The use of technical-tactical and physical performance indicators to classify between levels of match-play in elite rugby league.

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Abstract

This study aimed to identify which physical and technical-tactical performance indicators (PI) can classify between levels of rugby league match-play. Data were collected from 46 European Super League (ESL) and 36 under-19 Academy (Academy) level matches over two competitive seasons. Thirty-one male ESL players and 41 male Academy players participated. Microtechnology units were used to analyse the physical PI and matches were videoed and coded for the individual technical-tactical PI, resulting in 157 predictor variables. Data were split into training and testing datasets (70:30). Random forests (RF) were built to reduce the dimensionality of the data, identify the variables of importance and build classification models. To aid practical interpretation, conditional inference (CI) trees were built. Nine variables were identified as the most important for backs, classifying between levels with 83% (RF) and 78% (CI tree) accuracy. The combination of variables with the highest classification rate was: $PlayerLoad_{2D}$, $PlayerLoad_{SLOW}$ per Kg body mass and high-speed running distance. Four variables were identified as most important for forwards, classifying with 68% (RF) and 64% (CI tree) accuracy. Defensive play-the-ball losses alone had the highest classification rate for forwards. The identified PI and their unique combinations, can be developed during training to aid in progression through the rugby league playing pathway.

Key words

Youth, team sport, microtechnology, performance analysis, machine learning

Introduction

Elite playing pathways and talent development programmes are crucial in the pursuit of sporting excellence[1]. To enhance success, organisations aim to understand the differences between the levels of competition within specific playing pathways[1]. This is important in professional team sports such as rugby league, as young players are often required to compete at the higher level whilst still training and competing at their contracted level. The process of determining which aspects of team sport performance are the most important to develop is complex, requiring a dynamic and multidimensional approach.

Many studies have quantified the characteristics of match-play using microtechnology[2,3] and video analysis[4]. In rugby league, differences in the whole-match[5,6], and duration-specific peak locomotive characteristics[6] of match-play have been reported between playing standards (i.e., Super League *vs.* Championship) and levels (i.e., Under 19s *vs.* Senior); although there is inconsistency in which physical characteristics are deemed important for performance and development[5,7]. For example, McLellan and Lovell[5] found National Rugby League (NRL) match-play to have a greater average match speed, and cover more total and sprint (> 6.1 $m \cdot s^{-1}$) distance than National Youth Cup (NYC) and Queensland-cup match-play. In contrast, Gabbett[7] found no differences in average match speeds or distances covered between NRL and NYC match-play.

Differences in video analysis derived technical-tactical performance indicators (PI) have also been identified between playing standards and levels[4,8,9]. It has been found that more successful (i.e., higher standard) teams perform more ‘play the balls’ and less ‘missed tackles’ than the less successful teams[8,9]. Collectively, such research has revealed a number of important aspects of both physical- and technical-tactical-performance that can differentiate between playing standards and levels in rugby league.

Recently, studies[4,10] have employed machine learning techniques to allow for multivariate patterns to be revealed within the characteristics of rugby league match-play. For example, Woods et al.[4] identified that senior professional (NRL) match-play was classified by a greater number of ‘all runs’ and ‘tackles’, and lower number of ‘missed tackles’ relative to the elite youth competition. However, studies using both the physical and technical-tactical PI are limited across team sports[11]. To our knowledge, no study in rugby league has investigated the combined importance of technical-tactical and physical PI of match-play to determine differences between playing levels using appropriate methods that consider the interaction between the predictor variables and overcome the common issues of complex datasets (e.g. multicollinearity)[12]. Therefore, this study aimed to (1) build a comprehensive data set of both physical and technical-tactical PI of rugby league match-play across two levels (i.e., academy and senior) within the English professional playing pathway, and (2) use machine learning techniques to determine which physical and technical-tactical PI best discriminate between the two levels of competition.

Methods

A longitudinal, observational study design was used to determine differences between senior and academy rugby league match-play using 157 explanatory variables (physical and technical-tactical PI). Data were collected from one professional rugby league club during 46 European Super League senior (ESL) and 36 ESL Under-19 Academy (Academy) matches across two competitive seasons. Thirty-one male ESL players (height: 186.0 ± 7.0 cm, body mass: 98.28 ± 10.73 kg, age: 27.3 ± 4.8 years) and 41 male Academy players (height: 178.6 ± 6.4 cm, body mass: 90.1 ± 13.2 kg, age 17.7 ± 1.0 years) participated. The study was approved by the Institutions Ethics Committee, and written informed consent was obtained from all participants.

Match observations per player were 22 ± 13 (range: 1 – 43) and 14 ± 9 (range: 1 – 36) in the ESL and Academy teams respectively, with a total of 1,236 match files. Three players competed in both ESL and Academy level match-play and so, the players Academy match files were excluded from analysis. Match-observations with any missing data (due to poor GPS quality [n = 5], players in both datasets [n = 4], missing collision or PlayerLoad^{TM} data [n = 152], and missing technical-tactical PI [n = 30]) were removed due to the systematic bias it could induce in the random forest analysis, resulting in 1,045 match files and match observations per player of 18 ± 11 (range: 2 to 38) and 11 ± 7 (range: 1 to 31) for ESL and Academy teams respectively. Players were split into two positional groups to provide position specific findings, whilst maintaining a sufficient sample size to build accurate models: forwards (ESL, n = 325; Academy, n = 259) and backs (ESL, n = 240; Academy, n = 221). The ESL team won 62% of matches, with a score difference of 3.7 ± 18.7. The Academy team won 68% of matches, with a score difference of 11.1 ± 26.6.

Physical PI

Microtechnology units (Optimeye S5, Catapult Innovations, Melbourne, Victoria), housing a 10-Hz Global Positioning System (GPS) receiver, a 100-Hz tri-axial accelerometer, gyroscope and magnetometer (firmware version 5.27), were used to quantify the physical PI. The validity and reliability of microtechnology devices for measuring instantaneous velocity[13], collision count[14], and accelerometer derived PlayerLoad™ [15] has been established. Players wore the units in specifically designed pouches within the players tight fitted playing jersey, with the device positioned between the scapulae. The same units were worn for repeated observations, and the devices were switched on 30-minutes prior to the commencement of match-play[16].

For both levels, data were downloaded from the microtechnology devices using the proprietary software (Catapult Openfield, v.1.21.1). Speed was calculated via the Dopler shift method, and the minimum effort duration was set at 1-second[13]. Data during periods of substitution were removed, but natural stoppages in play (e.g., try, injury, video replay) were included. The minimum length of match-play to be included in the analysis was 10-min. The instantaneous 10-Hz speed data and collision event files were exported, and all further analysis was carried out in *R* (v 3.5.1, R Foundation for Statistical Computing). Rows of instantaneous speed data were removed if any of the following criteria were met: (1) velocity > 10 $m \cdot s^{-1}$; (2) connection to less than 10 satellites; (3) horizontal dilution of precision was > 2.0; (4) acceleration/ deceleration values of > ± 6 $m \cdot s^{-2}$ [16]. When the total number of excluded rows exceeded more than 10% of the match file, that instantaneous speed data file was removed (n = 5), thus the match observation was removed from the dataset given the missing data.

A comprehensive analysis of physical PIs was carried out to include the range of microtechnology derived variables are commonly rugby league research and capture the demands of the sport [3,5,7,14]. A range of mircrotechnology derived locomotive, collision and PlayerLoad™ variables were analysed for the whole-match. Speed thresholds were set at 5 – 7 $m \cdot s^{-1}$ for high-speed running (HSR) and > 7 $m \cdot s^{-1}$ for sprint speed distances[17]. The PlayerLoad™ variables were calculated relative to the players individual body mass, to take into consideration the differences in body mass between the levels[18]. The duration-specific peak characteristics (60- to 600-s), and their concurrent demands (e.g., the collisions completed during the peak average speed period[17]), were calculated in the *zoo* package[19], using the moving averages (or moving sum for collision count) approach[3], as per previous methods[6,17]. The maximum value of each variable was extracted for each duration for each match. The collision event files were aligned with the 10-Hz instantaneous speed data via the UNIX timestamps, and the time-stamp of the identified peak demand was obtained to determine the concurrent characteristics of the period. Variables derived from a power law relationship[20] were used to quantify the relationship between the investigated moving average durations and peak average running speeds for each player per match. Supplementary Table 1 lists, and describes, the physical PI analysed (137 total).

Technical-tactical PI

Each match was filmed using a Cannon xF105 camera, and subsequently coded (Sportscode, version 10) by an expert analyst (8 years' experience). Individual technical-tactical PI were reduced from those coded based on the requirements of the club, to include only PI that had been used in previous research[4,8,10], resulting in 20 PI. Each technical-tactical PI was clearly defined by the performance analysts carrying out the coding of match-play. The intra-rater reliability was established through the same rater coding a game more than six months apart and assessed using intra-class correlation coefficient (ICC). The definitions and ICC (range: 0.57 to 1.00) for the 20 PIs are shown in Supplementary Table 2.

Data analyses

All data analyses were carried out using *R*. A correlation matrix was built to assess the level of multicollinearity of the predictor variables within the data set[21]. Supervised machine learning classification techniques (random forest, conditional inference [CI] trees) were used to build models of the distribution of class labels (i.e., ESL or Academy) in terms of the predictor features. The random forest algorithm[22] is a classification technique that uses an ensemble approach; it is robust in nature, can handle a mixture of data types, and provides information on relative variable importance[22,23]. Therefore, it was used to: (1) reduce the dimensionality of the training dataset and (2) build classification models using the identified 'important' variables.

The data were split into training and testing (70:30) datasets for each positional group. Random forests were carried out using the default settings of the *randomForest* package (v4.6-14) [24] with the 'set.seed' command set at '123', 500 trees used in each model and with the number of variables tried at each split equal to the square root of the number of variables inputted. Firstly, to identify the variables of greatest importance for forwards and backs, relative variable importance was determined on the training data by the Gini index; with a greater decrease in Gini index signifying greater variable importance. Pairs of variables with an $r > 0.95$ were considered for removal, with the variable with the lowest Gini-index removed[22], resulting in the removal of nine variables for backs, and seven for forwards. The top variables of relative importance were determined independently by two researchers, agreeing on a visual break (i.e. the ‘elbow’) within the Gini-index plot. These variables were inputted into a final random forest model to classify between the two levels of match-play. Confusion matrices (*caret* package)[25] and receiving operating characteristics (ROC) were generated to summarise and assess the accuracy of the models, respectively, for both training and testing datasets. Interpretation of the ROC curves were as follows: 0.5 (*no value*), 0.51-0.69 (*poor*), 0.7 to 0.79 (*fair*), 0.8 to 0.89 (*good*), 0.9 to 0.99 (*excellent*) and 1 (*perfect*)[26].

Conditional inference trees were grown in the *party* package[27] on the training dataset, using the identified important variables, to provide more practical interpretation of how the PI interact to classify between levels. The alpha value was set at 0.01 to prune the tree. The testing datasets were used validate the CI trees identified from the training dataset.

Results

Random Forests

For the backs, the random forest identified nine variables that created the largest decrease in Gini impurity and were therefore deemed as important: $\text{PlayerLoad}_{\text{2D}}$, number of quick play-the-balls (PTBs), $\text{PlayerLoad}_{\text{SLOW}}$, HSR distance covered, number of carries, total distance covered, number of collisions, average match-speed and PL_{SLOW} per Kg body mass. These predictor variables could correctly classify Academy match observations on unseen data (i.e., the testing dataset) 79% of the time and ESL match observations 86% of the time providing an overall accuracy of 83%, with an OOB error rate of 10.85% (Table 1).

For the forwards, four variables were identified as important: number of defensive PTB losses, peak 60-second AveAcc, number of defensive collisions lost. These variables could correctly classify Academy matches on unseen data 62% of the time, and ESL matches 72% of the time providing an overall accuracy of 68% and OOB error rate of 32% (Table 1). The summary statistics and ROC results of the random forest models are shown in Table 1.

*** Table 1 here***

Conditional Inference Trees

Figure 1 highlights the CI tree for backs including only the variables deemed important from the random forest. This CI tree had an overall accuracy of 78% within the testing dataset demonstrating slightly less overall accuracy than the random forest. However, only five out of the nine variables identified as important within the random forest were retained in the final tree (Figure 1). Progressing to the left of the root node (PlayerLoad_{2D}), terminal node 8 indicates that when a player had a PlayerLoad_{2D} of > 466 AU, a PlayerLoad_{SLOW}/kg of ≤ 3.87 $\text{AU}\cdot\text{kg}^{-1}$ and covered > 384 m of HSR, this was correctly identified as ESL match-play for 109/110 (99.1%) observations. Terminal node 4 indicates that when a player had a PlayerLoad_{2D} of ≤ 466 AU and completed > 3 quick PTBs this was correctly identified as ESL match-play for 95% of 41 observations. Conversely, where PlayerLoad_{2D} was ≤ 466 AU but players completed ≤ 3 quick PTBs, 75% of 259 observations were Academy match-play.

*** Figure 1 here***

Figure 2 highlights the CI tree for the forwards. The CI tree demonstrated an overall accuracy of 64% within the testing dataset suggesting similar overall accuracy to the random forest (Table 1). Three out of the four variables modelled were retained in the final tree. The root node is split at 5 defensive PTB losses; progressing to the left leads to terminal node 7 where 90% of 93 observations when a player has > 5 defensive PTB losses was during ESL match-play. Terminal node 4 indicates that 82% of 110 observations, when a player has ≤ 5 defensive PTB losses, a peak 60-second AveAcc of ≤ 0.84 $m \cdot s^{-2}$ and ≤ 1 defensive collisions lost were during Academy match-play.

*** Figure 2 here***

Discussion

This is the first study to explore the combination of technical-tactical and physical PI to explain differences between playing levels in team-sport. It aimed to build a comprehensive dataset of PI in Academy and ESL level match-play to identify which are important when discriminating between match-play at the two levels within an English rugby league club. The initial 157 PI were reduced based on variable importance, and the key combination of these PI for forwards and backs were identified through the CI trees to aid in coaching practices.

The random forest algorithms identified which PI are most important for the classification of match-play between the levels of competition within one professional club, whilst taking into account their complex interactions. They identified nine variables for backs and four for forwards out of the 157 investigated. While there were three common important PI between the positional groups, overall there were distinct differences in the identified most important PI, supporting the need to approach talent development as separate positional groups[5,6]. When testing the importance of these identified variables on unseen data, for the backs, both the random forest and conditional inference trees produced strong models that could classify the two levels with *good* accuracy (78 to 83%; Table 1) demonstrating confidence in the PI for distinguishing between Academy and ESL match-play. For both the random forest and conditional inference trees, the forwards variables produced a model with *poor* accuracy (Table 1) which suggests that the current 157 PI are not sufficient for classifying between ESL and Academy match-play.

The CI trees provide further practical insight into how the unique combination and interaction of these PI were able to classify between the players competing in ESL or academy match-play. For the backs, the combination of PI with the highest percentage classification was $PlayerLoad_{2D}$, $PlayerLoad_{SLOW}$/kg and HSR distance covered (terminal node 8; Figure 2). Given the relationships between the different PlayerLoad™ variables and total distance, change of direction and collisions[28], terminal node 8 suggests that ESL backs complete greater “global” external workloads ($PlayerLoad_{2D}$), complete either more, or the same amount of high-intensity movements at low locomotor velocities (e.g., change of direction) but whilst carrying more body mass ($PlayerLoad_{SLOW}$kg), and cover greater HSR distance than backs during Academy match-play. Therefore, Academy coaches and practitioners should prescribe training practices that expose players to HSR and high intensity acceleration and decelerations, such as manipulations of small-sided games. But alongside this players are required to increase their body mass whilst maintaining the intensity of training. The CI tree for the backs also indicated that a low PL_{2D} (< 466 AU) and a low number of quick PTBs (<3) are indicative of Academy match-play. Coaches can use this to guide Academy training practices with the inclusion of quick PTBs in training whilst the "global" external workload of training is high. These combinations of external load variables and quick PTBs identified can provide Academy coaches and practitioners with a refined area of focus during training to aid in progression to ESL match-play. However, more research on how these skills can be optimally acquired during training through the manipulation of task constraints and then quantified using deeper levels of performance analysis indicators is required to explore how this process can be used effectively in practice[29].

For forwards, terminal node 7 of the CI tree demonstrated the highest classification rate (Figure 2); 90% of 93 observations with greater than 5 defensive PTB losses occurred during ESL match-play. This finding is surprising given the increased level of skill associated with higher playing levels[30], but could be due to the different playing standards nested within the two levels of competition. Considering more defensive PTB losses occur in the ESL competition, Academy coaches should focus on creating scenarios of defensive PTB losses during training so that players can learn how to respond to such situations during match-play at the higher level. However, overall, the technical-tactical and physical PI investigated for the forwards produced *poor* classification models in comparison to the backs. This could be due to the unique technical-tactical roles within the positional group (e.g., middle *vs.* edge forwards)[31], which aren't captured when analysed as 'forwards' only.

The technical-tactical PI identified as important in the current study differ to the research by Woods et al.[4] which identified that 'all runs', 'tackles' and 'missed tackles' were able to classify between playing levels in the Australian professional playing pathway. This could be due to the current study classifying player observations rather than team observations, or the fact that there are variances in the sport played at the senior professional level in Australia (NRL) compared to Europe (ESL), for example NRL match-play generates fewer ‘line breaks’, ‘errors’, ‘tackles’ and ‘dummy half runs’, suggesting different game strategies and skill capabilities[10] and therefore likely differences in the development pathways. More importantly, the differences in findings could be due to the addition of the physical characteristics in the current study and the greater number of PI included. This further supports the need to consider both physical and technical-tactical PI together in both research and practice.

Despite the current study being the first to use both physical and technical-tactical PI to classify between match-play at different playing levels in rugby league[32], it is not without its limitations. The academy and senior teams being from only one professional club limits the generalisability of the findings. Additionally, contextual-related variables (e.g., match-location, match-outcome, opposition) were not accounted for and given their effect on physical and technical tactical PI[33], this should be considered in future. Furthermore, further research with a larger sample is required to investigate more specific positional groupings within the broader forwards and backs categories used in the current study. The identified important PI and differences indicate areas of focus for Academy training to prepare players for ESL match-play however further research into what PI are important for success at the senior level (ESL) would further support training practices. Additionally, whilst the important PIs identified can be used to guide the focus of training practices, the use of technical-tactical PI counts only limits the practical application of the important PI identified to inform the design of specific drills.

Further research is required to align practice and performance analysis techniques to theories of motor learning to assist in the practical utility of these findings[29,34].

In conclusion, this is the first study to carry out a comprehensive analysis of both the physical and technical-tactical PI at different levels within rugby league. The 157 PI included were used to classify between the two levels of competition using machine learning techniques, allowing for the complex interactions to be considered. Nine and four important physical and technical-tactical PI were identified for backs and forwards respectively; these identified PI, and their unique combinations provide coaches and practitioners with distinct PI to focus on developing during training to aid in appropriate progression of players through the pathway to compete in ESL match-play.

Practical applications

- Physical and technical-tactical performance indicators of match-play should be combined to determine differences between levels of competition in team-sports and machine learning models should be applied to establish cut-off points for specific PIs to aid in the design and prescription of training drills.
- Academy coaches should consider the greater external loads found in ESL match-play for backs when planning training, specifically high speed running and high intensity movements, whilst increasing their body mass
- Academy coaches should consider the greater number of defensive PTB losses that have been identified for forwards in ESL match-play when planning training for forwards.

Acknowledgements

The authors thank the club involved for their assistance with this project. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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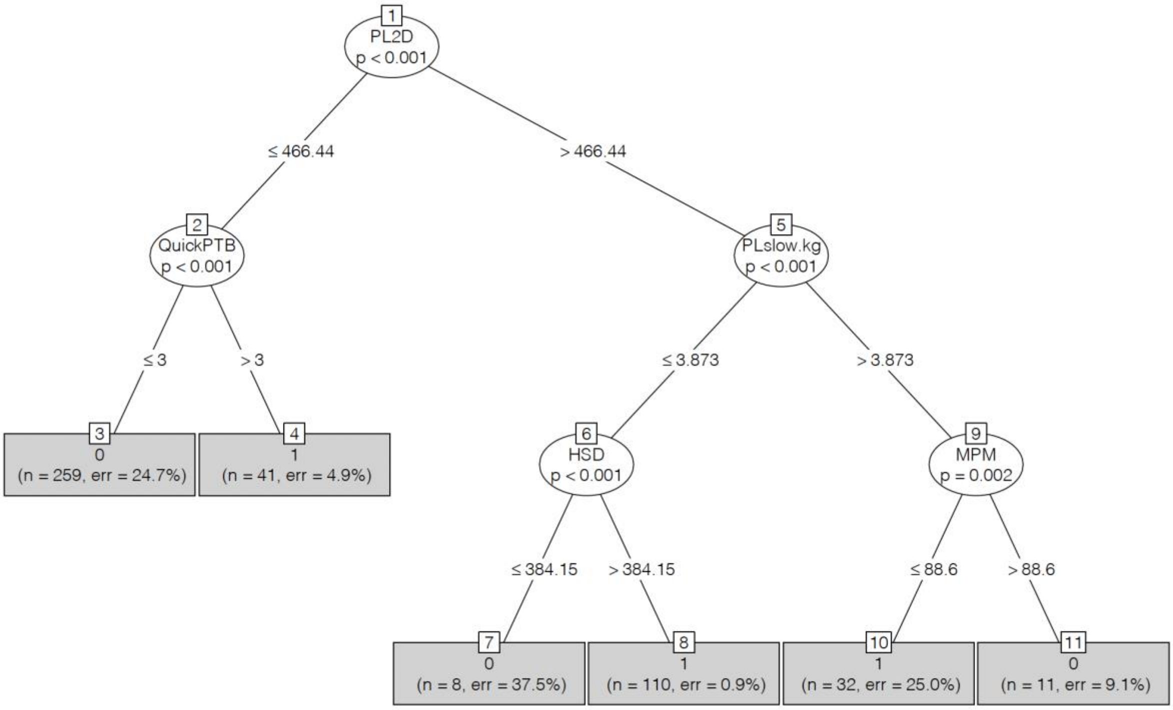

Figure 1. The conditional inference tree showing the classification of levels using the identified important variables for backs.

Note Numbers in the square boxes denote the node number. 0 = Academy match-play, 1 = European Super League match-play. n = the number of observations in each terminal node

err = error percentage i.e., the percentage of the observations that do not meet the overall classification. PL2D = Player Load 2D^{TM}, PTB = play-the-balls, PL.slow.kg = Player Load slow^{TM} per kg of body mass, HSD = high speed running distance, MPM = meters per minute (average match-speed).

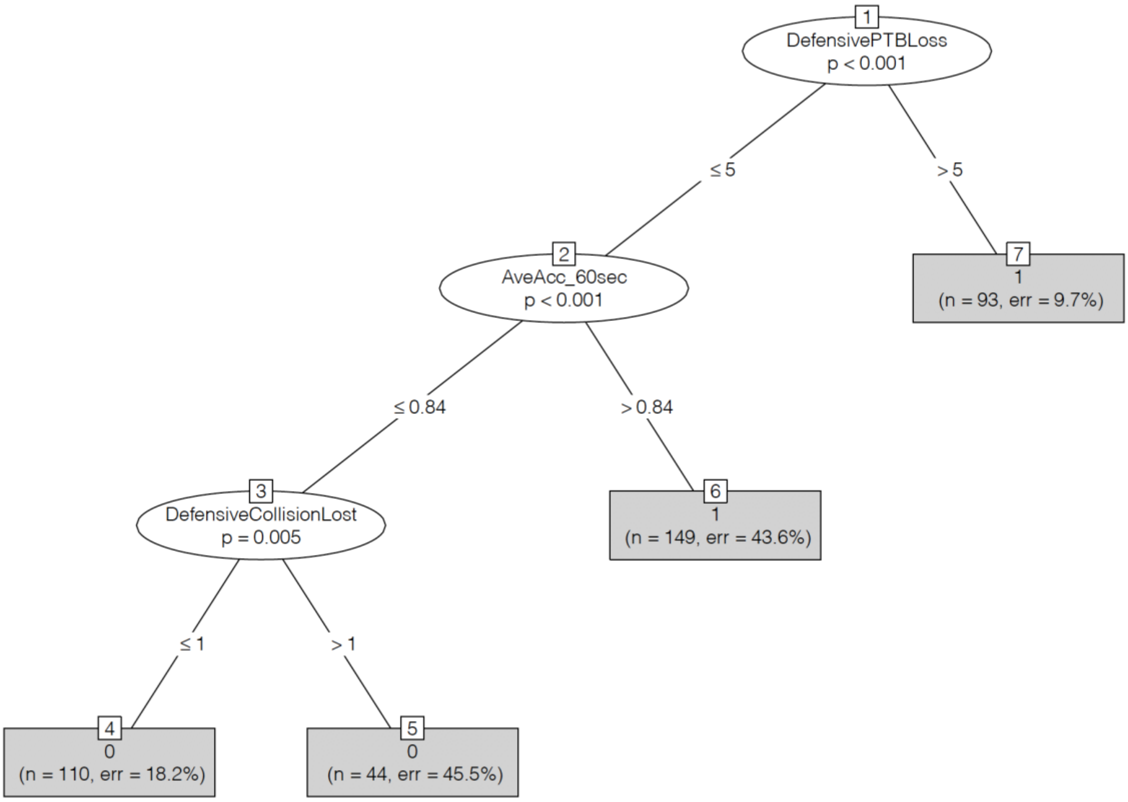

Figure 2. The conditional inference tree showing the classification of levels using the identified important variables for forwards.

Note Numbers in the square boxes denote the node number. 0 = Academy match-play, 1 = European Super League match-play. n = the number of observations in each terminal node

err = error percentage i.e., the percentage of the observations that do not meet the overall classification. PTB = play-the-ball, AveAcc_60sec = peak 60-second average absolute acceleration and deceleration.