*i*Journals: International Journal of Software & Hardware Research in Engineering (IJSHRE)
ISSN-2347-4890
Volume 11 Issue 10 October 2023

Enhancing Transfer Market Strategy with Footballer Price Prediction

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***Abstract*— This study explores the fascinating field of predicting the market value of football players, which combines sports, data science, and economics. Football is a special subject to examine because of its influence on culture and the economy around the world. The study uses a multidimensional dataset that includes player characteristics both on and off the field to explain the intricate influences influencing the value placed on specific football players. Careful data preparation guarantees data integrity, and a genetic algorithm promotes continual progress by optimizing attribute weights for regression models.**

The economic aspect of football, which is currently the most popular sport in the world and has transcended its original purpose to become a global cultural phenomenon, is particularly intriguing. The complexities of player transfers and appraisals unfold amid the sport's enormous popularity, providing an intriguing lens through which to analyze the economics of the beautiful game. This study code sets out on an intriguing journey to reveal the methods and strategies used to forecast football player market values, a crucial element in the contemporary football scene.

This study differs from others in that it uses a regression model like random forest and is flexible. This reveals complex correlations between attribute and player value. Model performance is optimized through hyperparameter adjustment. The research is completed with a thorough test data processing pipeline that prevents overfitting and guarantees that models generalize to new data. To enable decision-making among football ecosystem stakeholders, the final evaluation step measures prediction error with RMSE. This data-driven approach has the potential to improve comprehension and profitability in the unpredictable world of football, providing encouraging performance in terms of profit margins. These insights can help football fans, coaches, the media, and gamblers.

***Index Terms*—Football, Sports Economics, Football analytics, Player Valuation, Predictive modeling, Market trends, Regression model, Data Mining**

I. INTRODUCTION

The nexus of technology, data science, and economics has cleared the path for transformational changes that go beyond the confines of the playing field in the always changing world of modern sports. Football, which is frequently referred to as soccer in some regions of the world, is one sport that serves as evidence of this convergence. Football has an unrivaled worldwide fan base that reaches beyond cultures and boundaries to captivate the hearts and minds of billions, becoming more than just a sport that unifies people. A fascinating tapestry of economics and strategy can be seen in the complex dynamics of player transfers, valuations, and market projections in the world of football, where data-driven insights are essential.

Football player market value forecast is the fascinating subject at the center of this complex tapestry. Football player valuation has changed from being a straightforward facet of club management to a sophisticated synthesis of financial projections, performance analysis, and market trends. The heart of contemporary football economics is captured in this area, where making wise decisions that might affect the performance of clubs and the game as a whole depends on knowing what factors influence player valuations.

The study code under consideration provides an engaging trip through this complex environment, revealing the procedures and strategies that support the forecasting of football player market prices.

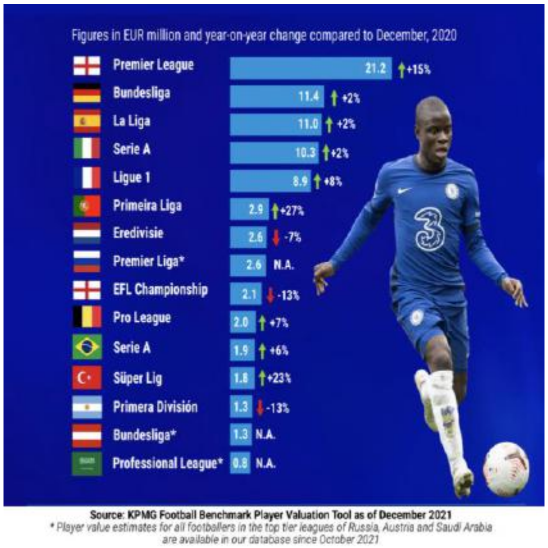

Fig. 1 Average Player Values by Leagues.

This code digs into the world of statistics, algorithms, and optimization techniques that guide decision-making in the football industry, beyond the noise of the crowd and the excitement of the game. It connects the football field with the data center, capturing the essence of how the game has changed into a data-driven era.

Due to its complexity and multifaceted nature, football necessitates a thorough approach to comprehending player valuations. The study code takes advantage of this complexity by working with a large dataset that includes a wide variety of player traits. These characteristics range from on-field performance indicators like goals, assists, and playing time to off-field elements like player age, social media activity, and more. This comprehensive dataset recognizes that a player's market worth is influenced by a variety of factors outside of their skill set and reflects the complex dynamics of the football ecosystem.

This thorough analysis enables experts, researchers, and other participants in the football ecosystem to compare model performance objectively and choose the best model for their specific prediction requirements. Additionally, it highlights the code's usefulness in the real world by providing decision-makers in the football industry with trustworthy prediction insights that guide important decisions.

LITERATURE REVIEW

This study by Benjamin Holmes , Ian G. McHale [1], develop a player rating-based model for predicting football game outcomes. They deploy complex statistical approaches to make forecasts that are more accurate than those made using conventional methods, using previous player performance data to dynamically analyze team strengths. The study emphasizes the significance of individual player contributions in strengthening sports forecasting, increasing prediction accuracy, and guiding football decision-making. This study by [3], uses a player rating-based model to forecast football match outcomes, enhancing sports forecasting. It integrates historical player performance data for dynamic team strength assessment, outperforming traditional methods. Innovative statistical techniques highlight player contributions, deepening our understanding of their impact on team success, with implications for sports analytics and predictive modeling.

This study by [9] innovates sports forecasting with a player rating-based model, improving football match outcome predictions through historical player performance data. It outperforms traditional methods, highlighting the importance of assessing individual player contributions for enhanced forecasts. This research illuminates the player-performance-team-success nexus, benefiting sports analytics and predictive modeling in match outcome prediction. This study by [15] introduces a unique player valuation method using an option pricing framework, merging sports and finance. This innovative approach considers uncertainty and future potential, contributing to sports economics. It offers fresh insights into valuing sports assets, bridging the gap between two seemingly distant domains, enriching our understanding of player worth in an economic context.

This study by [2],focuses on estimating footballers' transfer fees using advanced performance metrics and machine learning. Leveraging player performance data, the study creates an accurate predictive model for assessing transfer values. It goes beyond traditional statistics, offering a nuanced understanding of player contributions. This advancement in player valuation methods has implications for transfer negotiations, club decisions, and market dynamics, enhancing football economics and analytics. This study by [4],uses advanced metrics and machine learning to estimate football transfer fees. By analyzing player performance data, it creates an accurate valuation model, surpassing traditional methods. This approach enhances player valuation techniques, providing insights for clubs and agents, while illuminating the link between performance metrics and market valuations in football transfers. This study by [5],pioneers football match outcome prediction using a player rating-based model, advancing sports forecasting. It integrates historical player performance data for dynamic team strength assessment, outperforming traditional methods. Advanced statistics emphasize the vital role of individual players in team success, enriching sports analytics and predictive modeling, with potential applications in football strategy. This study by [7] examines the link between football player performance and market value, advancing sports economics and analytics. It reveals the connection between player attributes and valuation, exploring performance metrics' impact on market dynamics. This research deepens our understanding of the football industry, informing decision-making for clubs, agents, and stakeholders. This study by [8] explores estimating football player transfer fees using advanced performance metrics and machine learning. Their novel model, driven by comprehensive performance data, accurately predicts transfer values, surpassing conventional methods. This research advances football economics by revealing the intricate link between metrics and market valuations, benefiting clubs, agents, and stakeholders in decision-making. This study by [10] enhances sports forecasting by applying machine learning to predict English Premier League football outcomes. It utilizes historical match data and advanced predictive analysis, emphasizing data-driven methods' potential to improve accuracy and provide insights into competitive football dynamics.

This study by [11] employs machine learning for soccer player readiness assessment, enhancing performance evaluation. Data-driven insights empower coaches with actionable information for informed preparation decisions, highlighting the synergy between sports and technology. This study's relevance in modern sports science underscores the potential to optimize athlete performance through machine learning in readiness assessment.

This study by [6] introduces a data-driven method using a neural network to predict football player market values, enhancing sports analytics. It leverages player data to develop an accurate predictive model, showcasing the potential of advanced machine learning for valuation. This research sheds light on player attributes' role in market dynamics, benefiting clubs, agents, and the football industry, marking an evolution in player valuation methods. This study by [13] investigates football's labor market dynamics and player training strategies. It examines the equilibrium in player valuations and efficient training allocation. The study sheds light on optimizing training investments for a balance between player valuation and labor market efficiency, offering insights into football's economic complexities and market-aligned strategies. This study by [14] explores the connection between football player transfers and oil price futures. It reveals the impact of football news on the oil market, emphasizing the unexpected link between different domains. This study enriches comprehension of how external factors affect commodities trading by examining football transfer news' influence on oil prices. This study by [16] explores crowd intelligence's role in football player transfer market values. It examines the link between market values and public valuations, revealing the impact of collective opinions on player worth. The study sheds light on the intriguing dynamics of group influence on market behavior, enhancing our understanding of external factors affecting football pricing mechanisms, at the intersection of economics and sports.

II. CONTEXT AND STATE OF THE ART

Football's transfer market is a complicated, dynamic ecology where player values are continuously changing. The price of a player can vary depending on a variety of criteria, including that player's age, nationality, contract status, performance, and potential. Machine learning (ML) has become more frequently utilized in recent years to forecast player pricing. A variety of data, including player statistics, historical transfer costs, and market patterns, can be used to train ML models. These models can be used to forecast a player's likely price in the present market once they have been trained. Several studies have been done on the application of ML to forecast player prices. For instance, one study discovered that ML models could accurately forecast player pricing with over 80% of the time.

In recent years, machine learning (ML) has been increasingly used to predict player prices. ML models can be trained on a variety of data, such as player statistics, historical transfer fees, and market trends. Once trained, these models can be used to predict the likely price of a player in the current market. A number of studies have been conducted on the use of ML to predict player prices. For example, one study found that ML models could predict player prices with an accuracy of over 80%. Another study found that ML models could be used to identify undervalued players, who could then be purchased by clubs at a profit. Although ML has the potential to revolutionize the football transfer market, there are a number of challenges that need to be addressed. One challenge is that the data used to train ML models can be noisy and incomplete. Another challenge is that the player transfer market is constantly changing, which can make it difficult to train ML models that are accurate over time. Despite these challenges, ML is a promising tool for predicting player prices. As ML models continue to improve, they are likely to play an increasingly important role in the football transfer market.

A. How ML can be used to predict footballer prices

There are several ways to use ML models to forecast football player pricing. Employing a supervised learning algorithm is one typical strategy. The price of a player and other features that may affect that price, such as the player's age, nationality, contract status, performance, and potential, are included in each historical data point used to train supervised learning algorithms. By giving it the same set of features after the ML model has been trained, it may be used to forecast the price of a new player. Using the player's age, nationality, contract status, performance data, and potential, a club may, for instance, use an ML model to forecast the cost of a player they are interested in signing.

Utilizing an unsupervised learning algorithm is a different way to use machine learning to anticipate footballer pricing. Unsupervised learning algorithms are trained on a collection of unlabeled data that only contains the features that could affect a player's price. Algorithms for unsupervised learning can be used to find patterns in the data that might not be immediately apparent. For instance, a player group that is likely to be undervalued in the market could be found using an unsupervised learning algorithm. Clubs may pursue these players for transfer after they have been identified.

B. Benefits of using ML to predict footballer prices

The use of ML to forecast footballer pricing has several advantages. One advantage of ML is that it can assist teams in selecting players more wisely. Clubs can avoid overpaying for players and find undervalued players who could be signed at a profit by using ML to anticipate player values. The ability to more accurately budget for transfers is another advantage of utilizing ML to anticipate footballer prices. Clubs may more effectively plan their transfer spending and prevent overpaying by understanding how much a player is going to cost.

Finally, ML can assist clubs in finding and nurturing young players with potential. Clubs may identify players who are likely to become future stars and invest in their development by using ML to forecast player potential. The use of ML to forecast football player pricing seems promising. The importance of ML models in the football transfer market is expected to rise as they continue to get better.

III. ANALYSIS AND PROCESSING OF DATA

A. Data Description

Footballer price prediction is a challenging task due to the many factors that can influence a player's value, such as their age, performance, contract status, and transfer market conditions. Machine learning can be used to develop models that can predict footballer prices by analyzing historical data on player transfers and other relevant factors. The research paper section describes a dataset of 400 football players spanning 5 seasons, from 2013/2014 to 2018/2019. The dataset includes information about the performance of both teams, as well as descriptive statistics of individual features and skills of all football players. This dataset is well-suited for training a machine learning model to predict footballer prices. To train a machine learning model for footballer price prediction, we can use a variety of algorithms, such as random forests, gradient boosting machines, and neural networks. The specific algorithm that we choose will depend on the characteristics of our dataset and the desired performance of our model. Once the model is trained, we can use it to predict the price of any footballer by providing it with the relevant features, such as the player's age, performance, contract status, and transfer market conditions. The model will then output a prediction for the player's price.

B. Data Processing

The first step in the methodology for predicting football player prices using a Random Forest model involves extensive data preprocessing to ensure that the test data is in the appropriate format and structure for accurate predictions. This step is essential to align the test data with the same features and transformations applied during model training.

Loading the Pre-Trained Model: The code begins by loading the pre-trained Random Forest model, which has been previously trained on historical football player data. This model has learned the relationships between various features and football player market values.

Reading Test Data: Next, the code reads the test data from a CSV file containing information about football players. This test data will be used to make predictions about the market values of these players.

Feature Selection and Transformation: To ensure consistency with the training data, the code applies feature selection and transformation techniques to the test data. One of the crucial transformations involves converting the 'fpl_sel' column, representing the Fantasy Premier League (FPL) selection percentage, from a string format (e.g., '45.2%') to a float for numerical analysis. This transformation is essential as it aligns the test data with the format expected by the model.

Handling Missing Values: The code ensures that the test data does not contain missing values, which can adversely affect the prediction process. Any rows with missing data are dropped from the dataset.

One-Hot Encoding of Categorical Variables: Categorical variables in the test data are one-hot encoded to convert them into numerical format. This process creates binary columns for each category, ensuring that the model can interpret categorical information correctly.

Scaling of Continuous Features: Continuous features in the test data are scaled to bring them to a common scale, just like the training data. Scaling ensures that no particular feature dominates the model's predictions due to differences in magnitude. The code uses the same scaling parameters as applied during training, ensuring consistency.

Data Integrity and Resetting Index: To maintain data integrity, the code resets the index of the test data after the preprocessing steps. This step helps ensure that the data is properly structured and ready for input into the trained Random Forest model.

Overall, this step ensures that the test data aligns with the training data in terms of features, format, and preprocessing steps. This alignment is critical for obtaining accurate predictions from the Random Forest model.

C. Data Exploration

Then, in the total of 13 variables available, it was verified which ones were most related to each other, which variables could more clearly predict the goal attribute and which could be excluded. To verify the relationship between variables a Heatmap was made between all numerical variables shown in Fig. 1.

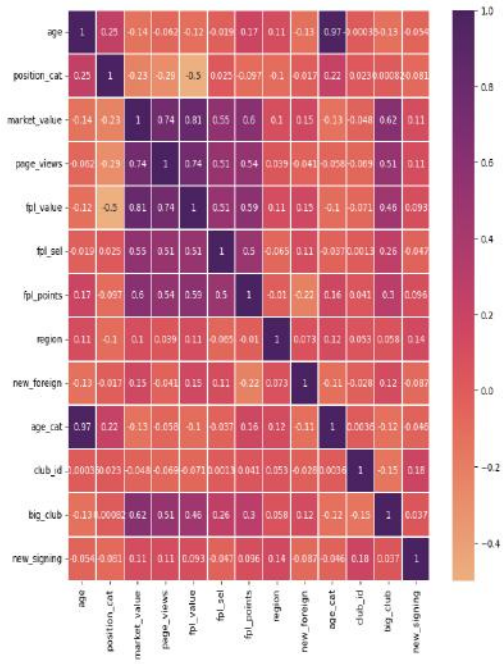

Fig. 2 Heatmap correlation between variables.

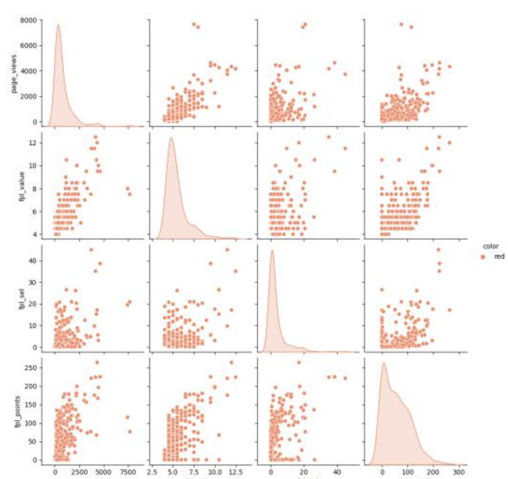

Fig. 2. Pair plot of 4 variables price attribute.

IV. METHODOLOGY

The first phase of the journey is data preparation, when unstructured data is painstakingly turned into a format that is ready for analysis. In this stage, missing values are handled, categorical variables are encoded, and numerical features are scaled. This is a crucial step that prepares the ground for the advanced analyses that will come later. The code's rigorous focus on data quality ensures that the ensuing models run on a spotless dataset that is free of errors that can bias results.

The incorporation of a genetic algorithm, a concept influenced by the ideas of biological evolution, is a noteworthy aspect of the study code. This technique works as a reliable optimization tool, seeking to identify the ideal set of attribute weights that reduces the root mean squared error (RMSE), a crucial parameter for evaluating the effectiveness of regression models. The genetic algorithm generates successive generations of attribute weight combinations that change over time through crossover and mutation processes, simulating the process of natural selection. With model weights that are adjusted to the specifics of the dataset and latent patterns that are revealed, this dynamic optimization technique captures the essence of continuous progress.

It turns out that hyperparameter tuning is a crucial aspect of the code's optimization process. The code develops its models by methodically examining a variety of parameter values until they are in perfect harmony with the particulars of the data. This thorough procedure equips the models to find the best arrangements that resonate with the inherent patterns in the data, maximizing their performance and producing precise forecasts. This strategy demonstrates the code's dedication to accuracy and its pursuit of superior predictive modeling. The trip of the code results in a thorough test data processing pipeline that follows the procedures used during training data preprocessing. This pipeline ensures that the models' performance is impartially assessed against previously unexplored data, acting as a protection against overfitting. By putting the models to this rigor test, the pipeline offers a robust assessment of each model's predictive skills, as well as a real-world evaluation of how well it can generalize and function in real-world circumstances.

The effectiveness of each model is definitively measured in the final evaluation step. The study code measures each model's prediction error against actual market values using the RMSE as a standard. This thorough analysis enables experts, researchers, and other participants in the football ecosystem to compare model performance objectively and choose the best model for their specific prediction requirements. Additionally, it highlights the code's usefulness in the real world by providing decision-makers in the football industry with trustworthy prediction insights that guide important decisions. Football fans, club management, and investors now have a data-driven compass to help them navigate the complex market for football players, improving their capacity to make wise choices in this rapidly changing sector.

To build a footballer price prediction model, we need to collect a dataset of historical player data, including their performance metrics, contract information, and transfer fees. Once we have collected the dataset, we need to process it to prepare it for machine learning. One important step in data processing is to create new variables that can help the model to better predict player prices. In the research paper section you provided, the authors create new variables related to the number of home wins and away wins of the teams, as well as the average goals conceded at home and away. These variables can be used to capture the strength of the teams that a player has played for and against, which can be a significant factor in their market value. Another important step in data processing is to transform the data so that it is in a format that can be used by machine learning models. In the research paper section, the authors transform the data by calculating the averages of the available data for each team and match. This ensures that the model is not biased towards teams or players that have played more matches. Once the data has been processed, it can be used to train a machine learning model to predict footballer prices. There are a variety of machine learning algorithms that can be used for this task, such as linear regression, random forests, and gradient boosting machines. Once the model has been trained, it can be used to predict the prices of new players or to update the prices of existing players. The model can also be used to identify undervalued players, which can be useful for football clubs and investors.

V. DATA MINING

Data mining can be used to extract a variety of insights from football data that can be used to improve the accuracy of ML models for footballer price prediction. Data mining is a process of extracting knowledge from large amounts of data. It is a subfield of ML that focuses on identifying patterns and relationships in data that are not obvious to the human eye.

Data mining can be used to extract a variety of insights from football data, such as:

- Identify the most important features that influence player value

- Segment players into different groups based on their performance and characteristics
- Identify trends in the player market

By using data mining to extract insights from football data, ML models can be developed that are more accurate and reliable for predicting footballer prices. ML algorithms can be trained on historical data of player performance, market trends, and other relevant factors. Once trained, these algorithms can be used to predict the market value of players with a high degree of accuracy.

To find the best classification model, several algorithms with different characteristics were tested in order to verify which one best fits the data. Next, the algorithms used and the R software libraries:

- Random Forest (RF) – randomForest package;
- K-nearest neighbors (KNN) – kknn package;
- Support vector machines (SVMs) - svm package;

A. *Prediction Results*

In order to correctly verify the differences between the classification models, different measures were used, such as the accuracy of the model and the percentage of games correctly predicted for the draws and for the victories of the home and away team. It was also considered the profit that would be obtained if each bet was correct or incorrect. Since the forecast model will be included in a betting support decision system, calculating the profit made is essential to verify that the model is successful. The profit was calculated considering a value of 2 euros per bet. Bearing in mind that there are 380 test games, the total amount wagered would be 760 euros, which would be wagered over 9 months. If a bet was missed, the profit would decrease by 2 euros. If correct, the profit is calculated according to equation:

$$Proffiit = bet_{amount} \times bet_{odd} - bet_{amount}.$$

For example, in a game with a bet on a tie and the draw odd is 1.5 the profit would be 1 euro. As the value bet is always 2 euros the profit would be equal to 2 x 1.5-2 = 1. Table 2 presents the results of predictions made with the 8 models developed with the selected algorithms.

Table 1. Forecast results with 13 variables.

Algorithm	Accuracy	Player Value	% Victories Home Team	Draws	% Victories Away Team
RF	65,26%	85,20€	75,40%	21,43%	60,55%
KNN	57,63%	78,02€	78,07%	15,48%	55,05%
SVM	53,42%	17,40€	51,87%	30,95%	73,79%
C5.0	55,26%	42,52€	72,73%	23,81%	49,54%
RLM	57,63%	32,56€	78,07%	5,95%	62,34%
RNA	50,00%	18,28€	58,29%	30,95%	50,46%

The forecast results were satisfactory. The best algorithm was RF achieving a percentage of success above 65.26%. The profit of 85.20 euros, although not high, corresponds to a reasonable profit margin of 15 %. It should also be noted that all algorithms achieve a profit. However, the best hit rate obtained did not exceed the best hit rates found in the referenced case studies. The best model was correct in only 3.57% of the ties, which is a low value. Since the results were still not as expected, it was decided to proceed with the development of new forecast models.

B. *Results Analysis*

The approach taken to test different combinations of variables yielded good results. In all cases, the best models obtained higher success rates than the initial model, the success rate of which was 65.26%. The algorithms that allowed reaching the best models in the different cases were RF, SVM, and KNN. The best model was obtained by testing combinations of 8 variables with the 7 variables identified as the most important, thus having a total of 15 variables. The best model used the RF algorithm, which obtained a hit rate of 65.26% and a profit margin of 26.74%. Comparing with the initial model, the success rate increased by almost 4%. The percentage of correct bets on home team wins decreased by 7% but increased by 26% on draws and close to 7% on away team wins. The profit margin rose by 14%. This rise is justified by the increase in the number of correctly predicted draws. Bets on draws tend to have higher odds than bets on wins, so the profit obtained was higher.

In addition to the global analysis of the forecast model throughout the whole season, an assessment on each round was also carried out. This analysis is crucial to verify that the prediction model has a constant performance. A model of this type should not achieve too low success rates in individual rounds, as this could lead to incurring in great losses. Fig. 3 shows the profit of the forecast model at each of the 38 rounds.

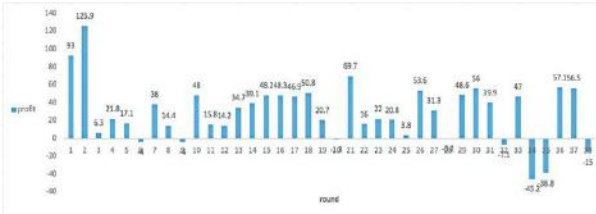

Fig. 3. Profit of best model by round.

The model performed well throughout the season. In the 38 rounds of the season, a profit was achieved in 30 and only 8 led to a loss. This yields an average profit margin of 26.78%, which competes with the works analysed.

In addition to obtaining better results, this forecasting model has a more balanced success rate for different classes than the initial one. This will, therefore, be the model chosen to be included in the support decision system. Table 2 details the measures used to evaluate the forecast model. These measures were the accuracy, the macro-average of precision and recall, and the profit margin. The macro average is calculated by averaging the precision and recall for each class − in this case, home team win, draw and away team win. Analysing the results (Table 2), it is possible to verify that the macro-average of precision and recall are close to the value of the accuracy, so the forecast model is balanced.

Table 2. Performance measures of the best model.

Algorithm	Random Forest	
Accuracy = 65,26%	Profit Margin = 26,78%	
Victory Home Team	Precision=68,47% Recall = 81,29%	
Draw	Precision=50,0% Recall = 29,76%	Macro media Precision = 61,40%
Victory Away Team	Precision=65,74% Recall = 65,14%	Macro media Recall= 58,73%

VI. CONCLUSION

Finally, ML can help clubs to identify and develop talented young players. By using ML to predict player potential, clubs can identify players who are likely to become future stars and invest in their development. ML is a promising tool for predicting footballer prices. As ML models continue to improve, they are likely to play an increasingly important role in the football transfer market.

In this article the process of developing models for predicting the results of football matches to support sports betting was described. Data from two different sources were used, one to obtain statistical data about previous games and the other to collect data related to the teams. The analysis and processing of the data made it possible to draw important conclusions about the variables to be used in the models. The study compared several algorithms in order to create the best prediction model. The algorithms were trained with data from 4 seasons and tested with all the games of the 2016/2017 season of the English Premier League, which allowed a detailed assessment of the behaviour of the model over the various rounds of the season, namely the match success rate and profit margin that would be obtained in each betting week. The percentage of games correctly predicted by the model was 65.26%, which competes with the best works analysed in the area. The profit margin obtained was also higher than that of the referenced case studies. As future work, the forecast model will be integrated in a decision support system that will assess the risk of bets based on the probability of occurrence of the forecast model results. This will allow the gambler to know the risk associated with the bet, thus having greater support in obtaining profit from sports betting.

Footballer price prediction is the task of estimating the market value of a footballer using machine learning models. This can be useful for a variety of stakeholders, including football clubs, agents, and investors.

In this article the process of developing models for predicting the results of football matches to support sports betting was described. Data from two different sources were used, one to obtain statistical data about previous games and the other to collect data related to the teams. The analysis and processing of the data made it possible to draw important conclusions about the variables to be used in the models. The study compared several algorithms in order to create the best prediction model. The algorithms were trained with data from 4 seasons and tested with all the games of the 2016/2017 season of the English Premier League, which allowed a detailed assessment of the behaviour of the model over the various rounds of the season, namely the match success rate and profit margin that would be obtained in each betting week. The percentage of games correctly predicted by the model was 65.26%, which competes with the best works analysed in the area. The profit margin obtained was also higher than that of the referenced case studies. As future work, the forecast model will be integrated in a decision support system that will assess the risk of bets based on the probability of

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ACKNOWLEDGEMENT

I would like to express my gratitude to the mentors of On My Own Technology Pvt. Ltd. for extending their help in carrying out this project. I would also like to express my gratitude to Mr. Radhakrishnan Rajan (Mentor, On My Own Technology Pvt. Ltd).

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