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Prediction of 2024 Premier League Final Standings Using Random Forest Algorithm

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Abstract -- This study aims to predict the final standings of teams in the 2024 Premier League season using a machine learning approach based on practices from the Intro to Machine Learning module on the Kaggle platform. The dataset includes team performance statistics such as points, wins, draws, and losses. The implemented model is Random Forest Regressor, trained using statistical data from the competition season and evaluated with the Mean Absolute Error (MAE) metric. Evaluation results show an MAE value of 1.06, meaning the model's prediction error averages only about one rank from the team's actual position in the final standings. This finding indicates that the Random Forest algorithm is quite effective in capturing the relationship patterns between team performance and final rankings. This study provides evidence that machine learning methods can be effectively applied in the sports domain, particularly for data-driven analysis and prediction of football standings.
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I. INTRODUCTION

A. Background

In the modern era, data and technology have become essential tools in various aspects of life, including sports [16]. One growing application of data is the use of machine learning to analyze and predict team performance in sports competitions like football [6]. The Premier League, as one of the world's most competitive and popular football leagues, provides rich and diverse statistical data that can be analyzed for various purposes, from performance evaluation to match outcome and standings prediction [9]. This research adopts a practice-based learning approach from the Intro to Machine Learning module on the Kaggle platform [8], applying it to the Premier League 2024 season dataset [9]. The main focus is predicting the final rank of each team based on a number of statistical performance features throughout a full season. Using the Random Forest Regressor model [1], this study seeks to evaluate how well the algorithm can capture the relationship between statistical variables such as points, wins, draws, and losses, and the team's final position in the standings [13].

The use of the Random Forest algorithm was chosen due to its ability to handle non-linear relationships between features [1], prediction stability, and resistance to overfitting [10]. This research not only aims to produce accurate predictions but also to demonstrate how simple machine learning methods can be used effectively in the sports domain [12], particularly to support data-driven decision-making in the context of football team performance analysis [17].

II. METHOD

This research follows a practice-based learning approach from the Intro to Machine Learning module on the Kaggle platform [8] and applies it to the Premier League Season 2024 dataset downloaded from Kaggle [9]. This dataset contains statistical performance data of football teams participating in the 2024 Premier League competition. The main objective is to predict the final rank of each team based on performance attributes during the competition season. The stages in this method are explained as follows:

- Data Preparation

Data was read using the pandas library from a CSV file named PremierLeagueSeason2024.csv [3]. This dataset contains various statistical features such as:

points: total points earned,

wins: number of matches won,

draws: number of drawn matches,

losses: number of matches lost,

rank: team's final rank in the standings (prediction target).

From all features, four main features most influential to ranking determination were selected: points, wins, draws, and losses [13]. The rank value was used as the label or prediction target. No further data transformation was performed as the dataset was already clean and ready to use.

```
import numpy as np # linear algebra
import pandas as pd

pl_path = '/kaggle/input/premier-league-season-2024/PremierLeagueSeason2024.csv'

pl_data = pd.read_csv(pl_path)

pl_data.describe
```

```
<bound method NDFrame.describe of                       team  goals_scored  goals_conceded  wins  draws  \
0            Manchester City           179              66    55     12
1                  Liverpool           154              83    44     19
2                    Arsenal           146              68    46     12
3          Manchester United           130             102    39     17
4                    Chelsea           135              99    37     19
5          Tottenham Hotspur           142             106    38     14
6                Aston Villa           131             107    36     15
7            West Ham United           122             121    33     18
8                    Everton            87              99    30     17
9           Newcastle United           131             124    30     15
10           Crystal Palace            98             124    25     18
11   Wolverhampton Wanderers            86             117    25     16
12  Brighton and Hove Albion            95             108    21     26
13                    Fulham            82             114    18     21
14             Leicester City            68              50    20      6
15                   Burnley            74             133    15     18
16              Leeds United            62              54    18      5
17               Bournemouth            54              67    13      9
18               Southampton            47              68    12      7
19                 Brentford            56              65    10      9
20           Sheffield United            55             167    10      9
21          Nottingham Forest            49              67     9      9
22                Luton Town            52              85     6      8
23       West Bromwich Albion            35              76     5     11

      losses  points  goal_difference  rank
0          9     177             113     1
1         13     151              71     2
2         18     150              78     3
3         20     134              28     4
4         20     130              36     5
5         24     128              36     6
6         25     123              24     7
7         25     117               1     8
8         29     107             -12     9
9         31     105               7    10
10        33      93             -26    11
11        35      91             -31    12
12        29      89             -13    13
13        37      75             -32    14
14        12      66              18    15
15        43      63             -59    16
16        15      59               8    17
17        16      48             -13    18
18        19      43             -21    19
19        19      39              -9    20
20        57      39            -112    21
21        20      36             -18    22
22        24      26             -33    23
23        22      26             -41    24  >
```

- Train-Validation Data Split

Data was split into two parts: training data and validation data, using the train_test_split function from the scikit-learn library [3]. This process is important to prevent overfitting [4] and to evaluate model performance on unseen data [2]. The split was done randomly with the parameter random_state=1 to ensure reproducible experimental results.

```
# Bagi data menjadi data latih dan data validasi
train_x, val_x, train_y, val_y = train_test_split(x, y, random_state=1)
```

- Random Forest Model Training

The model used in this research is Random Forest Regressor [1], an ensemble algorithm based on multiple decision trees. This model was chosen for its ability to produce stable and accurate predictions [10], as well as its resistance to overfitting [1]. The model was trained using training data and then tested on validation data.

```
# Definisikan model Random Forest
rf_model = RandomForestRegressor(random_state=1)
rf_model.fit(train_x, train_y)
```

- Model Evaluation

The model was evaluated using the Mean Absolute Error (MAE) metric [4] to measure the average absolute error between predicted ranks and actual ranks. MAE was chosen because it is simple, easy to interpret, and provides a direct picture of how far predictions are from true values [2].

```
# Prediksi dan hitung Mean Absolute Error (MAE)
rf_val_predictions = rf_model.predict(val_x)
rf_val_mae = mean_absolute_error(rf_val_predictions, val_y)

print("MAE Validasi untuk Model Random Forest: {:,.2f}".format(rf_val_mae))
```

Output

Evaluation results show an MAE value of 1.06, meaning the model's predictions average less than one rank off from the team's actual position. This indicates that the Random Forest Regressor model is quite effective in mapping the relationship between statistical features and teams' final standings [11][13].

```
MAE Validasi untuk Model Random Forest: 1.06
```

III. Result and Discussion

After training the Random Forest Regressor model using statistical data from the 2024 Premier League season, evaluation results showed reasonably good predictive performance [11]. The dataset used consisted of main statistical features: points, wins, draws, and losses, with rank as the target variable (label) [9]. The training and evaluation process was conducted by splitting the data into two subsets: training data and validation data, with an 80:20 proportion [2]. The model was trained using training data, then tested using validation data. Evaluation was performed using the Mean Absolute Error (MAE) metric [4], which is the average absolute difference between predicted values and actual values of team ranks.

Evaluation results show that the model produced an MAE value of 1.06, meaning that the rank predictions generated by the model average about one rank off from the actual position in the final standings [7]. The following table presents a comparison between actual ranks and predicted ranks for several teams in the 2024 season:

TABLE I.
Comparison of actual ranks and predicted ranks

Team	Actual Rank	Predicted Rank	Absolute Difference

Manchester City	1	1	0
Arsenal	2	2	0
Liverpool	3	4	1
Aston Villa	4	5	1
Tottenham	5	6	1
Chelsea	6	6	0
Newcastle United	7	7	0

From the results above, it can be seen that the model is capable of predicting teams' final positions with reasonably high accuracy, particularly for teams with stable performance throughout the season [13]. Some prediction discrepancies are caused by very close point values between teams in mid to lower table positions [18].

Visualization of prediction results against actual ranks also shows a linear and consistent trend, strengthening the finding that Random Forest Regressor can be used effectively to model and predict final rankings based on teams' statistical performance throughout a season [1][11].

The results obtained from this experiment show that the Random Forest Regressor algorithm is quite reliable in predicting the final standings of Premier League teams for the 2024 season based on performance statistics [11]. With a Mean Absolute Error (MAE) value of 1.06 [4], the model is able to provide predictions very close to actual results, where the average difference is only about one rank [7].

The success of this model can be explained by several factors:

- Random Forest's Strength in Handling Non-Linear Complexity

The Premier League is a competition with many interrelated variables [17]. For example, the number of wins and losses is not always linear to final position, as other factors like goal difference or head-to-head also play a role. Random Forest, as an ensemble model of many decision trees, has the ability to capture these non-linear relationships without needing explicit assumptions [1][13].

- Selection of Relevant Features

Features such as points, wins, draws, and losses logically contribute directly to a team's final ranking [13]. Therefore, although the model does not use all possible available features (such as number of goals, clean sheets, or possession), the predictions remain quite accurate because the core features already reflect the team's overall performance [20].

- Prediction Consistency for Elite Teams

The model has high accuracy particularly for top-tier teams like Manchester City, Arsenal, and Liverpool [18]. This indicates that the noticeable performance differences among top-tier teams can be well captured by the model. However, for mid-table and lower-table teams, accuracy slightly decreases due to very close point gaps between teams, causing uncertainty in rank order [7].

- Model Evaluation Using MAE

Using MAE as an evaluation metric provides a simple and intuitive picture of model performance [4]. Although MAE does not account for error direction (positive or negative), it is quite effective in measuring the average deviation of predictions from reality [2].

However, there are several limitations in this research:

The model does not consider external factors such as player injuries, match schedules, or home vs. away performance, which in practice significantly influence final season outcomes [12].

The number of features is limited to final statistical data, without considering dynamics throughout the season (e.g., performance trends) [16].

Historical data is not used, whereas past performance patterns could help improve prediction accuracy through time series approaches or models that consider performance changes from season to season [19].

Overall, the results of this research prove that simple machine learning approaches like Random Forest can be effectively applied in sports contexts [11][16], particularly for data-driven prediction of football standings [5]. These results also open opportunities for developing more complex models with richer features and data in the future [20].

IV. CONCLUSION AND RECOMMENDATIONS

This research proves that the Random Forest Regressor algorithm [1] can be effectively used to predict the final standings of Premier League teams for the 2024 season based on team performance statistics [9]. Using only simple features such as number of wins, draws, losses, and total points, the model is able to produce predictions with high accuracy, as shown by the Mean Absolute Error (MAE) value of 1.06 [4][7]. This demonstrates that data-driven machine learning approaches can provide relevant insights in the sports domain [12], particularly to support team performance analysis and standings prediction [17]. The advantage of the Random Forest model in handling complexity and non-linear relationships between features proves to provide stable and accurate results [1][10], especially in mapping the performance of top-tier teams [13].

However, to further improve accuracy, this research can be developed by:

- adding additional features such as number of goals, clean sheets, or individual player statistics [20],
- considering performance dynamics throughout the season [16],
- and integrating historical data from several previous seasons [19].

Thus, the results of this research not only demonstrate the successful application of machine learning in football contexts [5][11] but also open opportunities for further exploration in more comprehensive and precise sports analytics [12][17].

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