Foundation of Betting in the English Premier League: Predicting the Outcome of a Soccer Match Using Machine Learning Models

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***Abstract*—We will write this last.**

***Index Terms*—Sports Betting, Machine Learning Models, XGboost, Random Forest, Support Vector Machine, Neural Network, Convolutional Neural Network, Football Betting, English Premier League.**

I. Introduction

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It is well recognized that a profitable betting strategy relies on the optimal use of odds data from the bookmakers as well as accurate prediction of match outcome as a foundation. This phase of the research will focus on the development of a machine learning (ML) or artificial intelligence (AI) model for the accurate prediction of match outcomes.

II. Existing Work

The use of ML algorithms for the development of sports betting strategies has proliferated in the last three years. For example, these papers [1]–[9] were published in 2023. Several overviews in this regard can also be found in [10] or [8]. The survey paper by Tokic et al [11] is also useful though it is published in 2022.

The use of ML algorithms in predicting outcomes of a sports event including those for a soccer match dates back to the mid 2010's. For example, using a data set extracted from 110 matches played in the 2014-2015 English Premier League (EPL) season with features that include Home and Away goals, Home and Away shots, Home and Away corners, Home and Away Odds, Home and Away attack strength, Home and Away Players' performance index, Home and Away Managers' performance index, Home and Away managers' win, as well as Home and Away streak, Igiri et al [12] in 2014 implemented a logistic Regression (LR) and an Artificial Neural Network (ANN) model to predict the outcome of 20 matches in 2014-2015. Results of the research showed that an accuracy rate (not explicitly defined in the paper) of 85% with ANN and 93% with LR is possible. One interesting aspect of the approach by the authors was the use of a genetic algorithm to "calculate the weights of the features" of the data set before they are input to ML algorithms.

Constantinou in 2019 [13] described an ambitious project to build Dolores, "a model designed to predict football match outcomes in one country by observing football matches in multiple other countries." This model used a mixture of the dynamic ratings and the Hybrid Bayesian Networks approach to train a single dataset that incorporates match outcomes from 52 football leagues around the world and was used to predict 206 future match outcomes from 26 different leagues from March 31 to April 9 in 2017. Dolores placed 2nd in the international special issue competition, Machine Learning for Soccer.

Carloni et al in 2021 [14] presented the design and implementation of ML models for predicting the outcome of soccer matches for sports betting. Data were extracted from the Web through a scraping process and used as input to a comprehensive suite of ML algorithms such as Logistic Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Naive Bayes (NB), Random Forest (RF), and a Four-layer Artificial Neural Network (ANN). Based on the criteria of accuracy (not clearly defined in the paper), the ANN model developed is the best for the over-under 2.5 market. Further experiments also showed "encouraging performance in terms of the Return on Investment (ROI) criteria.

Wheatcroft and Sienkiewicz [15], also in 2021, examined the need for the calibration of probability forecasts of soccer matches produced by various ML models. The authors found that it is important to evaluate the performance of the models with and without calibration to ensure that the extra step is indeed required. Through the use of the forecasts and two betting strategies, the authors demonstrated how the hyperparameters of ML models could be selected to optimize the decision of betting or not betting forecasts.

Nivetha et al in 2022 explored the use of a deep learning framework to forecast soccer outcomes. The project team used a Long Short Term Memory (LSTM) algorithm, a modified version of a Recurrent Neural Network (RNN) for this purpose. Using data from the "International Football results from 1872 to 2018", "FIFA world cup 2018", and the "FIFA Soccer Rankings" data sets, Rahman [16] used a similar approach, that is an LSTM deep learning network, but a different data set to predict the outcome of the FIFA World cup 2018 group stage matches and achieve an accuracy rate of 63.3%. The author believes that "this accuracy can be increased with proper datasets and more accurate information of the teams. For more accurate performance of the prediction, prior and more information about each team, player and match is desirable."

Peters and Pacheco [17] used line-up statistics of teams in the EPL from 2020 to 2022 to build heuristic and ML models to predict soccer scores. The research found that the Support Vector Regression (SVR) algorithm outperforms others in predicting final scores. Moreover, the researchers managed to "predict correctly all relegated teams after forecast 100 consecutive matches" and the use of the forecasts was profitable (42% return). Interestingly, the researchers concluded that "lineups do not improve predictions".

A Convolutional Neural Network (CNN) is a special type of deep learning algorithm that is designed for classification and other pattern detection tasks such as image classification. Several research projects in the last three years have used this algorithm to predict sports event outcomes and soccer games. Wagenaar et al [18] is the first research team to use the CNN algorithm in the sports prediction arena. Instead of predicting the outcome of a soccer match, the team uses a "deep CNN" to predict goal-scoring opportunities in soccer using position data from "29 matches played by a German Bundlesliga team." While their ideas are very interesting, they cannot be used directly in predicting the outcome of a soccer match.

On the other hand, Chen [19] used three typical machine learning algorithms, CNN, RF, and SVM, to develop models to predict the result of a football match based on a "player ability index" derived from data found in the website of the International Federation of Association Football (FIFA). The accuracy of these three methods is between 54% and 58%. The researcher argued that these results "are acceptable since they are all higher than the prediction accuracy of the famous football analyst of BBC, Mark Lawrenson, which is only 52%. In addition, the accuracy of the convolution neural network is higher than the prediction accuracy of the authoritative football gambling organization Pinnacle Sports, which is only 55%." In any case, the research concluded that the four-layer CNN algorithm produced the best results.

Randrianasolo [20] used a CNN to develop models for predicting the 2020 man's EURO and 2022 women's EURO, resulting in a 69.8% accuracy and an 80% accuracy respectively. The research claimed that these results represent a 2% improvement and a 10% improvement over those using an ensemble technique approach in predicting the outcomes of these two soccer tournaments.

Based on these results, it seems that the CNN algorithm is a viable alternative for developing models to predict the outcome of a soccer match. The other side of the coin would be the structure of the network as well as the selection and engineering of features that should be fed to the algorithm.

Other research projects published in 2022-2023 and with a focus on using ML or AI algorithms to predict outcomes of a soccer match include the following:

Author(s)	Year	ML/AI Algorithm Used
Chang et al. [5]	2023	
Lirio [21]	2023	KNN, XGB, LR, SVM, LDA, NB, DT
Sjöberg [22]	2023	NB, LR, RF
Javed [23]	2023	
Athish et al. [24]	2023	NB, DT, SVM, NN
Satyapanich et al. [25]	2023	MLP and CNN
Jain et al [7]	2023	
Mattera [26]	2023	GARMA
Rodrigues et al. [27]	2022	NB. KNN, RF, SVM, DT, XGb, LR, NN
Duarte [28]	2022	NB. KNN, RF, SVM, DT, XGb, LR, NN
Peters [17]	2022	LN, KNN, DT, RF, SVR
Nivetha et al [29]	2022	LSTM
Rose et al. [30]	2022	
Heijboer [31]	2022	RF, SVR, GB, LR
da Costa et al. [32]	2022	
Ren et al. [33]	2022	LR, DT,RF,KNN,GB, XGB, CatB,Others
Henrik Kristinsson [34]	2022	Deep Learning
Cortez et al. [35]	2022	
Zulkiffi et al. [36]	2022	
Muszaidi et al. [37]	2022	

A. feature selection

There is a high level of diversity in the choice of features used as input to the ML models for predicting game outcomes. Depending on the game itself, the league within which the game is played, and the ML algorithms to be employed, the set of features could be very different.

As mentioned, Chen used a player ability index as input to the predictive models [19]. Peters et al [17] analyzed "the role of lineups in the final scores using machine learning prediction models" they developed. Historical data and machine learning models were employed to develop these models for predicting the outcome of English Premier

League (EPL) games in the years 2020 to 2022. Through the analyses of features used, they found that statistics on goalkeepers are more important than those for the attackers in predicted goals scored. Two other findings of interest are that data on lineups do not improve predictions and that Support Vector Regression outperforms other algorithms in predicting final scores. and that lineups do not improve predictions.

Rose et al [30] explored different Machine learning techniques to predict the score and outcome of soccer matches using a set of custom-generated features. The features are used to train the selected algorithms.

B. Machine Learning Models for Predicting Game Outcomes in Other Sports

ML has also been used to build models for predicting outcomes of other sports. Beal et al [38] built and evaluated nine algorithms using data sets of 1280 games over 5 seasons to predict outcomes of National Football League (NFL) games. Their experiments showed that the Naive Bayes algorithm was the best classifier with an accuracy of 67.5% and an F1 Score of 0.67. The team believed that this algorithm performs the best when features used are independent and dependencies between features are similar.

Hubacek et al in 2019 [39] incorporated the bookmaker's predictions into their prediction models with the reduction of correlation as an optimization tool. The models were developed through the implementation of a CNN with a convolution layer that "enabled to leverage a vast number of player-related statistics as its input." Combining with elements of modern portfolio theory, the authors yielded positive cumulative profits in experiments with NBA data.

C. Outcome Prediction and Betting

Paragraphs on outcome prediction, other predictions, and betting strategies.

D. Model Evaluation

Chicco et al [40] show the advantage of using the Matthews correlation coefficient (MCC), first introduced by Matthews [41], over the F1 score and accuracy in binary classification evaluation. There are many references in this regard, see for example [42].

III. Methodology

Given the symmetry of the problem, we will focus on the prediction of a home team win or a home team loss. Therefore, our problem could be viewed as one of classifying the outcome of a match into one of these two states (win or loss of the home team) by a ML model developed using the data in previous seasons.

A. Data Collection and Processing

Data on soccer, especially for those on the EPL, is widely available. For this research, we have chosen the data set that is made available for free from the website football-data.com.uk [43].

Included in the data set are the following variables that were used in this research:

- Div = League Division
- Date = Match Date (dd/mm/yy)
- Time = Time of match kick off
- HomeTeam = Home Team
- AwayTeam = Away Team
- FTHG and HG = Full Time Home Team Goals
- FTAG and AG = Full Time Away Team Goals
- FTR and Res = Full Time Result (H=Home Win, D=Draw, A=Away Win)
- HTHG = Half Time Home Team Goals
- HTAG = Half Time Away Team Goals
- HTR = Half Time Result (H=Home Win, D=Draw, A=Away Win)
- Attendance = Crowd Attendance
- Referee = Match Referee
- HS = Home Team Shots
- AS = Away Team Shots
- HST = Home Team Shots on Target
- AST = Away Team Shots on Target
- HHW = Home Team Hit Woodwork
- AHW = Away Team Hit Woodwork
- HC = Home Team Corners
- AC = Away Team Corners
- HF = Home Team Fouls Committed
- AF = Away Team Fouls Committed
- HFKC = Home Team Free Kicks Conceded
- AFKC = Away Team Free Kicks Conceded
- HO = Home Team Offsides
- AO = Away Team Offsides
- HY = Home Team Yellow Cards
- AY = Away Team Yellow Cards
- HR = Home Team Red Cards
- AR = Away Team Red Cards
- HBP = Home Team Bookings Points (10 = yellow, 25 = red)
- ABP = Away Team Bookings Points (10 = yellow, 25 = red)

In addition to the above, weather data associated with the soccer matches was also downloaded from xxxx and included the following variables:

The research team speculated that the weather may have an impact on the outcome of the matches. As weather forecasts are readily available, they could be used to predict match outcomes if its inclusion improves the accuracy of the prediction.

Data processing to clean and transform the data should be presented here.

B. Exploratory Data Analysis

Before splitting the data set into the training and testing data sets, we performed an exploratory data analysis and used the results for feature engineering.

C. Feature Engineering

Zimmermannm et al Features are more important than the algorithms [44]

Paragraphs on how some features were created. A final list of these features should be presented.

Intuitively, fatigue should be a feature included in any predictive model on game outcome. A more rested team should have a higher chance of winning. The question remains in which proxy variable(s) should be used to represent the fatigue factor. For this study, we use .....

Similarly, many fans and sports analysts believe in the impact of momentum on the winning of a team [45]. Again, the challenge is in the definition and in the selection of feature(s) to represent momentum.

To fully evaluate the potential of using historical data and a machine learning algorithm to predict match outcomes, data on bookmaker odds should not be included as features for the models [39]. Instead, we will contextualize our prediction results with those from the bookmakers through the odds.

D. Training and Testing Data

E. Machine Learning Algorithms

Four basic ML algorithms, Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), and XGboost (XGB) were considered in the research. They are selected for their differences in structure and approach in the modelling process. An excellent overview of using some of these basic algorithms in sports betting can be found in [46].

As documented above, a Convolution Neural Network CNN) for predicting soccer and other sports events has been implemented in several research projects, for example, Randrianasolo, Chen et al, or Wagenaar et al [18]–[20]. This algorithm was also used to build a prediction model to gauge whether a more advanced neural network structure would improve predictive accuracy.

F. Performance Evaluation

The popular measurement of performance in classification is based on a confusion matrix. The matrix compares the number of predictions for each class that are correct and those that are incorrect. There are four numbers to pay attention to:

- True positives (TP) - The number of positive observations the model correctly predicted as positive.
- False-positive (FP) - The number of negative observations the model incorrectly predicted as positive.
- True negative (TN) - The number of negative observations the model correctly predicted as negative.
- False-negative (FN) - The number of positive observations the model incorrectly predicted as negative.

Using these four numbers, we define the following performance measures for the classifier.

1) Accuracy: The overall accuracy of a model is simply the number of correct predictions divided by the total number of predictions. An accuracy score will give a value between 0 and 1, a value of 1 would indicate a perfect model.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

2) Precision: Precision measures how good the model is at correctly identifying the positive class. In other words out of all predictions for the positive class how many were actually correct? Using alone this metric for optimizing a model we would be minimizing the false positives.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

3) Recall: The percentage of Recall measures how good a model is at predicting correctly all the positive observations in the dataset. However, it does not include information about the false positives.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

Typically, the two percentages precision and recall are evaluated through a precision-recall curve.

4) F1 Score: From the formula below, we can see that the F1 score is defined as the harmonic mean of precision and recall:

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

As constructed, the F1 score takes a value between zero and one and therefore could also be expressed as a percentage. If precision and recall are 1, the F1 score is also 1. On the other hand, the F1 score is 0 when either the precision or the recall is 0.

5) Matthews Correlation Coefficient: In addition to the traditional measures defined above, our research also uses the Matthews correlation coefficient (MCC) as a measurement tool [41] giving its advantages as outlined in [40]. It is defined as follows

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{A}} \tag{5}$$

Here A is calculated as:

$$A = (TP+FP)(TP+FN)(TN+FP)(TN+FN) \tag{6}$$

6) Final Thoughts on Performance Measurements: Putting our performance into perspective, we should also compare the performance of a bookmaker (need to pick one), that is the predictor versus the actual outcomes. We will present this analysis in complete detail in Section IV.

We should also calculate the accumulated profit generated from betting 10 dollars for each match in the testing data set. This is to highlight the fact that accurate estimating of the outcome is only part of a profitable betting strategy.

Mention the papers [47]–[49]

IV. Results

In this section, we present the results obtained from the models built with the machine learning algorithms presented in Section III.

The following are the results of the initial model Models. These models were optimized using a grid search approach. The presented performance metrics are the averages of 3 training runs of the models. Over the three splits of the time series, the size of the training data set is therefore 200 and that for the testing data set is 50.

Error Rate	LR	RF	SVM	XGB	CNN
Accuracy	0.65	0.67	0.63	0.69	0.75
Precision	0.65	0.68	0.63	0.69	0.75
Recall	0.65	0.68	0.63	0.69	0.75
F1	0.64	0.67	0.63	0.68	0.74
MCC	0.30	0.36	0.26	0.38	0.50

Incorporating the weather data and using the same approach as above, the results are obtained as follows:

Error Rate	LR	RF	SVM	XGB	CNN
Accuracy	0.61	0.65	0.63	0.65	0.65
Precision	0.62	0.66	0.65	0.66	0.65
Recall	0.61	0.65	0.64	0.66	0.65
F1	0.60	0.64	0.63	0.65	0.65
MCC	0.23	0.31	0.3	0.32	0.30

Note from the above that the models developed with Weather Data Models are slightly worse. We suspect that these models might require different hyperparameters to account for the increase in parameters feeding into the model. Note also that there could be data leaking issues from the WinStreak and RecentWins columns - the first data point contains the information of the "recent wins" from the training data.

Training Times were not recorded given that the models were built usually within seconds. The training data set has a few thousand rows. It might be worthwhile to bring in millions of rows from unlabelled soccer games and use that to help predict the results of the EPL games.

V. Discussions and Future Work

As explained in [39], a highly accurate model is useless as long as it coincides with those used by the bookmaker. Therefore, it is important to compare any model developed with those articulated by the odds posted by the bookmakers.

More importantly, a profitable betting strategy must be developed to take advantage of the accurate outcome prediction by the machine learning model. Several approaches, for example [39], [49], [50]

VI. Conclusions

VII. Acknowledgment

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