The Elusive Features of Success in Soccer Passes: A Machine Learning Perspective

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Abstract: Machine learning has in recent years been increasingly used in the soccer realm. This paper focuses on investigating the factors influencing pass success, a chief element in team performance. Decision tree techniques are used aiming to identify which features are the most important in pass success. This process is applied to a data set of 13 matches of the men's French "Ligue 1". Two experiments are conducted using different feature sets: one containing the positional data and Voronoi area off all players, the second considering only the ball carrier and closest teammates and opponents. The results obtained with the first feature set indicate that the relative importance of features is match dependent and somehow related to teams' formation and players' tactical mission. The second feature set, being more directly related to the passing process, provided a more consistent ranking of features. Features related to the interaction with the opponent standout. Low precision and recall values show that the features and factors leading to pass success are in fact elusive.

1 INTRODUCTION

We currently live in the *Digital Age* (Techopedia, 2017), where new technologies emerge and take their place in society. Artificial Intelligence (AI) is part of this contribution to the society and became one of the biggest trends in the world today. The recent popularity of AI can be attributed to the following three factors: the growth of *Big Data*, easy access to computing power, and the development of new AI techniques (Obschonka and Audretsch, 2020).

In sports, soccer being no exception, AI has been applied in several areas. Examples of its use are the evaluation of player performance, team coordination and prediction of the *expected goals* (estimating the quantity and quality of goal opportunities a team has created in a match). With the introduction of AI in soccer, teams are able to discover new potentials and achieve new and ambitious goals, especially in increasing team competitiveness, decision making, and performance assessment. Albeit this interest and potential, the technology is still immature and needs improvement (Ks, 2020).

In the game of soccer, team's performance is strongly related to the way the ball carrier interacts with his teammates via passes. There is a multiplicity of indicators of passing performance that have been identified, notably: the zone of the field, the trajectory of the receiver, and the space where the ball is received (Cordon et al., 2020).

This paper aims to contribute to this enquiry on the indicators of pass success using AI techniques. Notably, it uses a computational approach based on AI techniques (decision tree) that processes real data in order to quantitatively assess the importance of features (e.g., location of players, available area) for pass success. The novelty on the paper is that the focus is not on investigating techniques for a better prediction of pass success but rather to understand, using existing techniques, what are the factors that contribute more strongly for pass success.

This paper is structured as follows: next section describes related work on AI and soccer match annotation; Section 3 presents the data sources used; Section 4 addresses the methods used to process the data and compute the importance of features; the results obtained are presented in Section 5; Final Remarks and Future Work close the paper.

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2 LITERATURE REVIEW

Soccer analytic companies have only recently started to analyse so-called big data (e.g., high-resolution video, tracking player movement and possession information). At the same time, only recently have major advances been made in machine learning, producing techniques that can handle these new high-dimensional data sets. The amount of data available in soccer has increased with different techniques to collect a large amount of data such as sensors, GPS, and computer vision algorithms. This helps the use of machine learning in soccer in its various areas such as in recruiting and analysing the performance of players, in selling tickets bringing fans closer to their club, and also in helping decision making that affects an entire area of a club.

2.1 Machine Learning in Soccer

Machine learning is the field of study that focus on how computers learn to perform a task without being explicitly programmed to do it. It can be defined as a set of methods that can automatically detect patterns in data to predict future data or to perform other types of decision making (Murphy, 2012). Machine learning is beginning to play an essential role within the following branches of computing: data migration, hard-to-program applications, and custom software applications (Mitchell, 1997). Machine learning algorithms generally fall into two paradigms: supervised learning and unsupervised learning (Stimpson and Cummings, 2014). In supervised learning a “teacher” is assumed to be present, where the correct answers are provided for each situation. Supervised learning techniques build predictive models that learn from a large number of training examples, where each training example has a label that indicates its truth output (Zhou, 2017) – a pair consisting of the input object and an output label value that belongs to a class or is a continuous value.

Machine learning, and AI in general, have been more and more used in the world of soccer not only in performance or tactical analysis, but also in the medical and marketing departments.

One such example outside the tactical field is injury prevention. For example, the study conducted by Rommers et al. (Rommers et al., 2020) who during one season tried to predict the injuries of 734 players aged between 10 and 15 years old from seven Belgian academies. At the beginning of the season a battery of tests were performed to evaluate motor coordination and physical fitness and characteristics (e.g., height, weight, strength, and flexibility). Based on these characteristics, the machine learning algorithm was able to predict injuries and distinguish between serious and light injuries with high accuracy. The application of this type of algorithms also helps coaches in decision making during the game, such as knowing the physical condition of a player and whether or not he should be substituted.

Another example of the application of machine learning in soccer is in analysing player performance. Jamil et al. (Jamil et al., 2021) applied several machine learning algorithms (Logistic Regression, Gradient Boosting, and Random Forest) to classify the performance of professional goalkeepers aiming to distinguish an elite goalkeeper from a sub-elite goalkeeper. The conclusions drawn in this study where that all elite goalkeepers shared the same common characteristics: short distribution, successfully passing and receiving the ball, and not conceding goals. This study suggested that it is the goalkeeper’s skill with his feet that distinguishes elite goalkeepers from the sub-elite.

Another example in the area of performance analysis is the work of Pappalardo et al. (Pappalardo et al., 2019) through a simulator recommendation. The work implemented PlayeRank, a data-driven framework that offers a principled multi-dimensional and role-aware evaluation of the performance of soccer players.

2.2 Match Data and Annotation

Annotations in soccer are an important tool to obtain data from a match. The analysis of soccer matches relies on the annotation of both individual player’s actions (e.g., passes and shoots), athletic performance and team events (e.g., substitutions). Consequently, annotating soccer events at a fine-grained level is an expensive and error-prone task (Barra et al., 2021).

On the other hand, positional data is usually obtained using automated or semi-automated tools that rely on devices such as GPS receivers, cameras and computer vision. One of the more interesting opportunities provided by the availability of position tracking data in soccer is the analysis of tactical behaviour. Tactical behaviour is an important determinant of performance in team sports like soccer, and refers to how a team manages its spatial positioning over time to achieve a shared goal.

3 MATERIALS

The material used in this paper is a database corresponding to annotation and positional data of 13 matches in the French Premier League (Ligue 1). This database contains 563 067 entries and 11 variables. Each entry corresponds to a technical action performed in the match; the variables correspond to player's positioning and other attributes describing the technical action (e.g., a pass). These include the following:

Match (integer)**:** unique game identifier;

Period (1,2): first (1) or second part (2) of the match

Time (decimal, seconds)**:** match time

Team (f, o): team identifier, (f)ocus or (o)pponent

Tactical Mission (class)**:** player's tactical mission (e.g., GK - Goal Keeper, LB - Left back)

x, y (decimal)**:** player's longitudinal (x) and lateral (y) position on the pitch (in meters). The centre of the pitch corresponds to coordinate (0,0)

Voronoi Area (decimal, m^2)**:** player's Voronoi cell area

Event (class)**:** technical action performed (e.g., Pass, Shot)

Distance (decimal)**:** distance from the player holding the ball to the opponent's goal (in meters)

Ball Zone (O, I)**:** if the ball zone is in an (O)utside or (I)nside area

Continuation (0, 1)**:** the ball remains in the team's possession (0) or changes to the opponent (1)

Angle (decimal)**:** angle to offensive goal

In addition to the information pertaining to each event, other annotation information was also used, notably the predominant tactical formation adopted by each team (in Figure 1 a 3-5-2 for the focus team, red, and 4-4-1-1 for the opponent team, blue).

Using these features two experiments were performed. In both experiments all passes (10 332) made in the first half of the 13 games were considered. Of these, only 1 405 (13.6%) were unsuccessful (this unbalanced data represents a challenge for machine learning techniques).

4 METHODS

This section presents the methods used in the experiments: a decision tree to model the outcome of a pass; how the importance of the different features for that outcome is estimated; the use of Voronoi cells as features; the use of cosine similarity to compare matches.

4.1 Decision Tree

Decision tree is a supervised learning method used in classification and regression tasks. The goal is to create a model that predicts the value of a target variable, the output, by learning simple decision rules inferred from data, the features (Pedregosa et al., 2011). Since the decision tree follows a supervised approach, the algorithm is fed a collection of pre-processed data that is used to train the algorithm.

In a decision tree, the top level is called the root, the root gives rise to links to other elements called nodes. A node that has no link is called an end node, otherwise is a decision node (see Figure 3). Decision nodes in the tree correspond to questions that are presented to the data (if a feature variable is larger or smaller than a threshold value). Each edge of the tree corresponds to an outcome of the question and lead to another decision node or to an end node representing a class distribution (i.e., a value of the output). This method is based on algorithms that divide the initial data set into more homogeneous subsets which in turn can be divided into even more homogeneous subsets (de Ville, 2006). The decision tree algorithm works through several aligned *if-else* statements in which successive conditions are checked unless the model reaches a conclusion on the output or a predefined depth of the tree is reached.the cases in the tree concern passes made by players. The Gini impurity metric indicates how well a tree splits the data.

4.2 Importance of Features

The chief assumption in the paper is that the importance of a feature (e.g., x coordinate) can be quantified by its importance in the decision tree. Feature importance is calculated as the decrease in node impurity weighted by the probability of reaching that node (the number of samples that reach the node, divided by the total number of samples). The importance for each feature in a decision tree is then calculated using Eq. 1 (Stacey, 2018).

$$\sigma_j = w_j C_j - w_{left(j)} C_{left(j)} - w_{right(j)} C_{right(j)} \quad (1)$$

σ_j	the importance of node j
w_j	probability of reaching node j
C_j	the impurity value of node j
$left(j)$	child node from left split on node j
$right(j)$	child node from right split on node j

4.3 Voronoi Area

A Voronoi diagram is a partition of a plane into regions close to each of a given set of objects. In the

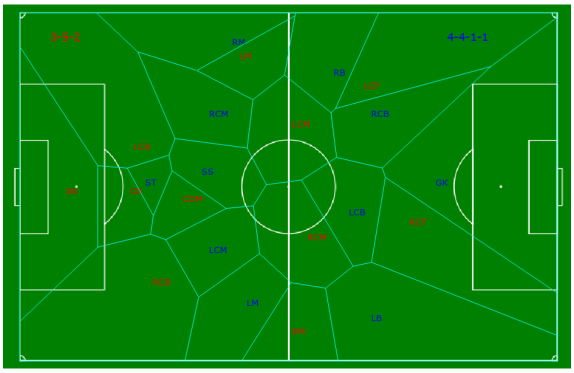


Figure 1: Players' Voronoi diagram.

simplest case, these objects are points in the plane (called seeds, sites, or generators). For each object corresponds one region defined by the points in the plane that closer to that object than to any other.

In invasion sports, the spatial distribution of players on the field is determined by the interaction behavior established at both player and team levels (Fonseca et al., 2013) making Voronoi diagrams a useful tool to analyze matches. In this context, Voronoi diagrams are computed using players' position in the pitch (see Figure 1). Voronoi diagrams may help coaches to see how well the players use space, find new spaces in which to attack, and identify areas in defense that the team leaves open. In this paper player's Voronoi cell area will be used as a feature influencing the success of the pass.

4.4 Comparing Matches

Passes occur within a context: a match. As our study involves different matches, it is thus important to assess quantitatively how (di)similar two matches are. Cosine similarity is a well know method that can be used for this. In order to assess how similar two matches are each match is described by a vector of attributes (say **a** and **b**) and the similarity value $\mathrm{sim}_{\cos}(\mathbf{a},\mathbf{b})$ computed using Equation 2.

$$\mathrm{sim}_{\cos}(\mathbf{a},\mathbf{b}) = \frac{\mathbf{a}\cdot\mathbf{b}}{\|\mathbf{a}\|\|\mathbf{b}\|} = \frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} a_i^2}\sqrt{\sum_{i=1}^{n} b_i^2}} \quad (2)$$

In this paper, three different types of attribute vectors are used to characterise each match:

- Team formation: a match is described by the typical formation adopted by each team. The match from Figure 1 is described by vector

$$[\underbrace{3,5,2,0}_{Focus},\underbrace{4,4,1,1}_{Opponent}].$$

- Tactical mission: a match is described by the tactical mission (e.g., GK, ST) of the players in the pitch

$$[\underbrace{GK,LB,LCB,\ldots,ST,SS}_{Focus},\underbrace{GK,LB,LCB,\ldots,ST,SS}_{Opponent}]$$

  Value 1 is used if a player with that tactical mission is on the pitch, 0 otherwise. The match from Figure 1 is described by vector

$$[\underbrace{1,0,0,\ldots,0,0}_{Focus},\underbrace{1,1,0,\ldots,1,1}_{Opponent}]$$

- Features importance: a match is described by the importance value, σ_i computed for feature i of the decision tree.

$$[\underbrace{\sigma_1,\sigma_2,\sigma_3,\ldots,\sigma_N}_{N features}]$$

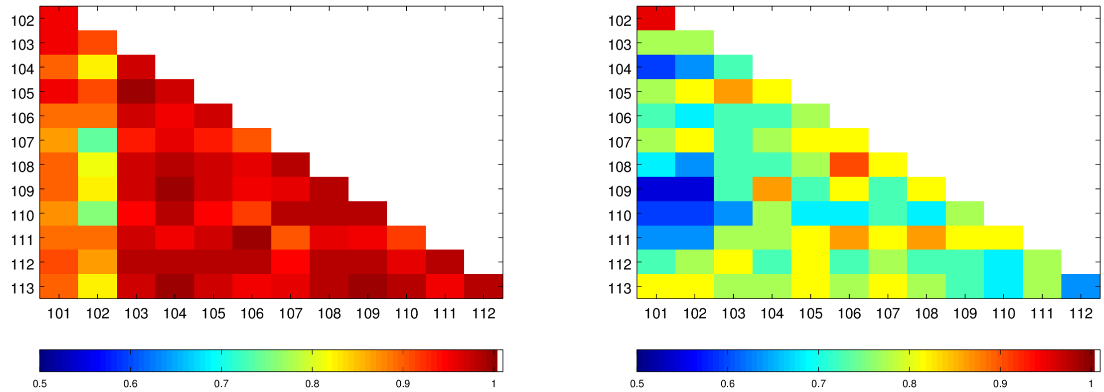
5 EXPERIMENTAL RESULTS

5.1 Match Similarity: Team Formation and Tactical Mission

The similarity of pair of matches according to the teams' formation (tactical mission of the teams' line-up) was computed for all possible pairs of matches as represented in Figure 2. As expected, similarity is typically higher in teams' formation than in tactical mission of the teams' line-up. Tactical mission of the teams' line-up similarity presents a higher variability. For both criteria, matches 101 and 102 present a high similarity between them but low similarity to all other matches. Considering the more discriminatory criteria based on players' line-up tactical mission one finds as the most similar the following pairs of matches: $(101,102)$; $(103-102)$; $(104-109)$; $(106-108)$; $(106-111)$ and $(108-111)$.

5.2 Experiment with Features from All Players

In order to pinpoint the more relevant features for pass success a first experiment was conducted using features (**x**, **y**, and **Voronoi Area**) of all 22 players on the field (66 features in total) and as output value the pass outcome (success or not, **Continuation** in Section 3). Two decision trees were created, one with 6 levels (represented in Figure 3) another with 20 levels.



(a) Teams' Formation. (b) Teams' Player Line-up Tactical Mission.

Figure 2: Cosine similarity between matches.

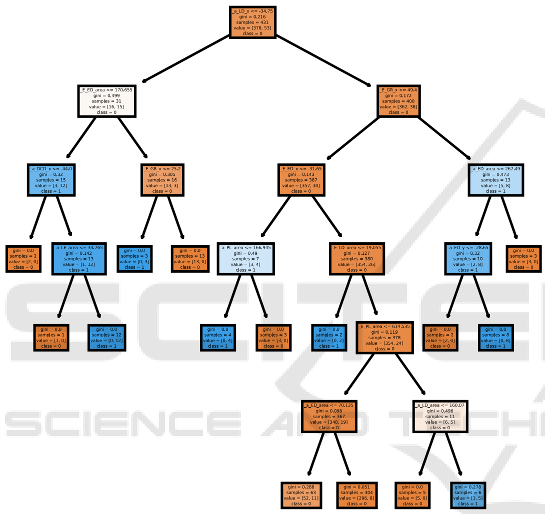


Figure 3: Decision Tree with 6 levels.

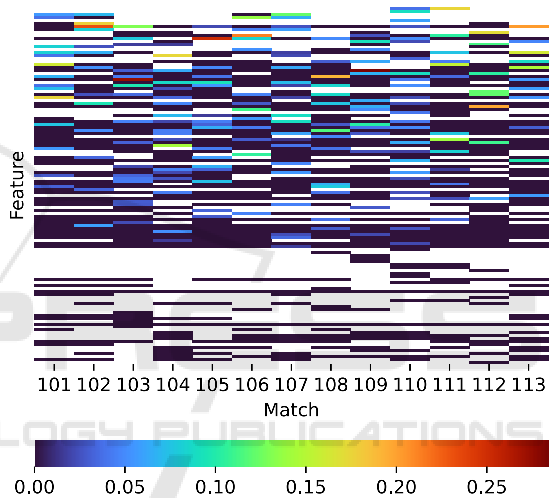


Figure 4: Features' importance across matches (by avg.).

Table 1: 1^{st} experiment cross validation results.

Tree	Accuracy	Precision	Recall
6 levels	0.82	0.158	0.083
20 levels	0.79	0.235	0.500

Table 1 presents the cross validation assessment values for the two trees.

Analyzing the results we can see that although the decision tree with 6 levels has a higher accuracy the other parameters are very low.

Using the method described in Section 4.2, the importance of each feature in the 13 matches was computed. Features were ordered according to their importance, using maximum and average values across matches in which it was present. Table 2 presents the top 5 features on both criteria. Figure 4 shows the importance of the 66 features on each match, ordered by their average.

Table 2: Top 5 features.

Top features by max.		Top features by avg.		
Feature	Value	Feature	Value	Matches
f_GK_x	0.29	o_CM2_area	0.11	2
o_RCB_x	0.27	f_RM_x	0.09	1
f_RB_x	0.24	f_CAM_x	0.06	4
o_LCB_x	0.23	f_CAM_y	0.06	4
o_CAM_y	0.21	f_LM_y	0.06	1

Analysing the ranking by average, in the first places appear features that do not appear in many games (between 1 and 4). These values are also low, which may indicate that there is no common feature that stands out in all matches. Notably, none of the different classes of features, **x**, **y**, and **Voronoi Area** can be considered as dominant. On the other hand, all top 5 features are associated to mid-field tactical missions (4 belonging to the focus team).

Considering the maximum value for the importance of features none of them has a very high value.

This indicates that the importance of features in all games is very disperse among the features and teams (2 focus, 3 opponent). Nonetheless, the **x** feature class stands out as well as defensive tactical missions.

Figure 4 confirms this dispersion of importance across the different features and matches. Dispersion across matches was investigated by computing the similarity between the importance of features for all matches pairs using the cosine similarity metric (as in Section 4.4). The values represented in Figure 5 indicate a low similarity between all pairs of matches. However, it is of note that most pairs presenting higher similarity (e.g., 106 – 108, 101 – 102 and 108 – 111) correspond to matches that have also high tactical mission similarity.

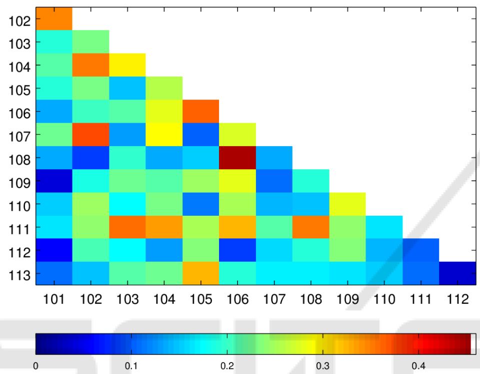


Figure 5: Features' importance Cosine Similarity.

Albeit the interesting relation between features' importance and players' tactical mission, this experiment does not identify a consistent set of features to be considered as the most relevant across matches for deciding pass outcomes. This was somehow to be expected as the features considered where not strongly associated to the process under observation: passing.

5.3 Experiment with Ball Carrier and Closest Players

In order to overcome the limitations of the previous experiment we used features of the player performing the pass (ball carrier) combined with features of the closest player from the same and opponent teams. In addition to the longitudinal and lateral coordinates, features related to "available" space (Voronoi area) and "support/pressure" (distance to teammate/opponent), were considered:

p_x(y) (decimal): longitudinal (lateral) position of ball carrier.

p_area (decimal): Voronoi cell area of ball carrier.

p_dist (decimal): distance to opponent's goal from ball carrier.

f(o)_sep (decimal): distance between ball carrier and closest teammate/opponent (f/o).

f(o)_area (decimal): Voronoi cell area of closest teammate/opponent (f/o).

f(o)_dist (decimal): distance to goal from closest teammate/opponent (f/o).

Table 3: 2^{st} experiment cross validation results.

Tree	Accuracy	Precision	Recall
6 levels	0.82	0.1	0.15
20 levels	0.78	0.31	0.32

Analysing the Table 3 we can see that although the 6-level decision tree has a higher accuracy the other parameters are lower.

Figure 6 shows the importance of each feature sorted by increasing average value. The most important feature is the distance between ball carrier and closest opponent. This makes sense, as the opponent is applying pressure, the difficulty of a successful pass increases. Actually, all three opponent related features are found in the Top 5, reinforcing the hypothesis that the interaction with the closest opponent is of chief importance on pass success. Conversely, features concerning the teammate are amongst the least important, especially distance to goal.

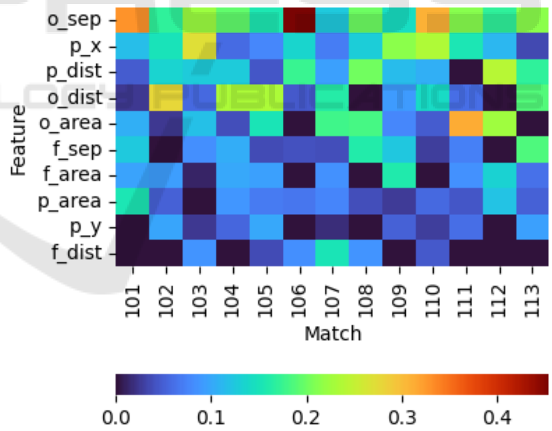


Figure 6: Ball carrier, Teammate and Opponent features'.

6 CONCLUSIONS AND FUTURE RESEARCH

From this exploratory work the following main conclusion can be obtained: identifying and quantifying the factors of passing success is in fact a difficult task. This is confirmed by the fact that, albeit the high accuracy, precision and recall scores are low in all experiments. Additional, more detailed, conclusions are the following:

- The pass success/insuccess imbalance impairs the assessment of the decision mechanism.
- The relative importance of features is somehow related to the match teams' formation and players' tactical missions.
- Using more features does not guarantee an increase on accuracy;
- Having a set of features that are more directly related to the process (passing) enabled a more consistent ranking of features across matches.
- Interaction with the closest opponent appears to be of key importance for pass success.

Concerning future work, we suggest:

- Explore techniques to mitigate data imbalance.
- Inquire other features related with the interaction with opponents.
- Investigate why Voronoi areas are not as relevant as expected. An hint is that the complete Voronoi area may not be considered as "usefull".

Albeit its limitations, notably low precision and recall, the results of the paper may be useful to practitioners. For example, they may help designing constrained pass practice tasks (e.g., with representative distances to opponent and team mates).

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REFERENCES

Barra, S., Carta, S. M., Giuliani, A., Pisu, A., Podda, A. S., and Riboni, D. (2021). Footapp: an ai-powered system for football match annotation. *CoRR*, abs/2103.02938.

Cordon, A., Garcia, A., Marquina Nieto, M., Calvo, J., Mon, D., and Román, I. (2020). What is the relevance in the passing action between the passer and the receiver in soccer? *Int. Journal of Environmental Research and Public Health*, 17.

de Ville, B. (2006). *Decision Trees for Business Intelligence and Data Mining: Using SAS Enterprise Miner*. SAS Institute.

Fonseca, S., Milho, J., Travassos, B., Araujo, D., and Lopes, A. (2013). Measuring spatial interaction behavior in team sports using superimposed Voronoi diagrams. *International Journal of Performance Analysis in Sport*, 13:179–189.

Jamil, M., Phatak, A., Mehta, S., Beato, M., Memmert, D., and Connor, M. (2021). Using multiple machine learning algorithms to classify elite and sub-elite goalkeepers in professional men's football. *Scientific Reports*, 11(1):22703.

Ks, M. (2020). Applications of artificial intelligence in the game of football: The global perspective. *Journal of Arts Science & Commerce*, 11:18–29.

Mitchell, T. M. (1997). Does machine learning really work? *AI Magazine*, 18(3):11.

Murphy, K. P. (2012). *Machine learning: a probabilistic perspective*. MIT press.

Obschonka, M. and Audretsch, D. (2020). Artificial Intelligence and Big Data in entrepreneurship: A new era has begun. *Small Business Economics*, 55(3):529–539.

Pappalardo, L. et al. (2019). PlayeRank: Data-Driven Performance Evaluation and Player Ranking in Soccer via a Machine Learning Approach. *ACM Trans. Intell. Syst. Technol.*, 10(5).

Pedregosa, F. et al. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830.

Rommers, N. et al. (2020). A Machine Learning Approach to Assess Injury Risk in Elite Youth Football Players. *Medicine & Science in Sports & Exercise*, 52:1745–1751.

Stacey, R. (2018). Towards Data Science: The Mathematics of Decision Trees, Random Forest and Feature Importance in Scikit-learn and Spark. https://tinyurl.com/3kca6xp8. Accessed: 2022-06-01.

Stimpson, A. J. and Cummings, M. L. (2014). Assessing intervention timing in computer-based education using machine learning algorithms. *IEEE Access*, 2:78–87.

Techopedia (2017). What does digital revolution mean? tinyurl.com/4xkk4mkr. Accessed: 2021-12-22.

Zhou, Z.-H. (2017). A brief introduction to weakly supervised learning. *National Science Review*, 5(1):44–53.