska et al., 2019). Therefore, high inter-individual differences between athletes are plausible due to varying quantity and quality of rehabilitative measures. However, the presented data mirror a real-world setting (Alt, Nolte, et al., 2022). It is to note that the results from our discrete testing might not be transferable to other test settings for example reciprocal tests (Coombs & Garbutt, 2002). In order to standardise the rehabilition process it is advised to progress through specific exercises until certain criteria are met which is also recommended for the general rehab process (Cavanaugh & Powers, 2017).

The present study identified characteristics and measures of quadriceps and hamstring strength that discriminate between athletes post ACLR and healthy controls with a multifactorial approach. Therefore, our findings can be further investigated and used as hypotheses in future longitudinal RTS studies and hopefully provide benefit to making more nuanced and robust RTS decisions. We used advances in the field of interpretable ML as a tool to gain information, which can be utilised in multifactorial analyses. Therefore, this approach could be applied to even more complex data including aforementioned information. Furthermore, investigating the behaviour of an ML model in regards to changes in a particular feature might even allow a new way of finding data driven cut-off scores. Currently, we sometimes still rely on values that gained acceptance without sufficient evidence like 0.6 for the conventional H:Q ratio (Coombs & Garbutt, 2002). Furthermore, ML might even support RTS decision making at some point, either by learning from successful and unsuccessful RTS data or maybe from an approach like ours, where the goal of a rehabilitation process after an injury becomes not being identified as injured by the model.

5. Conclusion

The findings of the presented study emphasised the general impact an ACL injury has as athletes 6 to 24 months post ACLR and a healthy control group are classified with high accuracy by an ML model based on isokinetic knee data. Therefore, differences between the two groups are apparent. In order to mitigate those differences for example during rehabilitation for RTS analysing leg symmetry is important but does not suffice as a sole criterion for assessing strength capacities. In addition, higher emphasis needs to be put on strengthening and analysing the knee flexor muscles of the injured leg during the process. When assessing isokinetic strength, utilising CW and eccentric testing is beneficial and recommended.

The conducted ML approach allowed both high predictive performance as well as information gain about single features within a multifactorial context. Advances in the field of interpretable ML should definitely support RTS decision making.

Acknowledgments

The authors would like to thank all subjects who volunteered to participate in this study and demonstrated great motivation and commitment.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The author(s) reported there is no funding associated with the work featured in this article.

ORCID

Kevin Nolte http://orcid.org/0000-0001-5535-4306
Thomas Jaitner http://orcid.org/0000-0003-3227-8106
Axel J. Knicker http://orcid.org/0000-0002-6286-5961
Tobias Alt http://orcid.org/0000-0002-4451-9512

Data availability statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics approval

The ethics commission of German Sport University Cologne confirmed that the requirements of the Declaration of Helsinki were met.

References

Alt, T., Breitenmoser, T., Vonhoegen, J., Horn, D., Severin, J., Nolte, K., Knicker, A. J., Jaitner, T., Strüder, H. K. (2022). The dynamic control ratio masks bilateral asymmetries – a gender-specific analysis of 264 healthy and acl-injured athletes. *Research in Sports Medicine*, *30*(1), 1–18. https://doi.org/10.1080/15438627.2021.1943389

Alt, T., Etzel, J. P., Knicker, A. J., Strüder, H. K. (2019). The effects of fixation and contraction mode on prone isokinetic knee flexor tests. *Isokinetics and Exercise Science*, *27*(2), 143–151. https://doi.org/10.3233/IES-192117

Alt, T., Knicker, A. J., Strüder, H. K. (2014). Factors influencing the reproducibility of isokinetic knee flexion and extension test findings. *Isokinetics and Exercise Science*, *22*(4), 333–342. https://doi.org/10.3233/IES-140555

Alt, T., Knicker, A. J., Strüder, H. K. (2017). The dynamic control ratio at the equilibrium point (DCRe): Introducing relative and absolute reliability scores. *Journal of Sports Sciences*, *35*(7), 688–693. https://doi.org/10.1080/02640414.2016.1184298

Alt, T., Knicker, A. J., Strüder, H. K. (2020). Assessing thigh muscle balance of male athletes with special emphasis on eccentric hamstring strength. *The Physician and Sportsmedicine*, *48*(3), 327–334. https://doi.org/10.1080/00913847.2019.1705934

Alt, T., Nolte, K., Horn, D., Modenbach, D., Knicker, A. J., Jaitner, T. (2022). Analyses of isokinetic thigh muscle strength: Camera-based assessment alters the magnitude, but not the message [published online ahead of print, 2022 Apr 15]. *Research Quarterly for Exercise and Sport*, *94*(3), 1–10. https://doi.org/10.1080/02701367.2022.2053648

Alt, T., Richert, M., Schwarz, Y. M., Knicker, A. J., Strüder, H. K. (2016). Minimal fixation suffices for supine isokinetic knee extension: A kinetic and 3D kinematic analysis. *Isokinetics and Exercise Science*, *24*(4), 301–311. https://doi.org/10.3233/IES-160630

Alt, T., Severin, J., Nodler, Y. T., Horn, D., El-Edrissi, O., Knicker, A. J., Strüder, H. K. (2018). Kinematic analysis of isokinetic knee flexor and extensor tests. *Isokinetics and Exercise Science*, *26*(1), 1–8. https://doi.org/10.3233/IES-175172

Apley, D. W., Zhu, J. (2020). Visualizing the effects of predictor variables in black box supervised learning models. *Journal of the Royal Statistical Society Series B, Statistical Methodology*, *82*(4), 1059–1086. https://doi.org/10.1111/rssb.12377

Ardern, C. L., Taylor, N. F., Feller, J. A., Webster, K. E. (2014). Fifty-five per cent return to competitive sport following anterior cruciate ligament reconstruction surgery: An updated systematic review and meta-analysis including aspects of physical functioning and contextual factors. *British Journal of Sports Medicine*, *48*(21), 1543–1552. https://doi.org/10.1136/bjsports-2013-093398

Ayala, F., De Ste Croix, M., Sainz de Baranda, P., Santonja, F. (2012). Absolute reliability of hamstring to quadriceps strength imbalance ratios calculated using peak torque, joint angle-specific torque and joint rom-specific torque values. *International Journal of Sports Medicine*, *33*(11), 909–916. https://doi.org/10.1055/s-0032-1311586

Bahr, R. (2016). Why screening tests to predict injury do not work—and probably never will. . .: A critical review. *British Journal of Sports Medicine*, *50*(13), 776–780. https://doi.org/10.1136/bjsports-2016-096256

Bennett, D. R., Blackburn, J. T., Boling, M. C., McGrath, M., Walusz, H., Padua, D. A. (2008). The relationship between anterior tibial shear force during a jump landing task and quadriceps and hamstring strength. *Clinical Biomechanics*, *23*(9), 1165–1171. https://doi.org/10.1016/j.clinbiomech.2008.05.005

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Buckthorpe, M., Danelon, F., La Rosa, G., Nanni, G., Stride, M., Della Villa, F. (2021). Recommendations for hamstring function recovery after ACLR. *Sports Medicine*, *51*(4), 607–624. https://doi.org/10.1007/s40279-020-01400-x

Bullock, G. S., Hughes, T., Arundale, A. H., Ward, P., Collins, G. S., Kluzek, S. (2022). Black box prediction methods in sports medicine deserve a red card for reckless practice: A change of tactics is needed to advance athlete care. *Sports Medicine*, *52*(8), 1729–1735. https://doi.org/10.1007/s40279-022-01655-6

Cavanaugh, J. T., Powers, M. (2017). ACL rehabilitation progression: Where are we now? *Current reviews in musculoskeletal medicine*, *10*(3), 289–296. https://doi.org/10.1007/s12178-017-9426-3

Coombs, R., Garbutt, G. (2002). Developments in the use of the hamstring/quadriceps ratio for the assessment of muscle balance. *Journal of Sports Science & Medicine*, *1*(3), 56–62.

Czamara, A., Szuba, Ł., Krzemińska, A., Tomaszewski, W., Wilk-Frańczuk, M. (2011). Effect of physiotherapy on the strength of tibial internal rotator muscles in males after anterior cruciate ligament reconstruction (ACLR). *Medical Science Monitor*, *17*(9), CR523–CR531. https://doi.org/10.12659/msm.881940

Dvir, Z. (2014). Relevant, less relevant and irrelevant isokinetic strength test parameters: Some critical comments. *Movement & Sport Sciences-Science & Motricité*, *85*(3), 15–21. https://doi.org/10.3917/sm.085.0015

Dvir, Z., Eger, G., Halperin, N., Shklar, A. (1989). Thigh muscle activity and anterior cruciate ligament insufficiency. *Clinical Biomechanics*, *4*(2), 87–91. https://doi.org/10.1016/0268-0033(89)90044-2

Ebert, J. R., Edwards, P., Yi, L., Joss, B., Ackland, T., Carey-Smith, R., Buelow, J.-U., Hewitt, B. (2018). Strength and functional symmetry is associated with post-operative rehabilitation in patients following anterior cruciate ligament reconstruction. *Knee Surgery, Sports Traumatology, Arthroscopy*, *26*(8), 2353–2361. https://doi.org/10.1007/s00167-017-4712-6

El-Ashker, S., Carson, B. P., Ayala, F., De Ste Croix, M. (2017). Sex-related differences in joint-angle-specific functional hamstring-to-quadriceps strength ratios. *Knee Surgery, Sports Traumatology, Arthroscopy*, *25*(3), 949–957. https://doi.org/10.1007/s00167-015-3684-7

Fawcett, T. (2004). ROC graphs: Notes and practical considerations for researchers. *Machine Learning*, *31*(1), 1–38.

Gokeler, A., Dingenen, B., Hewett, T. E. (2022). Rehabilitation and return to sport testing after anterior cruciate ligament reconstruction: Where are we in 2022? *Arthroscopy, Sports Medicine, and Rehabilitation*, *4*(1), e77–e82. https://doi.org/10.1016/j.asmr.2021.10.025

Grindem, H., Snyder-Mackler, L., Moksnes, H., Engebretsen, L., Risberg, M. A. (2016). Simple decision rules can reduce reinjury risk by 84% after ACLR: The Delaware-Oslo ACL cohort study. *British Journal of Sports Medicine*, *50*(13), 804–808. https://doi.org/10.1136/bjsports-2016-096031

Hewett, T. E., Myer, G. D., Zazulak, B. T. (2008). Hamstrings to quadriceps peak torque ratios diverge between sexes with increasing isokinetic angular velocity. *Journal of Science & Medicine in Sport*, *11*(5), 452–459. https://doi.org/10.1016/j.jsams.2007.04.009

Hohmann, E., Tetsworth, K., Bryant, A. (2011). Physiotherapy-guided versus home-based, unsupervised rehabilitation in isolated anterior cruciate injuries following surgical reconstruction. *Knee Surgery, Sports Traumatology, Arthroscopy*, *19*(7), 1158–1167. https://doi.org/10.1007/s00167-010-1386-8

Hosmer, D. W., Jr., Lemeshow, S., Sturdivant, R. X. (2013). *Applied logistic regression* (Vol. 398). John Wiley & Sons.

Królikowska, A., Reichert, P., Czamara, A., Krzemińska, K., Macaluso, A. (2019). Peak torque angle of anterior cruciate ligament-reconstructed knee flexor muscles in patients with semitendinosus and gracilis autograft is shifted towards extension regardless of the postoperative duration of supervised physiotherapy. *PLOS ONE*, *14*(2), e0211825. https://doi.org/10.1371/journal.pone.0211825

Larsen, J. B., Farup, J., Lind, M., Dalgas, U. (2015). Muscle strength and functional performance is markedly impaired at the recommended time point for sport return after anterior cruciate ligament reconstruction in recreational athletes. *Human Movement Science*, *39* 1 , 73–87. https://doi.org/10.1016/j.humov.2014.10.008

Lepley, L. K., Wojtys, E. M., Palmieri-Smith, R. M. (2015). Combination of eccentric exercise and neuromuscular electrical stimulation to improve quadriceps function post-acl reconstruction. *The Knee*, *22*(3), 270–277. https://doi.org/10.1016/j.knee.2014.11.013

Li, G., Rudy, T. W., Sakane, M., Kanamori, A., Ma, C. B., Woo, S. L. (1999). The importance of quadriceps and hamstring muscle loading on knee kinematics and in-situ forces in the ACL. *Journal of Biomechanics*, *32*(4), 395–400. https://doi.org/10.1016/s0021-9290(98)00181-x

Lynch, A. D., Logerstedt, D. S., Grindem, H., Eitzen, I., Hicks, G. E., Axe, M. J., Engebretsen, L., Risberg, M. A., Snyder-Mackler, L. (2015). Consensus criteria for defining 'successful outcome' after ACL injury and reconstruction: A Delaware-Oslo ACL cohort investigation. *British Journal of Sports Medicine*, *49*(5), 335–342. https://doi.org/10.1136/bjsports-2013-092299

McPherson, A. L., Feller, J. A., Hewett, T. E., Webster, K. E. (2019). Psychological readiness to return to sport is associated with second anterior cruciate ligament injuries. *The American Journal of Sports Medicine*, *47*(4), 857–862. https://doi.org/10.1177/0363546518825258

Molnar, C. (2020). *Interpretable machine learning*. Lulu. Com.

Norte, G. E., Goetschius, J. W., Slater, L. V., Hart, J. M. (2021). Influence of patient demographics and surgical characteristics on pass rates of return-to-activity tests in anterior cruciate ligament–reconstructed patients before Physician clearance. *Clinical Journal of Sport Medicine*, *31*(6), e354–e362. https://doi.org/10.1097/JSM.0000000000000790

Palmieri-Smith, R. M., Lepley, L. K. (2015). Quadriceps strength asymmetry after anterior cruciate ligament reconstruction alters knee joint biomechanics and functional performance at time of return to activity. *The American Journal of Sports Medicine*, *43*(7), 1662–1669. https://doi.org/10.1177/0363546515578252

Paterno, M. V., Huang, B., Thomas, S., Hewett, T. E., Schmitt, L. C. (2017). Clinical factors that predict a second ACL injury after ACLR and Return to sport: Preliminary development of a clinical decision algorithm. *Orthopaedic Journal of Sports Medicine*, *5*(12), 2325967117745279. https://doi.org/10.1177/2325967117745279

Petersen, W., Taheri, P., Forkel, P., Zantop, T. (2014). Return to play following ACLR: A systematic review about strength deficits. *Archives of Orthopaedic and Trauma Surgery*, *134*(10), 1417–1428. https://doi.org/10.1007/s00402-014-1992-x

Refaeilzadeh, P., Tang, L., Liu, H. (2009). Cross-Validation. *Encyclopedia of Database Systems*, 532–538. https://doi.org/10.1007/978-0-387-39940-9_565

Rothstein, J. M., Lamb, R. L., Mayhew, T. P. (1987). Clinical uses of isokinetic measurements. Critical issues. *Physical Therapy*, *67*(12), 1840–1844. https://doi.org/10.1093/ptj/67.12.1840

Schmitt, L. C., Paterno, M. V., Ford, K. R., Myer, G. D., Hewett, T. E. (2015). Strength asymmetry and landing mechanics at return to sport after anterior cruciate ligament reconstruction. *Medicine and Science in Sports and Exercise*, *47*(7), 1426–1434. https://doi.org/10.1249/MSS.0000000000000560

Shelburne, K. B., Pandy, M. G. (1998). Determinants of cruciate-ligament loading during rehabilitation exercise. *Clinical Biomechanics*, *13*(6), 403–413. https://doi.org/10.1016/s0268-0033(98)00094-1

Shoemaker, S. C., Adams, D., Daniel, D. M., Woo, S. L. (1993). Quadriceps/Anterior cruciate graft interaction. An in vitro study of joint kinematics and anterior cruciate ligament graft tension. *Clinical Orthopaedics & Related Research*, *294*, 379–390. https://doi.org/10.1097/00003086-199309000-00054

Stojanovic, M. D. M., Andrić, N., Mikić, M., Vukosav, N., Vukosav, B., Zolog-Șchiopea, D.-N., Tăbăcar, M., Melinte, R. M. (2023). Effects of eccentric-oriented strength training on return to sport criteria in late-stage Anterior Cruciate Ligament (acl)-reconstructed professional team sport players. *Medicina*, *59*(6), 1111. https://doi.org/10.3390/medicina59061111

Undheim, M. B., Cosgrave, C., King, E., Strike, S., Marshall, B., Falvey, É., Franklyn-Miller, A. (2015). Isokinetic muscle strength and readiness to return to sport following anterior cruciate ligament reconstruction: Is there an association? A systematic review and a protocol recommendation. *British Journal of Sports Medicine*, *49*(20), 1305–1310. https://doi.org/10.1136/bjsports-2014-093962

Unverzagt, C., Andreyo, E., Tompkins, J. (2021). ACL return to sport testing: It's time to step up our game. *International Journal of Sports Physical Therapy*, *16*(4), 1169–1177. https://doi.org/10.26603/001c.25463

Urhausen, A. P., Berg, B., Øiestad, B. E., et al. (2022). Measurement properties for muscle strength tests following anterior cruciate ligament and/or meniscus injury: What tests to use and where do we need to go? A systematic review with meta-analyses for the OPTIKNEE consensus [published online ahead of print, 2022 Sep 16]. *British Journal of Sports Medicine*, 105498. https://doi.org/10.1136/bjsports-2022-105498

Van Eetvelde, H., Mendonça, L. D., Ley, C., Seil, R., Tischer, T. (2021). Machine learning methods in sport injury prediction and prevention: A systematic review. *Journal of Experimental Orthopaedics*, *8*(1), 27. https://doi.org/10.1186/s40634-021-00346-x

van Melick, N., van Cingel, R. E., Brooijmans, F., Neeter, C., van Tienen, T., Hullegie, W., Nijhuis van der Sanden, M. W. G. (2016). Evidence-based clinical practice update: Practice guidelines for anterior cruciate ligament rehabilitation based on a systematic review and multidisciplinary consensus. *British Journal of Sports Medicine*, *50*(24), 1506–1515. https://doi.org/10.1136/bjsports-2015-095898

Wellsandt, E., Failla, M. J., Snyder-Mackler, L. (2017). Limb symmetry indexes can overestimate knee function after anterior cruciate ligament injury. *Journal of Orthopaedic & Sports Physical Therapy*, *47*(5), 334–338. https://doi.org/10.2519/jospt.2017.7285

Wiggins, A. J., Grandhi, R. K., Schneider, D. K., Stanfield, D., Webster, K. E., Myer, G. D. (2016). Risk of secondary injury in younger athletes after anterior cruciate ligament reconstruction: A systematic review and meta-analysis. *The American Journal of Sports Medicine*, *44*(7), 1861–1876. https://doi.org/10.1177/0363546515621554

Youden, W. J. (1950). Index for rating diagnostic tests. *Cancer: Interdisciplinary International Journal of the American Cancer Society*, *3*(1), 32–35. https://doi.org/10.1002/1097-0142(1950)3:1<32::AID-CNCR2820030106>3.0.CO;2-3

Appendix

Feature overview

Single parameters consisting of parameter, muscle and movement (8 parameters).

Depiction example: PM_{Qcon}

parameter	muscle	movement
peak moment (PM)	quadriceps (Q)	concentric (con)
contractional work (CW)	hamstrings (H)	eccentric (ecc)

Parameters for quadriceps-hamstring relationship (3 parameters)

parameter	definition
conventional H:Q ratio	PM_{Hcon}/PM_{Qcon}
functional H:Q ratio	PM_{Hecc}/PM_{Qcon}
dynamic control ratio equilibrium (DCRe)	moment at the equilibrium of PM_{Hecc} and PM_{Qcon}

All the above are derived for both, the disadvantageous (dis) and the advantageous (adv) leg and at two dynamometer speeds, 30°/s and 150°/s, resulting in 44 features.

For leg symmetry lateral differences (Δ) are calculated for PM, CW and DCRe, resulting in additional 18 features and a total of 62 available features.