

Importance of fundamental movement skills to predict technical skills in youth grassroots soccer: A machine learning approach

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This study determined the contributors to soccer technical skill in grassroots youth soccer players using a machine learning approach. One hundred and sixty two boys aged 7-14 (Mean \pm SD = 10.5 \pm 2.1) years, who were regularly engaged in grassroots soccer undertook assessments of anthropometry and maturity offset (the time from age at peak height velocity (APHV)), Fundamental Movement skills (FMS), perceived physical competence, and physical fitness and technical soccer skill using the university of Ghent (UGent) dribbling test. Coaches rated player's overall soccer skill for their age. Statistical analysis was undertaken, using machine learning models to predict technical skill from the other variables. A stepwise recursive feature elimination with a 5-fold cross-validation (RFECV) method was used to eliminate the worst performing features and both L1 and L2 regularisation were evaluated during the process. Five models (linear, ridge, lasso, random forest, boosted trees) were then used in a heuristic approach using a small subset of suitable algorithms to achieve a reasonable level of accuracy within a reasonable time frame) to make predictions and compare them to a test set to understand the predictive capabilities of the models. Results from the machine learning analysis indicated that total FMS score (0-50) was the most important feature in predicting technical soccer skill followed by coach rating of child skill for their age, years playing experience and APHV. Using a random forest, technical skill could be predicted with 99% accuracy in boys who play grassroots soccer, with FMS being the most important contributor.

Keywords: Motor Skill; Talent Identification; Children; Football; Motor Competence

Introduction

Soccer remains the most popular sport in the world with over 265 million players engaged in the sport from grassroots levels up.¹ The majority of this engagement comes via grassroots soccer which FIFA define as recreational soccer taking place predominantly in children from the age of 6 years on to promote mass participation in the sport.² This definition of grassroots soccer was employed in the current study. Grassroots soccer provides a means to engage in physical activity to promote health in children, but also provides the foundation and pathway to more specialised soccer performance via long term athlete development (LTAD) and talent development programmes employed by professional soccer academies and national governing bodies in various countries across the world.^{3,4} Within such programmes there has traditionally been a focus on measuring physical fitness as predictors of soccer potential^{5,6,7,8,9} and the use of physical fitness as a key driver of selection or deselection in junior academy football.¹⁰

Such an approach ignores the fact that development of soccer related motor ability is essential for success in soccer.¹¹ This is particularly the case for youth players where skill development is a key determinant of success in the sport.¹² It has consequently been recognised that coaches need to consider potential talent from a multidimensional standpoint.¹³ Recently, there has been an emerging interest on the importance of fundamental movement skills (FMS) play in the development of soccer related talent in children,^{14,15,16,17} with this aforementioned work^{14,15,16,17} suggesting that development of FMS is important in development of technical soccer skill.¹⁴ FMS are the basic motor skills that form the foundation of specialized skills needed to engage successfully in sports, games, dance and other contexts of physical activity and are considered as the foundation for subsequent sports skills.¹⁸ Importantly, the development of FMS are a feature of governing body coaching awards in soccer.^{3,4} However, despite the theoretical basis suggesting that children with better FMS will

perform better in sports, there appears to be a theory-practice gap in coaching behaviour and practice from grassroots to elite levels of youth soccer.¹⁹

Research in the last three years has emerged which suggests FMS are key prerequisites of soccer skill in children and youth. For example, Jukic et al.¹⁵ reported that children classified as first team players had better FMS, but similar physiological fitness, than those classed as second team players in a small sample (N=23) of 9–10-year-olds. Kokstejn et al.¹⁶ also demonstrated that the relationship between physical fitness and soccer dribbling skills was mediated by FMS in a sample of 40 elite Czech youth players. More recently, Duncan et al.¹⁴ reported that FMS and perceived competence mediated the effect of fitness on technical skill in soccer (comprising dribbling, passing and shooting) in a sample of 70, 7-12 year old boys. Duncan et al.¹⁴ suggested that focusing on physical fitness, without an emphasis on FMS and perceived competence in FMS, is likely to be less effective in the development of technical ability in grassroots soccer.

Despite interest in how factors other than physical fitness, such as FMS, might contribute to soccer performance, only one of these studies¹⁴ considered psychological variables where perceived ability was identified as a key variable in the study of soccer-related skill development.¹⁶ There are also other key variables that have been related to soccer skill development in the literature, such as quartile of birth,²⁰ maturation,²¹ years' experience in soccer training²² and coach perception of player skill²³ which have either only been considered in isolation in the literature or have not been considered alongside FMS, perceived ability and physical fitness in explaining technical skill in soccer. Machine learning approaches offer potential to address this multidimensional issue as machine learning is better at handling large amounts of input variables.²⁴ Such machine learning approaches have been used in the context of soccer performance in predicting winning/losing,²⁴ and have been successful in predicting injury¹⁷ and physical performance⁹ in youth soccer. There is robust evidence demonstrating use of machine learning to predict playing position from in-game behaviour in professional players.²⁵ However, to date, the use of machine learning approaches to predict

performance in youth soccer is relatively sparse. Based on a Pubmed search at the time of writing, only four studies using machine learning in youth soccer have been published and none have examined prediction of soccer skill.^{26,27} Machine learning methods such as neural networks and random forests are capable of discovering multidimensional and non-linear patterns in data.⁹ The present study therefore sought to determine the contributors to soccer technical skill in grassroots soccer players aged 7-14 years using a machine learning approach.

Methods

Participants

One hundred and sixty two boys aged 8-14 years (Mean \pm SD of age = 10.5 \pm 2.1 years, height= 145.1 \pm 14.8cm, and body mass = 38.0 \pm 11.4kg) who were regularly engaged in grassroots soccer participated in the study following institutional ethics approval [Coventry University Ethics Committee: P131207], informed parental consent and child assent.

To be eligible to participate, children had to be aged between 7 and 14 years and registered (and playing) with a grassroots soccer club with at least 1 years playing experience prior to taking part and including participation in training and organized fixtures against other grassroots teams within the County FA structure in England. Eligibility criteria also stipulated that participants had to be currently training and playing in grassroots football with a minimum of one training session and one match per week, as this is the common minimum standard for grassroots football in England. Mean \pm SD of years playing experience for the sample was 4.3 \pm 2.4years. Participants in the current study were engaged in two-to-three grassroots football sessions per week, including one organised fixture against another grassroots soccer club within the same County FA. Participants were recruited from junior grassroots clubs (n=4) within Birmingham County FA via contact with club officials. Players then volunteered to participate, providing they were eligible. In regard to age band distribution, participants were

from the following age bands under 8 (n=24), under 9 (n=19), under 10 (n=36), under 11 (n=39), under 12 (n=19), under 13 (n=14), under 14 (n=9).

Procedures

All assessments took place over two days, separated by 24 hours. On the first day of assessment psychometric questionnaires were completed, followed by anthropometric assessment, assessment of FMS and fitness. This was followed on the second day by technical skill assessment. All assessment was conducted by trained researchers and the participants' soccer club coaches were not involved in any way. Prior to participation parents also provided information regarding quartile of birth to account for potential relative age effects in subsequent analysis.²⁸ Assessment (with the exception of anthropometry and self-report methods) took place on a 3G synthetic astroturf pitch as is typically used for grassroots football in the UK. During the assessment period environmental conditions were stable with no rain, temperature between 17-19°C, and wind speed of 2mph which is considered 'calm' according to the MET Office.²⁹

Anthropometry and Maturity Offset

Stature (cm), sitting height (cm) and body mass (kg) were assessed to the nearest 0.1cm and 0.1 kg using a SECA anthropometer and weighing scales (SECA Instruments Ltd, Hamburg, Germany), respectively. The Moore et al prediction equation was used to determine maturity offset using measures of height and body mass as a marker of biological maturation.³⁰

Fundamental Movement Skills

Fundamental movement skills (FMS) were assessed using the TGMD-3.³¹ The following skills were selected: run, jump, hop, overhand throw, underhand throw, and catch to

reflect a balance of locomotor and object control skills, without the inclusion of kick to avoid confounding the assessment of FMS and technical soccer skills. This is congruent with recent research examining the utility of FMS in soccer.¹⁴ Each skill is comprised of 3-4 behavioural components, and skill mastery on the TGMD-3 requires each component to be present. For example, for the run skill, the behavioural components are: 1) Arms move in opposition to elbows with elbows bent, 2) brief period where both feet are off the ground, 3) Narrow foot placement landing on heel or toe, and 4) Non-support leg bent to approximately 90 degrees.

Trials of each skill were video recorded (Sony Handicam CX405b, Sony, UK) and subsequently edited into single film clips of individual skills with Quintic Biomechanics analysis software v21 (Quintic Consultancy Ltd., UK). Scores from two trials were summed to create a total FMS score (scored 0-50) following recommended TGMD-3 test administration guidelines.³¹ Two experienced FMS researchers analyzed the video clips after training in two separate 2–3-hour sessions by watching videoed skills of children's skill performances and rating these against a previously rated 'gold standard' rating. Congruent with prior research,³² training was considered complete when each observer's scores for the two trials differed by no more than one component per trial from the instructor score for each skill (>80% agreement).²⁸ We performed inter- and intra-rater reliability analysis for all skills between the two raters on 10% of all the videos. Intraclass correlation coefficients for inter and intra-rater reliability were .92 and .98 respectively, implying satisfactory inter- and intra-rater reliability.

Perceived Competence

The Perceived Physical Ability Scale for Children (PPASC) was used to assess perceived competence.³³ The PPASC is a valid and reliable tool for children of the ages taking part in this study which assesses physical self-efficacy.³³ It is a 6-item measure comprising questions reflecting strength and coordinative abilities. Items are structured in response scales with a 1 to 4 format. Labels are attached to each point of the response scales to assist giving meaning

to the items for the children. For example, scores for the first item range from 1 (I run very slowly) to 4 (I run very fast). The children were asked to think of themselves when playing/training in soccer and were asked to choose one of the four sentences that best represented their perceived ability. Administration followed recommended guidelines²⁹ with a potential score of 6-24, where higher scores represented a high self-perception of physical competence.

Physical Fitness

Two measures of physical fitness were computed: 15m sprint time and standing long jump. Each participant's 15-meter sprint time was assessed using infra-red timing gates (Fusion Sport, Coopers Plains, Australia) with sprint time converted to speed in m/s. Standing long jump was determined as distance from take-off to the back of the closest heel on landing and was assessed using a tape measure. For sprint speed and long jump, the best of two trials (fastest speed in m/s; longest jump in centimetres) was selected for analysis. Intraclass correlation coefficients for the two measures of fitness were .9 for the 15m sprint, .94 and for the standing long jump, indicating good reliability. Testing was completed individually, and we calculated a Z-score for each of our three measures of fitness and summed these Z-scores to create a composite product measure of physical fitness. The use of a composite Z-score was employed as a means to bring together three aspects of physical fitness as a theoretical concept as per guidelines for use of composite variables.³⁴ Such a process has also been used previously in the context of youth football performance.¹⁴

Technical Skills

The university of Ghent (UGent) dribbling test was employed as a measure of technical soccer skills in this study. This test was chosen given its documented reliability in children,³⁵ where the reliability of other available soccer skill tests has not been demonstrated.³⁶ All

testing took place on a grass surface with participants wearing soccer boots and was completed with the official ball size for age band (Size 3 for U8-U9, Size 4 for U10-14) as recommended by the Football Association. Testing was completed individually by the participants to minimise any peer pressure to perform as previously described by Vandendriessche et al.⁷² Participants completed a set circuit with four left and four right turns at different angles with a distance between cones ranging between 1 and 2.2 metres.³⁷ Following familiarisation and a practice trial each participant undertook two attempts at the test. Each test was performed as quickly as possible in two steps per test: the first step was made without the ball and the second step with the ball. The time of each attempt was measured to the nearest 0.01 seconds with a handheld stopwatch. The time taken to complete the dribbling course without the ball was deducted from the time with the ball to give a skill differential reflecting dribbling skill (labelled as Z_UGentBall in the machine learning analysis and supplementary material). This is the outcome variable of interest from this test reflecting dribbling ability. This test has a good reliability for the dribbling with the ball component in children.³⁵

Coach Rating of Player Skill

Prior to assessment, the coaches of the participants were asked to rate the football skill of each child. The stem question 'Please rate player [name of player] in terms of their ability relative to their current age group' on a scale of 1-10 with 1 being poor and 10 being excellent., was posed to the coaches. Each coach was asked questions with the same stem question but specifically asking them to rate the players' technical football ability (labelled as 'coach rating of technical skill'), social ability (labelled as 'coach rating of social skill'), physical ability (labelled as 'coach rating of physical skill'), the effort made by players in training and games (labelled as 'coach rating of effort') and their overall football ability (labelled as 'coach rating of player skill' and overall coach rating for their age (labelled as 'coach overall rating for age'). Similar assessment methods have been used by coaches to rate the skill ability of youth

players in prior work and have demonstrated reliability in rating and validity in predicting soccer skill.²³

Birth quartile

Recognising that the relative age effect (RAE) has been demonstrated in both FMS³³ and soccer skills,²⁰ each participant provided dates of birth which were subsequently grouped into quartile of birth (starting at the school year cut-off date of 1st September) and subsequently labelled: Q1, Q2, Q3, Q4) with Q1 corresponding to the period of 1st September to 31st November, Q2 from 1st December to 30th February, Q3 from 1st March to 31st May, and Q4 from 1st June to 31st August, as per prior studies in this topic.³⁸

Statistical Analysis

The statistical analysis approach undertaken sought to train machine learning models to predict the output variable of interest (Technical soccer skill via the UGent dribbling test). The feature correlation matrix and the UGent dribbling test (Z_UGentBall) distribution analysis that were used to examine the influence of multiple input methods and for eliminating collinear features are presented in Supplementary Figures 1, 2 and 3. A 80%/10%/10% training/validation/test split per age group was employed. The data set and its feature transformation were normally distributed (See Supplementary Figures 2-3). The Gaussian distribution test data for the UGent dribbling test (Z_UGentBall) is presented as supplementary Figures 3 and 4 at the end of the manuscript. As a consequence, a parametric modelling approach was appropriate where UGent dribbling test performance was predicted from 11 other variables; chronological age, years playing experience, quartile of birth, height, body mass, leg length, APHV, 15m sprint time, perceived competence, total FMS and coach rating of player skill. To help determine the best performing predictor variables a recursive feature elimination method was used to eliminate the worst performing features and any collinear

features using linear regression (See Supplementary Figure 4). Five models (linear, ridge, lasso, random forest and boosted trees) were then used in a heuristic approach to analyse the predicted values against the test set to better understand their potential predictive capabilities (Please see Supplementary Figures 4-7 for penalty parameters that were used). The initial experiment produced an accuracy range of baseline scores from 34% to 66% (See Table 1). For the ridge regression model the penalty value of 100 was used (See supplementary Figure 5). For the lasso regression model a penalty value of 0.1 was used (See supplementary Figure 7). The objective of the heuristic approach was to analyse the dataset using a small subset of suitable machine learning algorithms using a stepwise recursive feature elimination with a 5-fold cross-validation (RFECV) method to achieve a reasonable level of accuracy within a reasonable time frame. All analysis was performed in Python (Python Software Foundation. Delaware, USA). The approach used provides a reference point from which to compare various machine learning algorithms and a means to measure performance changes and has been proven effective in other domains related to human movement.³⁹

Results

Features in the dataset were selected to avoid correlated features. Correlated features were removed to improve the model's generalisation ability⁴⁰. A correlation matrix depicting pairwise significance of the correlated features is presented in Supplementary Figure 1 (Leg Length, Mass, UGent with ball, Run, Hop, Catch, Object Control Score and Hoff Passing Test were correlated). A subset of the correlated features with the lowest average correlation were included with the uncorrelated features resulting in 'Age on test' and 'UGent Fastest with ball' being included in the machine learning model. Initially, a first test was run using a linear regression model using accuracy as a measure of prediction success with a random split of the initial dataset between training data set and test data set. The linear regression model was

the first model used for analysing the correlation, identifying both positive and negative correlations, and for evaluating the validity and usefulness of the simple predictive model. We used a random 70%/15%/15% training/validation/test split respectively. The model produced an initial accuracy level of just over 50%. However, when trying to optimize the model it was overfitting and predicting poorly. Hence, we subsequently employed a random 80%/10%/10% training/validation/test split from each age group for testing, which resulted in a significant improvement in the predictive performance. To improve the machine learning model instead of randomising the choice of the test-set data throughout the entire dataset, the machine learning models were set to extract a certain percentage of data points from the test-set (e.g., 10% or 20%) from each chronological age band (e.g., under 11s, under 12s, etc). This process was undertaken as when randomly selecting training samples from the entire dataset some age groups are under-represented or not represented in the training at all. By making sure that each age group is equally represented in the training it ensures that the modelling includes the whole sample and, as a consequence, independently represents the whole sample. Randomization where there may be possibility that some age groups are under-represented or not represented may be a valid reason for obtaining a model with low prediction accuracy, hence why we chose to ensure all age bands were represented in the data. After implementing the described split of the original dataset into training and test according to all the age band values there was a significant improvement in prediction accuracy to above 90% irrespective of machine learning technique that was employed. A 5-fold cross validation approach was employed based on the sample size and the distribution of samples across the age bands to further help verify the validity of the results (See supplementary Figure 8).

Following determination of prediction accuracy, a variable importance analysis was conducted to determine the most important features included in the dataset. The results are represented in Figure 1 and suggest that "Total FMS" was the most important feature closely followed by "Coaches Overall Rating for Age", "Playing Experience", and "APHV". The

participant's "Chronological Age on Test" and "Birth Quartile" were the least important features to account for the variability in participants soccer performance.

Figure 1 Here

Results from machine learning training

Table 1 below presents the prediction accuracy using different machine learning techniques when applying a randomised training and testing approach without accounting for age band within the sample. Table 2 below presents the prediction accuracy when including each age band in the machine learning training model to predict soccer skill.

Table1 Here

Table 2 Here

Discussion

This study extends understanding related to technical development in grassroots soccer. This is the first study to evaluate how different machine learning models predict the participant's soccer skill performance (UGent dribbling test) in grassroots youth soccer. The present study identifies important impact factors including FMS, Coaches Overall Rating for Age, Years Playing Experience, and APHV in predicting technical soccer skill in youth soccer. FMS was

the most influential variable in predicting technical skill in youth grassroots soccer. A Random Forest achieved 98.6% prediction accuracy with FMS, Coaches Overall Rating for Age, Years Playing Experience, and APHV as predictors.

A key strength of this study is the use of machine learning. Machine learning, a branch of artificial intelligence, is becoming more popular as a modelling technique to understand various aspects of soccer performance. This has included predicting injury in youth players¹⁷ and predicting physical performance based on anthropometric variables in youth soccer.⁹ The benefit of machine learning is in using mathematical models able to discover multidimensional linear and non-linear patterns in data in an unbiased manner. We recognise that the present study is exploratory in examining how technical skill might be explained by other variables that are often cited as important in youth soccer development. There exists robust research using machine learning techniques alongside performance analysis data from videos of games in professional leagues.²⁵ One outcome of this aforementioned work is a suggestion that machine learning techniques might be applied to youth teams to detect and identify players with particular qualities.²⁵ The current study aligns with this assertion, albeit different in nature to Garcia-Aliaga et al.²⁵, in that we use machine learning techniques to identify some of the predictors that explain technical skill in youth grassroots soccer players.

Total FMS score was the most important predictor of technical skill in the present study. Such a finding agrees with recent research.^{14,15,16} The results of the current study would also support the assertions of the Athletic Skills Model in regard to the importance of FMS and might suggest soccer coaches at grassroots levels may benefit from refocusing away from solely concentrating on soccer specific practices during training and focus more broadly on the movement skills that form the foundation of technical skill.¹⁸ That is not to say soccer specific practices cannot also develop some FMS but the Athletic Skills Model¹⁸ highlights that a sole focus on sport specific practice only, will not develop the broad base of movement skills that underpin sport specific skills. Once the player is proficient in those FMS then a sole sport specific focus may be beneficial.¹⁸ It is also perhaps not surprising that playing experience and

the coach's rating of player skill were the 2nd and 3rd most important predictors of technical skill as prior work has demonstrated that coaches can successfully evaluate player performance²³ and the role of experience in developing skill is well known.⁴¹ It is however perhaps surprising that perceived competence was not as important a contributor to technical skill compared to some of the other variables in our model. Prior work has posited perception of competence as a key facilitator of movement skill development⁴² and soccer skill development in youth.¹⁴ The results of the current study in this respect suggest that perceived competence may not be as important as actual motor competence and experience in the development of technical skill

The current study has limitations. The participants were all boys and, therefore, the conclusions drawn here should not be inferred for girls. Future work on this topic should focus on girls in particular, especially given the increasing numbers of girls participating in grassroots soccer. Longitudinal research examining the trajectories of development of FMS, technical skills and related factors would also be useful alongside use of machine learning models to predict soccer talent in children and youth. While we used a measure of technical skill as our outcome variable in the present study, a useful next step would be to establish how the variables used as predictors in the current study might relate to in-game soccer performance.

Conclusions

This study demonstrates that machine learning models can predict technical soccer skill in boys who play grassroots soccer with up to 99% accuracy, with FMS being the most important contributor in addition to coach rating of skill, playing experience and APHV. We are not suggesting coaches should depart from soccer specific practices. However, coaches should not solely focus on sport specific practice if their child athletes have not yet become proficient in their FMS, as FMS provide the foundation for subsequent sport specific skill development. The machine learning analysis presented in the present study confirms this assertion.

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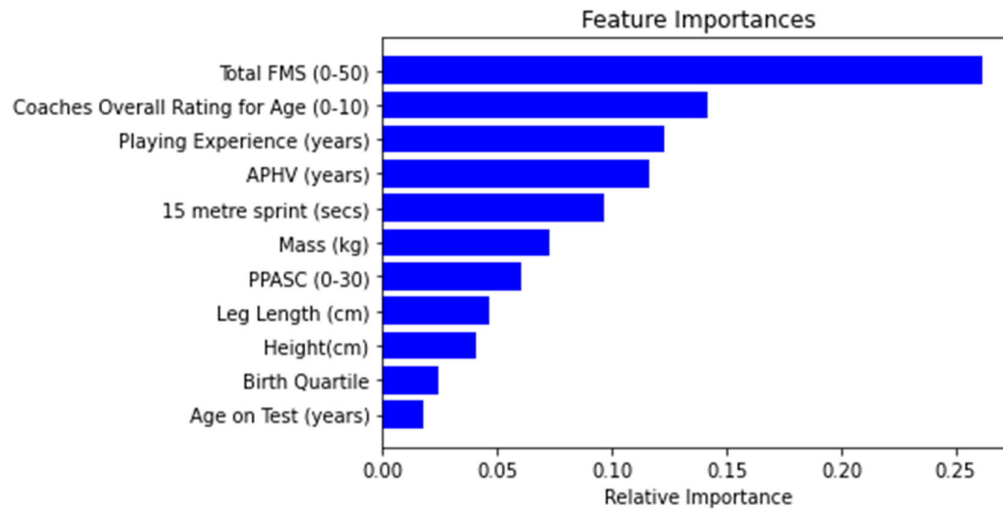


Figure 1. Feature importance analysis of the dataset (higher relative importance indicates a more important feature in the data set in predicting technical skill)

Model	Prediction Accuracy
<i>Linear Regression</i>	56.9%
<i>Ridge Regression</i>	47.8%
<i>Lasso Regression</i>	34.1%
<i>Random Forest</i>	67.7%
<i>Boosted Trees</i>	66.1%

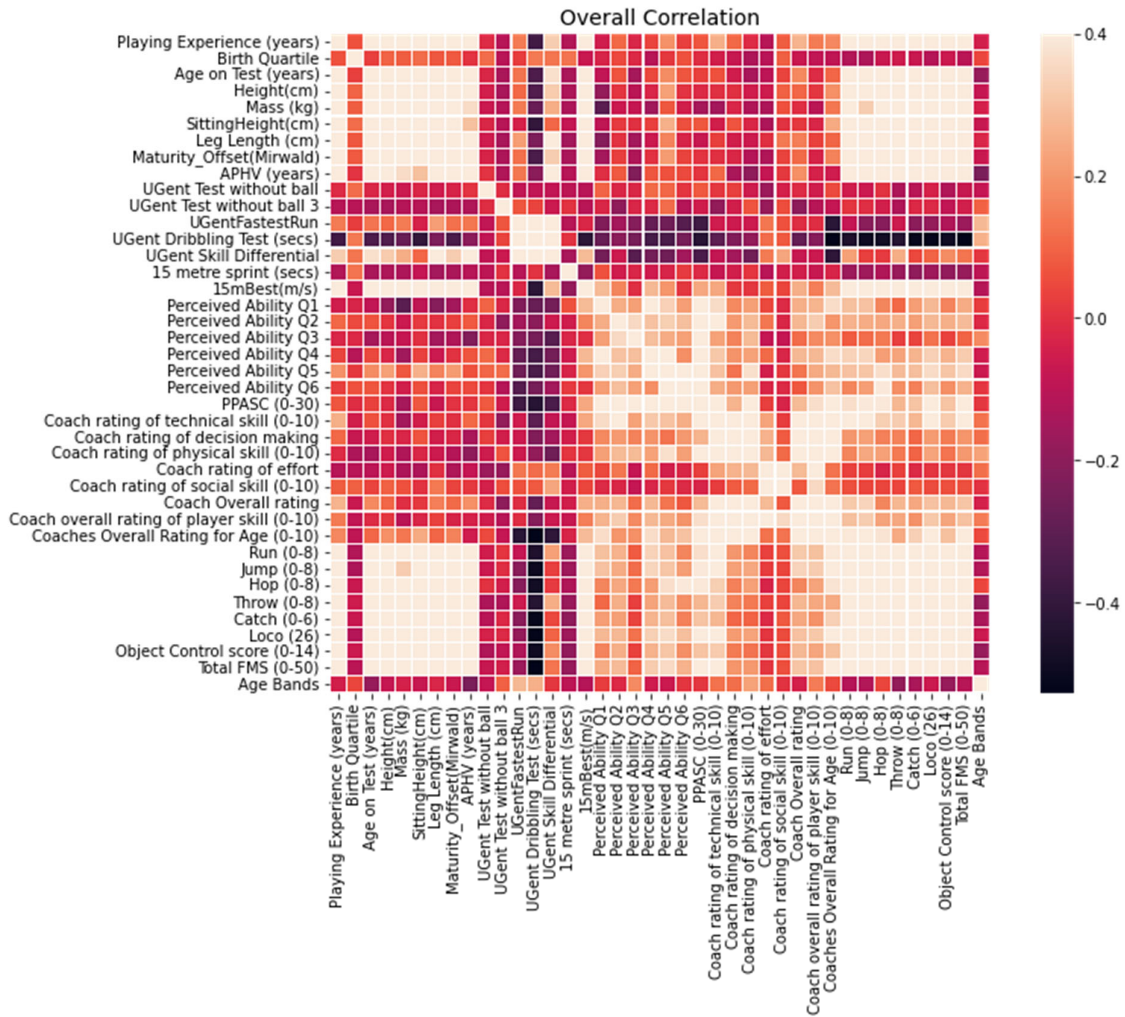
Table 1: Prediction accuracy using different machine learning techniques when applying a randomised training and testing approach without accounting for age band within the sample.

Model	Prediction Accuracy
<i>Linear Regression</i>	91.9%
<i>Ridge Regression</i>	91.2%
<i>Lasso Regression</i>	94.1%
<i>Random Forest</i>	98.6%
<i>Boosted Trees</i>	96.1%

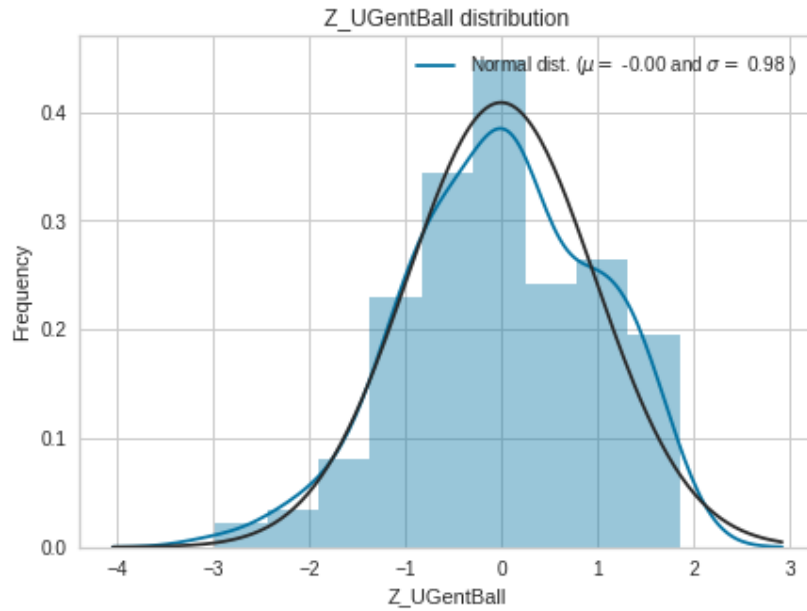
Table 2: Prediction accuracy when including each age band in the machine learning training model to predict soccer skill

Supplementary Figures

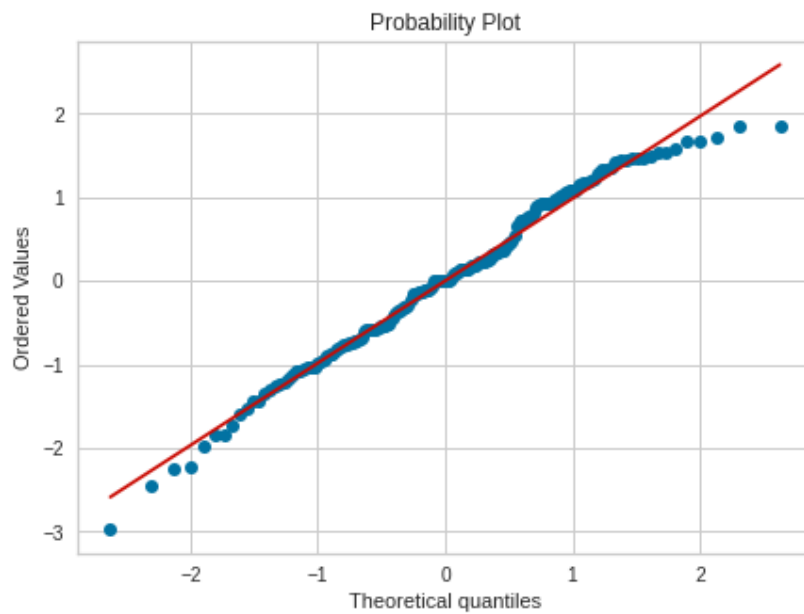
Supplementary Figure 1. Correlation matrix of collinear features.



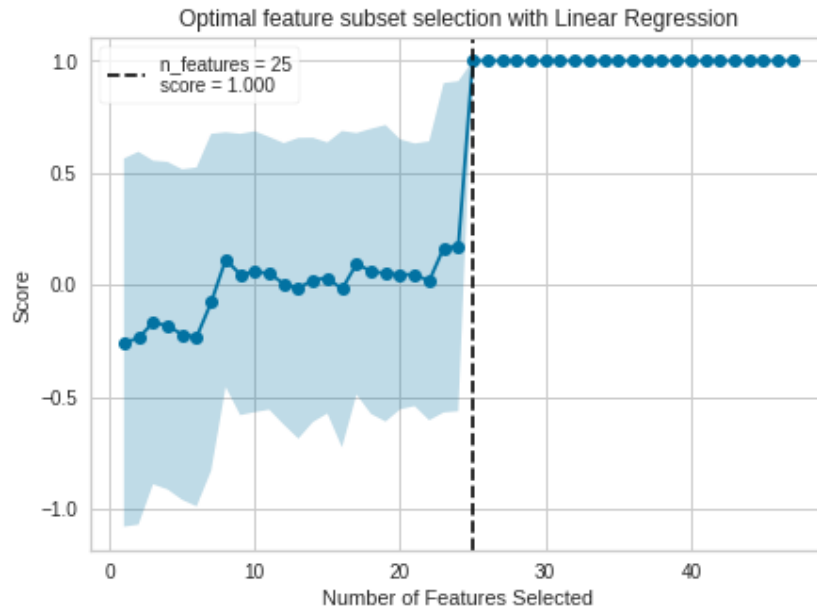
Supplementary Figure 2. Distribution for the Z_UGentBall test showing bell shaped curve with a skewness of -0.256941 and kurtosis of -0.237157, indicating a normal univariate distribution.



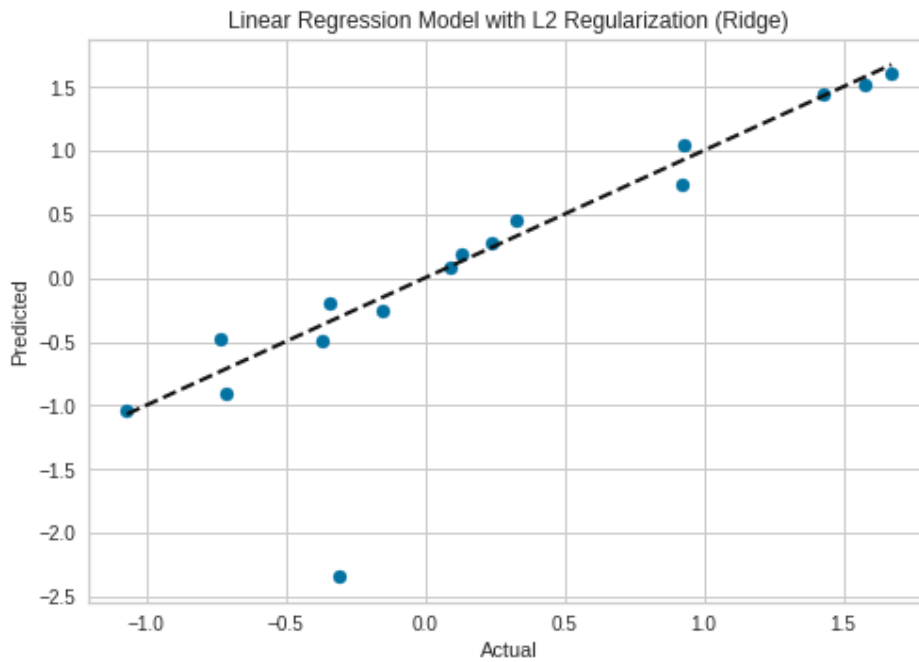
Supplementary Figure 3. Normal Q-Q plot for Z_UGentBall.



Supplementary Figure 4. The plot shows the number of features in the model along with their cross-validated test score and variability and visualises the selected number of features (predicting the Z_UGentBall value). The shaded area represents the variability of cross-validation (default 5-Fold), one standard deviation above and below the mean accuracy score drawn by the plot.



Supplementary Figure 5. The plot from the ridge regression model with a penalty parameter that is equivalent to the square of the magnitude of the coefficients ($\alpha=100$) in the first experiment showing the predicted Z_UGentBall values vs the Actual Z_UGentBall values.

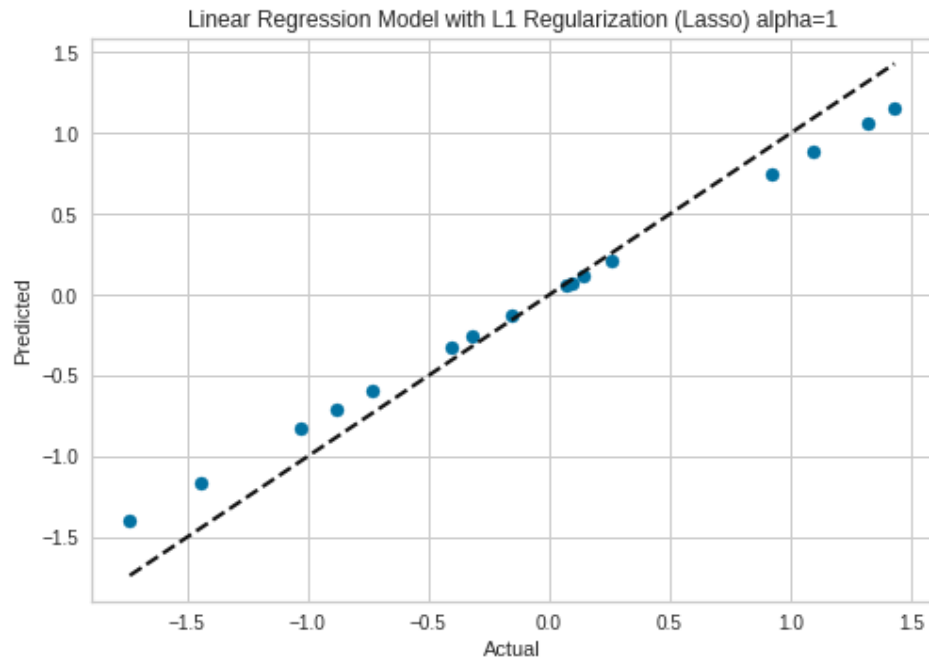


The following procedure was followed to help find the L2 penalty value (α)

1. Split the dataset into training, validation and testing (80%/10%/10%)
2. Split the training data into 5 equal folds
3. Used an alpha value of 10 to train 4 folds to evaluate the model and use the 5th fold as validation data and retrieve the performance score of the model
4. Repeat earlier step 4 times and on each run use a different fold for validation and record the scores
5. Calculate the average performance score of the 4 runs.

Repeat the Steps 1 to 5 with a new alpha value (+10) until the average predicted performance score is lower than the previous run.

Supplementary Figure 6. The plot from the lasso regression model with a penalty equivalent to absolute value of the magnitude of coefficients ($\alpha=1$) shows that it over penalises the model. The predicted Z_UGentBall values vs the Actual Z_UGentBall values are shown below.

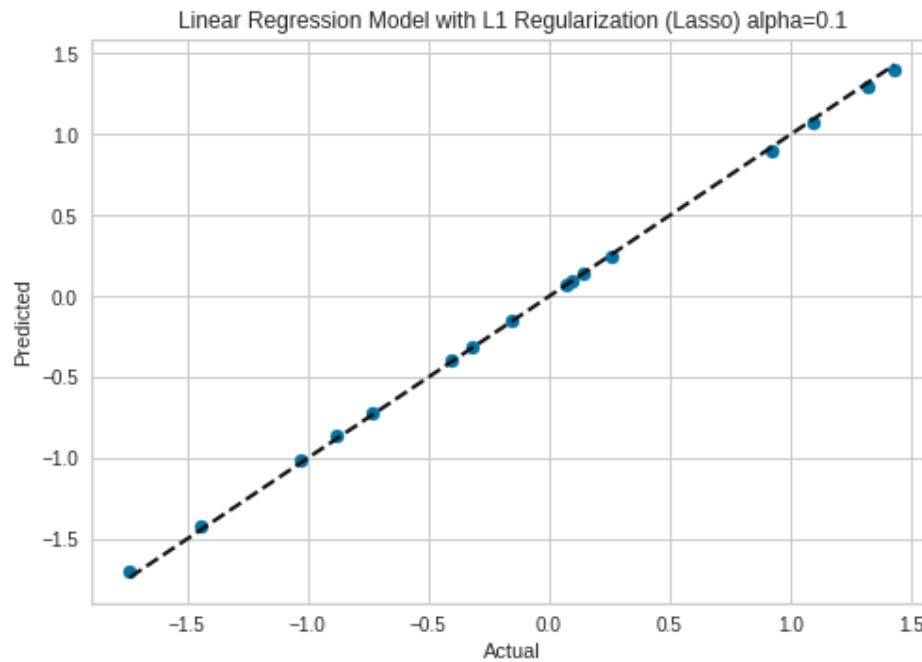


The following procedure was followed to help find the L1 penalty value (α)

1. Split the dataset into training, validation and testing (80%/10%/10%)
2. Split the training data into 5 equal folds
3. Used an alpha value of 0.1 to train 4 folds to evaluate the model and use the 5th fold as validation data and retrieve the performance score of the model
4. Repeat earlier step 4 times and on each run use a different fold for validation and record the scores
5. Calculate the average performance score of the 4 runs.

Repeat the Steps 1 to 5 with a new alpha value (+0.05) until the average predicted performance is lower than the previous run.

Supplementary Figure 7. The plot from the lasso regression model with a penalty equivalent to absolute value of the magnitude of coefficients ($\alpha=0.1$). The predicted Z_UGentBall values vs the Actual Z_UGentBall values are shown below.



The following procedure was followed to help find the L1 penalty value (α)

1. Split the dataset into training, validation and testing (80%/10%/10%)
2. Split the training data into 5 equal folds
3. Used an α value of 0.1 to train 4 folds to evaluate the model and use the 5th fold as validation data and retrieve the performance score of the model
4. Repeat earlier step 4 times and on each run use a different fold for validation and record the scores
5. Calculate the average performance score of the 4 runs.

Repeat the Steps 1 to 5 with a new α value (+0.05) until the average predicted performance is lower than the previous run.

Supplementary Figure 8. The line plot used in the cross-validation approach, employed to model the random forest regression model. The result indicates that $k=5$ produced a 98.6% accuracy estimate for use in this data set across the age bands.

