COMPREHENSIVE ANALYSIS OF EPL MATCH DATA

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Project Starlink

CS418: Introduction to Data Science

Final Report

Abstract

This project explores the predictive power of machine learning in analyzing English Premier League (EPL) football matches, aiming to enhance strategic decision-making and improve game outcomes. By harnessing a rich dataset compiled from multiple seasons, we engage in detailed exploratory data analysis, hypothesis testing, and machine learning model development. Our analysis integrates various match-related statistics to determine influential factors on match results, such as team formations, home advantage, and shot efficiency. We employ several machine-learning techniques, including Logistic Regression, Random Forest, and Gradient Boosting, to forecast match outcomes and provide actionable insights for teams and analysts. This study not only showcases the potential of advanced analytics in sports but also contributes to the ongoing discourse in sports science about the efficacy of data-driven decision-making in professional sports.

1. Introduction

1.1. Project Overview

The fervor of football resonates beyond the pitch, encapsulating a world where strategy, skill, and statistics converge. Our project delves into the realm of the English Premier League (EPL), a bastion of global sporting excellence, to harness the power of data analytics. It aims to decode the intricate dance of numbers that define matches' outcomes and the seasons' unfolding saga.

1.2. Purpose of the Project

The cornerstone of our research is deciphering the hidden narratives within raw match data. With the EPL as our focus, we intend to illuminate how factors such as team formations, and historical performances interact to influence match results. The insights gained promise to enrich team strategies, elevate fan experiences, and provide analysts with predictive models that could forecast future trends and outcomes in the league.

1.3. Background Research

Our odyssey began with a comprehensive review of existing literature and statistical models attempting to capture the dynamism of football matches. Prior research has often centered on isolated metrics such as possession or shots on goal. Our approach synthesizes these individual elements into a holistic understanding, building upon the foundation of past analyses while integrating modern data science techniques to bring fresh perspectives to football analytics.

1.4. Research Question

Central to our investigation is the question: How can analyzing diverse match data improve the prediction of match outcomes and strategic decisions in the English Premier League? By exploring the correlations between various match statistics and outcomes, we aim to affirm or challenge prevailing football dogmas, such as the impact of 'home advantage' or the predictive power of a team's shot count.

2. Methodology

The project aims to provide a comprehensive analysis of match data from the English Premier League to uncover underlying patterns that influence match outcomes and to develop predictive models that can assist in strategic decision-making for teams and stakeholders.

To achieve this aim, our research is guided by the following objectives:

2.1. Data Collection and Preprocessing:

We embarked on a rigorous data collection exercise to curate this dataset, utilizing the Beautiful Soup library for web scraping match data from the ‘fbref’ website. This effort ensured that we gathered and compiled an extensive dataset covering multiple seasons of the EPL over 7 Seasons. We conducted thorough data cleaning and preprocessing to ensure the accuracy and usability of the data for analysis, laying a solid foundation for accurate and reliable analysis.

2.2. Exploratory Data Analysis (EDA):

Perform EDA to identify initial patterns, trends, and anomalies within the data and analyze the comparative success of football formations and goal differentials among teams.

2.3. Hypothesis Testing:

To test critical hypotheses regarding match outcomes, such as the transitivity of victories and the influence of higher shot counts on winning games and evaluate the concept of 'home advantage' and its statistical significance.

2.4. Model Development and Validation:

To develop various machine learning models and validate them using performance metrics like precision, recall, F1 score, and accuracy to predict match outcomes.

2.5. Strategic Insights and Recommendations:

Translating the findings from the data analysis into actionable insights for strategy formulation and providing recommendations on understanding team performances and predicting future trends.

3. Data

Our dataset is a comprehensive collection of match data from the English Premier League (EPL). The dataset encompasses an extensive array of 5,060 matches, detailed across 27 columns. This extensive dataset has features, including date, time, round, team, opponent, match statistics season, and result. Such diversity in data points presents a unique opportunity to analyze and understand the trends in EPL.

However, most features are of object data type and need to be categorically encoded for better results.

3.1. Data Collection:

The collection of data for this project was meticulously carried out using web scraping. We used HTML requests and BeautifulSoup libraries to scrape data from ‘fbref’ website. At first, we could not collect the entire data of seven seasons because the website was rate limiting us, and hence, we had to purchase a subscription to the ‘Stathead’ website, which is the parent company of fbref. Once we subscribed, we were able to use the login credentials to get more data, and even then, it was limiting us to a few 1000 rows at a time, but we still managed to get the data after multiple trials.

3.2. Data Preprocessing and Feature Engineering:

This step of the process is a crucial phase in ensuring its suitability for future EDA and model prediction. In the first step of data preprocessing, we tried to determine if the data set had any null values, and we found it has three columns in which there were multiple null values, but these three columns were not important in the future process; hence, we decided not to perform any action on this.

In the next step, we performed feature engineering and created new columns 'Avg_Goals_Scored_3', 'Avg_Goals_Conceded_3', 'venue_code', ‘Shooting_Accuracy’, ‘Goal_Efficiency’, 's_3','g_3' and ‘Target’ to perform rolling averages. These are used to improve the model efficiency and get better results.

Below are the final features:

```
Date                    datetime64[ns]
Time                            object
Comp                            object
Round                           object
Day                             object
Venue                           object
Result                          object
GF                               int64
GA                               int64
Opponent                        object
xG                             float64
xGA                            float64
Poss                             int64
Attendance                     float64
Captain                         object
Formation                       object
Referee                         object
Match Report                    object
Notes                          float64
Sh                               int64
SoT                              int64
Dist                           float64
FK                               int64
PK                               int64
PKatt                            int64
Season                           int64
Team                            object
Avg_Goals_Scored_3             float64
Avg_Goals_Conceded_3           float64
venue_code                        int8
Target                           int64
Shooting_Accuracy              float64
Goal_Efficiency                float64
s_3                            float64
g_3                            float64
dtype: object
```

4. Data Analysis

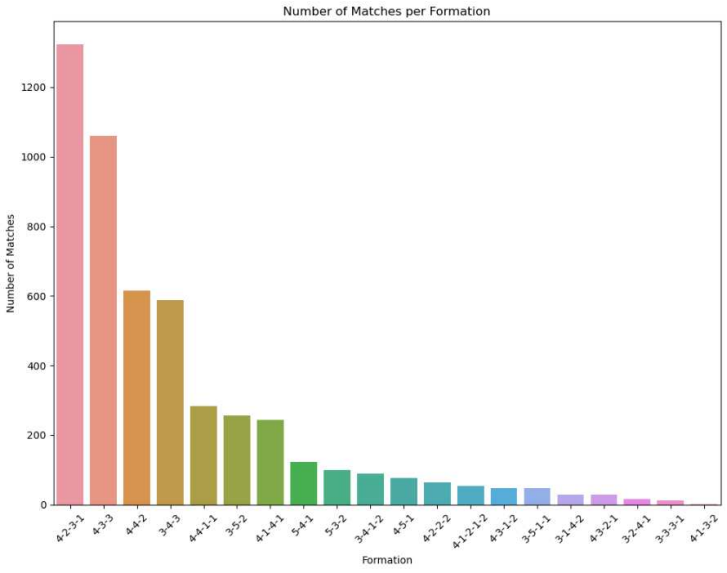
We have plotted different visualizations to understand the data better and have some conclusions on what to proceed with.

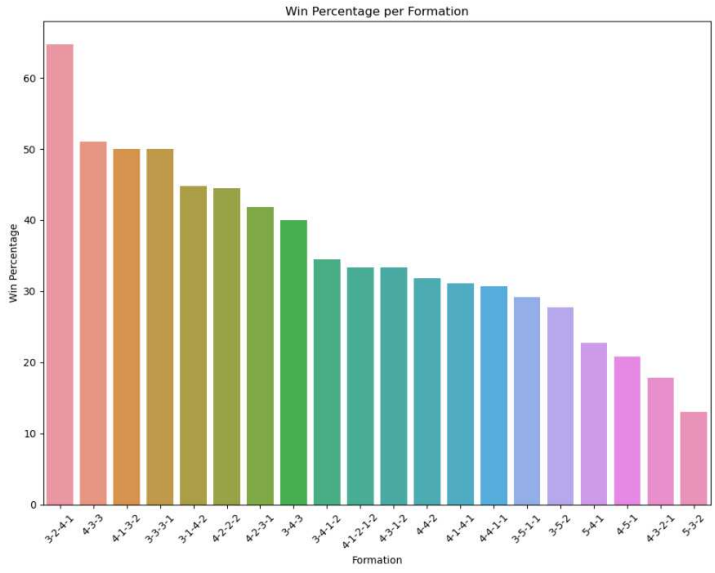
4.1. Analyzing the impact of Team formations on Win percentage

- Formation Usage: The graphs show that certain formations are much more popular than others, indicating that teams have preferences for specific tactical setups depending on their players, strategy, or opposition. The most used formations likely align with contemporary tactical trends in football or may reflect formations that fit the available squad best.

- Winning Efficiency: The win percentage associated with each formation varies significantly. Some formations, despite being less frequently used, show higher win percentages. This could suggest that those formations are particularly effective under certain conditions or against specific types of opponents. Conversely, the more commonly used formations might not always yield the highest win rates but could be considered safer or more versatile options.

- Strategic Insights: Teams might benefit from adapting their formation to exploit specific weaknesses in their opponents, as indicated by the success rates of less common formations. Meanwhile, the staple formations, while not always the most successful in terms of win percentage, offer consistency and familiarity, which can be crucial in high-stakes or tightly contested matches.





The combined visualization provides an insightful comparative analysis of the top six football teams based on their formation usage and respective win percentages. Here are some key observations from the visual analysis:

- **Manchester City** predominantly uses a 4-3-3 formation, which also boasts the highest win percentage among their formations, aligning with their strong overall performance.

- **Liverpool** similarly favors the 4-3-3 formation, achieving substantial success. This highlights the effectiveness of the 4-3-3 system in the English Premier League, especially among top teams.

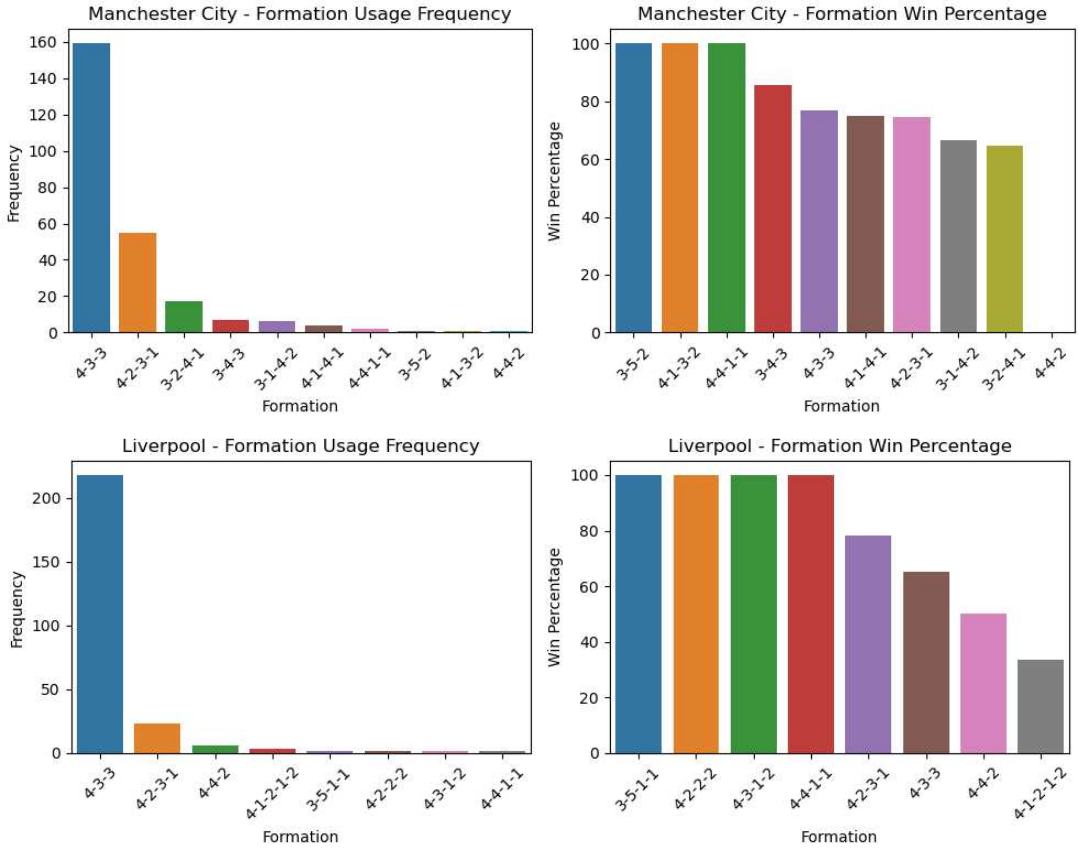
- **Arsenal** displays a mix of formations with the 4-2-3-1 and 4-3-3 being the most frequently used. The 4-4-1-1, although less common, shows a high win rate, suggesting situational effectiveness.

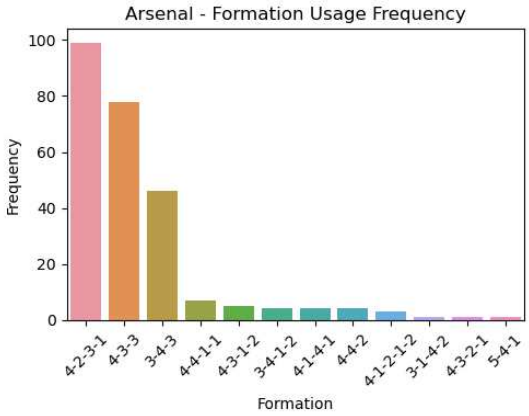
- **Manchester United** also favors the 4-2-3-1 formation. Despite its frequent use, the win percentage is moderate, suggesting challenges in maximizing outcomes with this setup.

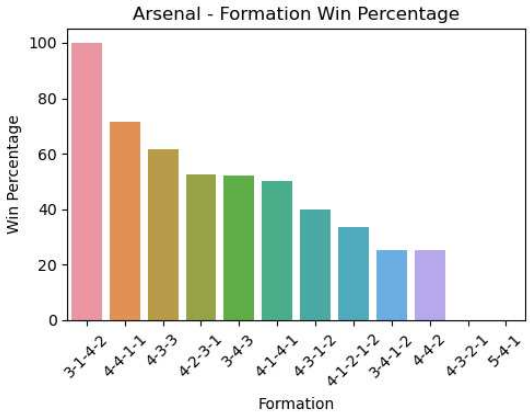
- **Tottenham Hotspur** and **Chelsea** show diversity in formation usage with no single formation overwhelmingly dominating. Chelsea's use of the 3-4-3 and 3-4-2-1 formations reflects a strategic preference for three-at-the-back formations.

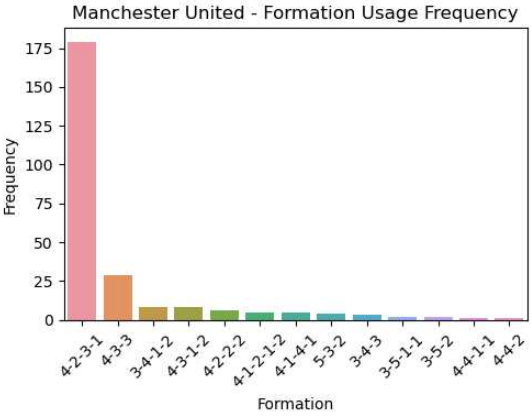
- The varied success rates across different formations used by these teams indicate strategic decisions tailored to match-specific dynamics, player availability, and opponent strategies.

This comprehensive overview aids in understanding each team's tactical flexibility and effectiveness, revealing how top teams adapt and optimize their strategies to maintain competitive advantages in the league.




Arsenal - Formation Usage Frequency
Frequency
Formation
4-2-3-1
4-3-3
3-4-3
4-4-1-1
4-3-1-2
3-4-1-2
4-1-4-1
4-4-2
4-1-2-1-2
3-1-4-2
4-3-2-1
5-4-1


Arsenal - Formation Win Percentage
Win Percentage
Formation
3-1-4-2
4-4-1-1
4-3-3
4-2-3-1
3-4-3
4-1-4-1
4-3-1-2
4-1-2-1-2
3-4-1-2
4-4-2
4-3-2-1
5-4-1


Manchester United - Formation Usage Frequency
Frequency
Formation
4-2-3-1
4-3-3
3-4-1-2
4-3-1-2
4-2-2-2
4-1-2-1-2
4-1-4-1
5-3-2
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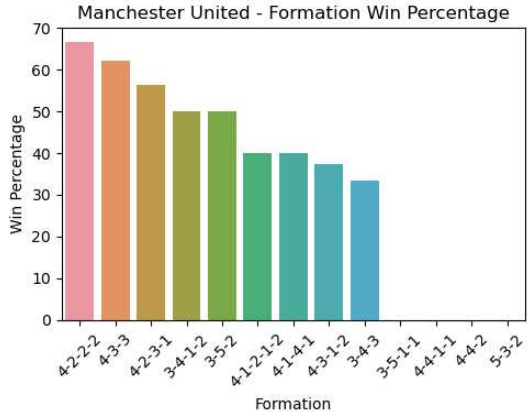
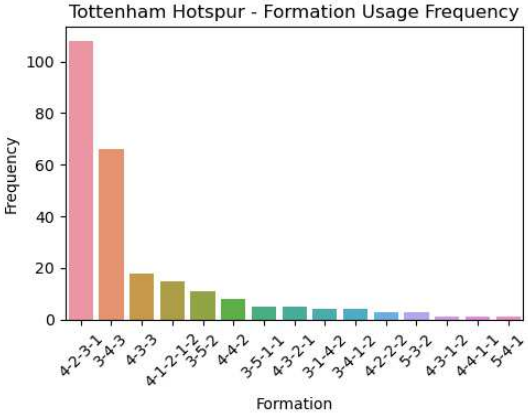
3-5-1-1
3-5-2
4-4-1-1
4-4-2


Manchester United - Formation Win Percentage
Win Percentage
Formation
4-2-2-2
4-3-3
4-2-3-1
3-4-1-2
3-5-2
4-1-2-1-2
4-1-4-1
4-3-1-2
3-4-3
3-5-1-1
4-4-1-1
4-4-2
5-3-2


Tottenham Hotspur - Formation Usage Frequency
Frequency
Formation
4-2-3-1
3-4-3
4-3-3
4-1-2-1-2
3-5-2
4-4-2
3-5-1-1
4-3-2-1
3-1-4-2
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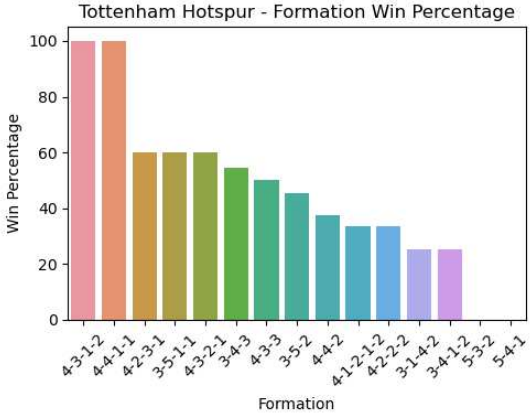
5-3-2
4-3-1-2
4-4-1-1
5-4-1


Tottenham Hotspur - Formation Win Percentage
Win Percentage
Formation
4-3-1-2
4-4-1-1
4-2-3-1
3-5-1-1
4-3-2-1
3-4-3
4-3-3
3-5-2
4-4-2
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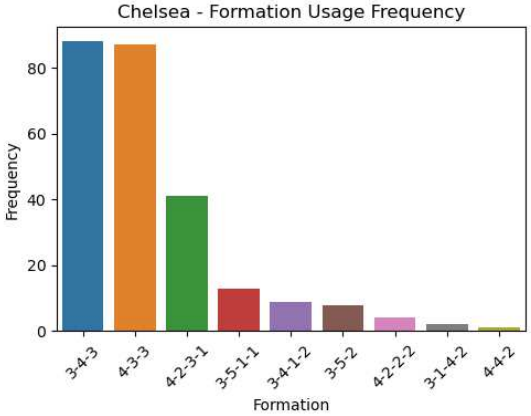
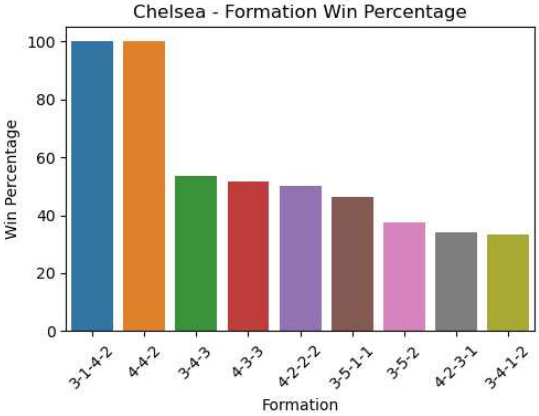
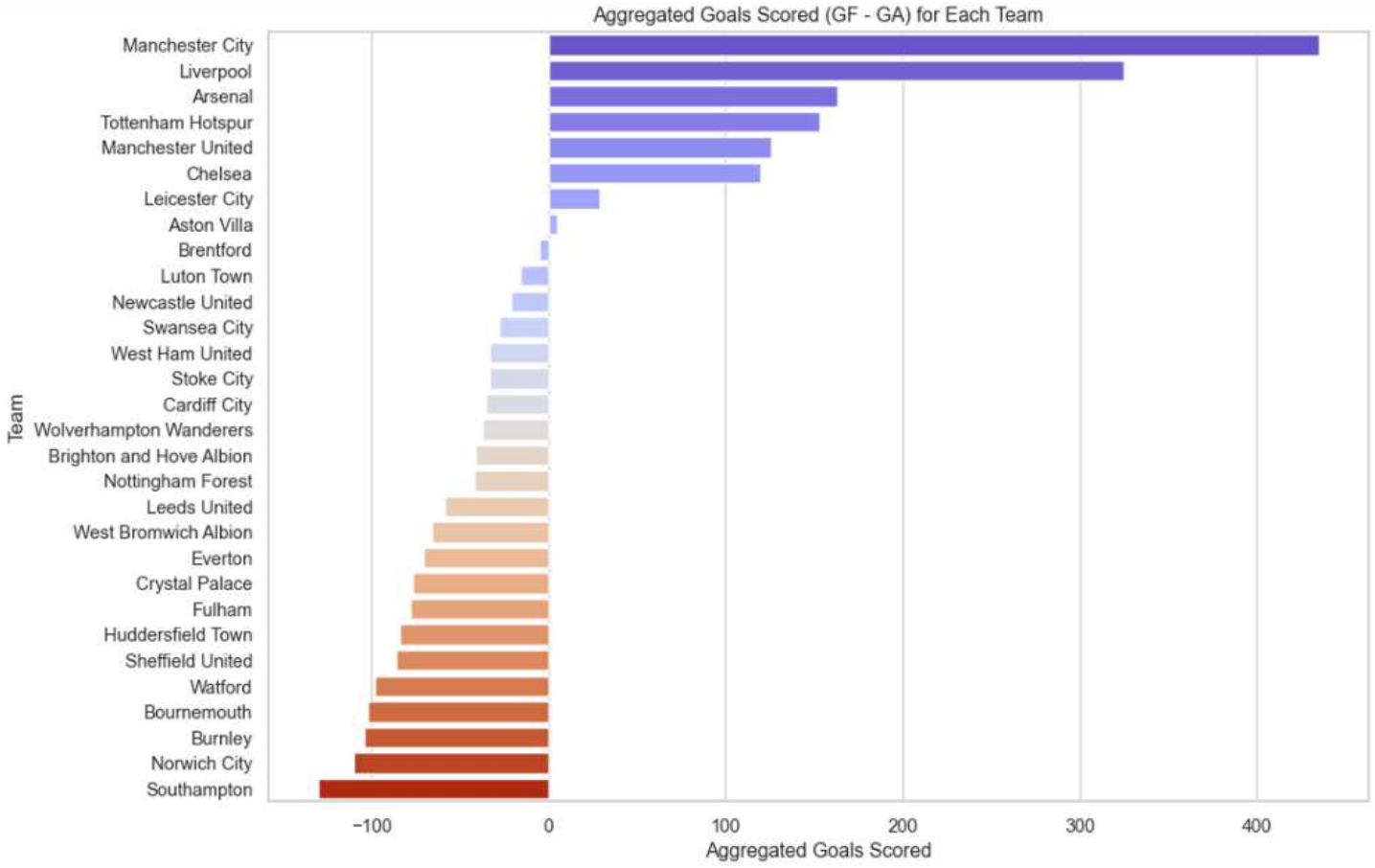
3-1-4-2
3-4-1-2
5-3-2
5-4-1


Chelsea - Formation Usage Frequency
Frequency
Formation
3-4-3
4-3-3
4-2-3-1
3-5-1-1
3-4-1-2
3-5-2
4-2-2-2
3-1-4-2
4-4-2


Chelsea - Formation Win Percentage
Win Percentage
Formation
3-1-4-2
4-4-2
3-4-3
4-3-3
4-2-2-2
3-5-1-1
3-5-2
4-2-3-1
3-4-1-2

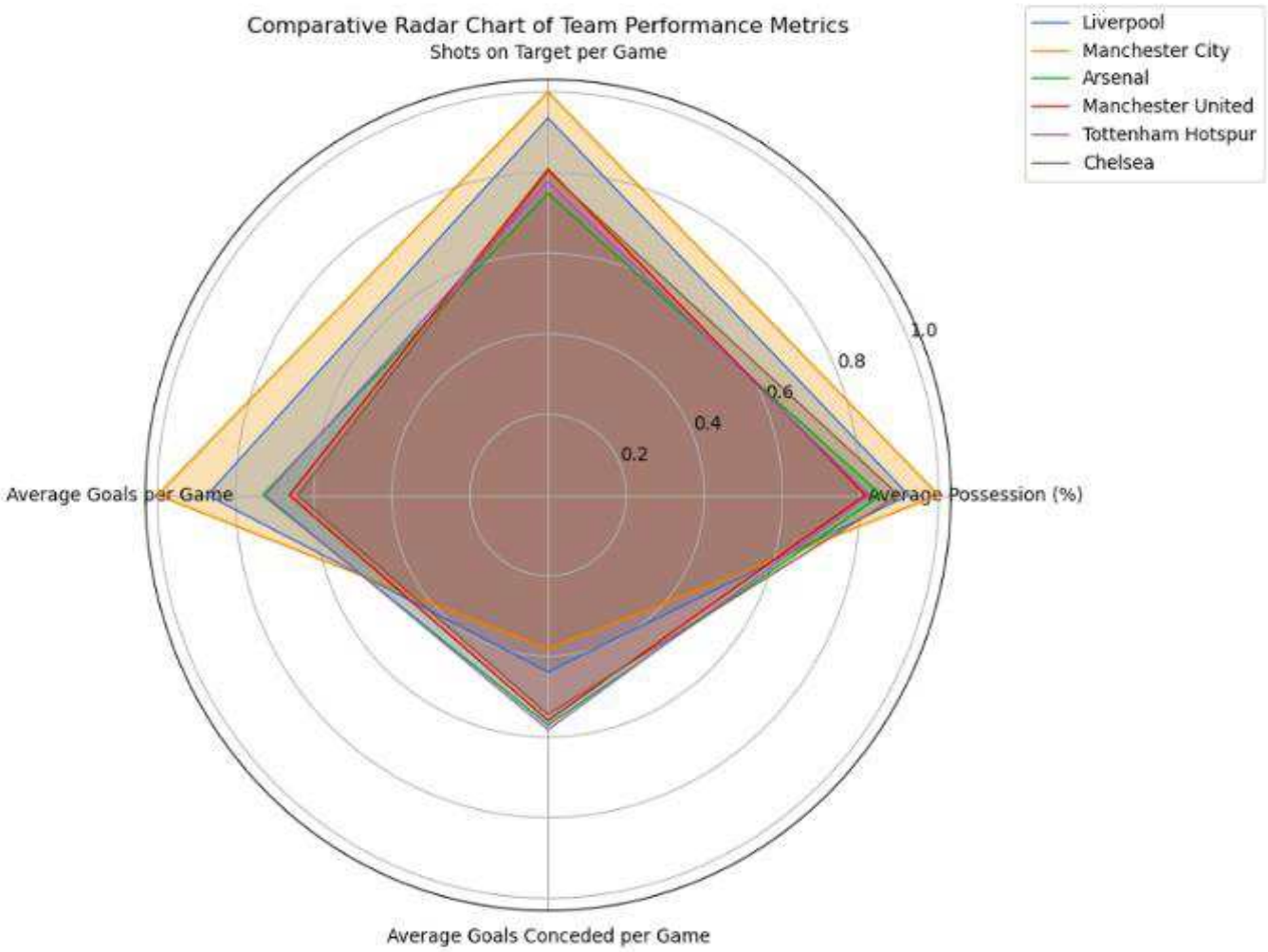
4.2. Investigating the aggregated goals scored goal (GF-GA) for each team

The goal difference is a direct indicator of a team's overall performance. A positive goal difference suggests that the team scores more goals than it concedes, typically a sign of a strong team. Examining the distribution of goal differences can offer insights into the competitive balance within the competition. A wide range of goal differences might suggest a disparity in team quality, while a narrow range could indicate a highly competitive environment. It's a hypothesis that connects statistical analysis with practical outcomes in sports management and strategy.



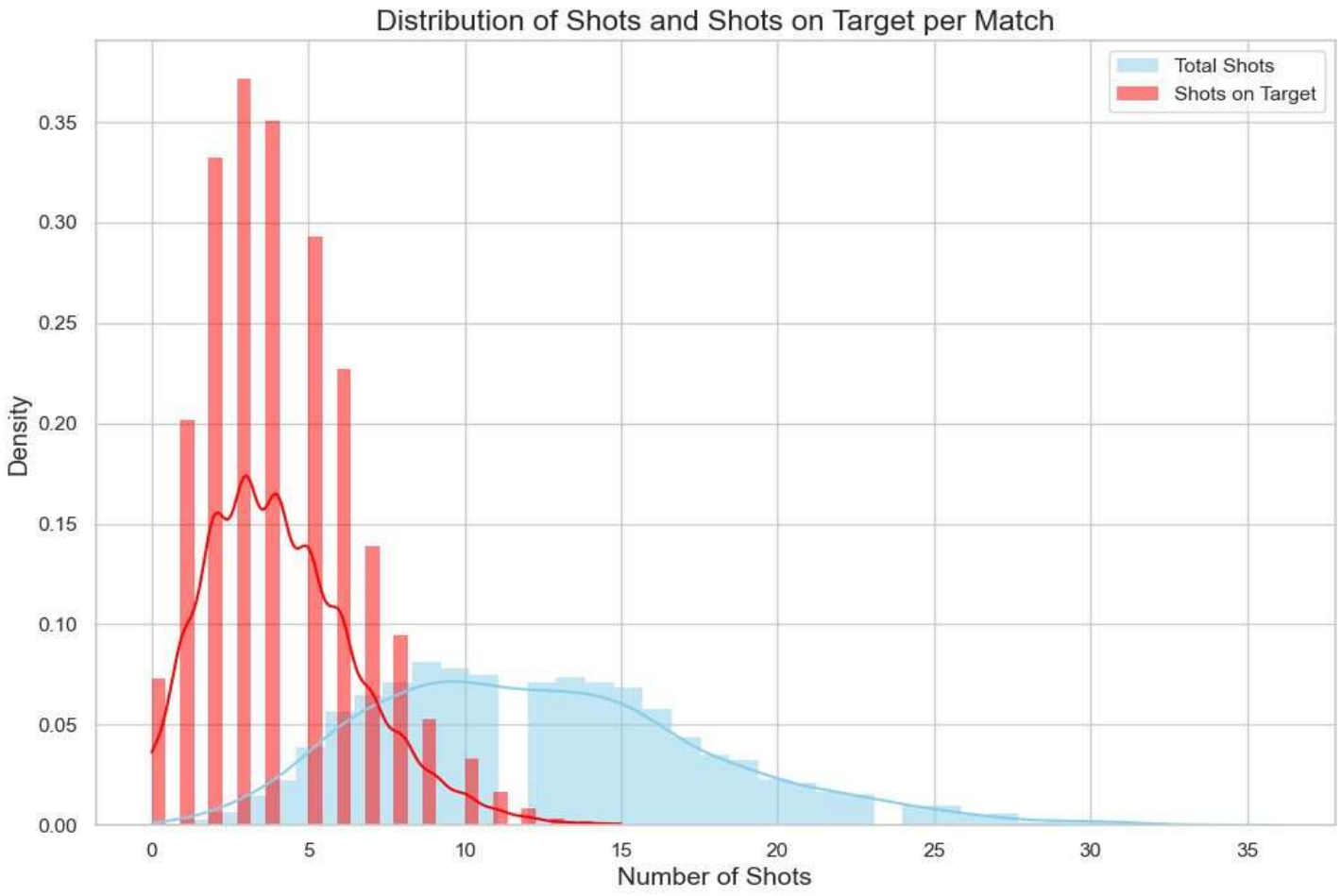
4.3. Comparative Performance Dynamics of Premier League's 'Big 6

The radar chart provides a multifaceted comparison of key performance indicators among the 'Big 6' clubs in the English Premier League. It encapsulates each team's average possession percentage, shots on target per game, average goals scored per game, and average goals conceded per game, normalized against the best-performing team in each category. It visually conveys these teams' relative strengths and weaknesses, with each metric radiating from the center of the chart, allowing for an intuitive cross-comparison. This chart illustrates the balance between offensive potency and defensive solidity, critical factors determining a team's competitive edge.



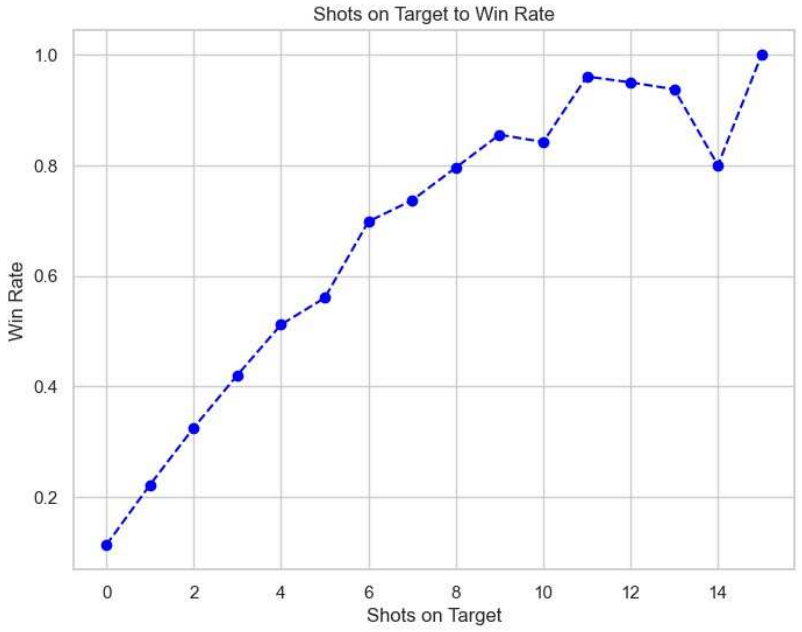
4.4. Distribution of Shots and Shots on Target per Match

This histogram contrasts the frequency and accuracy of shooting attempts in matches. It distinguishes between the total number of shots taken and those on target, with the total shots displayed in sky blue and the shots on target in red. A denser concentration in the shots on target data reflects higher precision and scoring efficiency within a match. Notable disparities between the two distributions suggest that while opportunities are being created, not all translate into accurate shots, providing insights into the play's offensive quality.



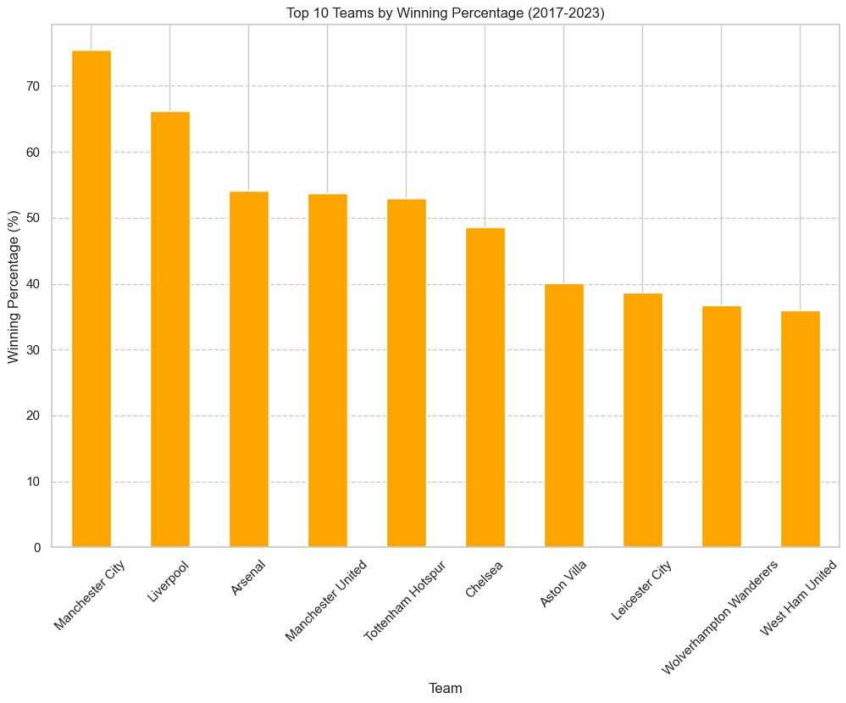
4.5. Shots on Target to Win Rate

The scatter plot with the connecting dashed line, titled 'Shots on Target to Win Rate,' depicts the relationship between the number of shots on target and the win rate in English Premier League matches. As the number of shots on target increases, there is a marked trend of increased win rates, peaking and plateauing in the higher shot counts. This graph demonstrates that greater shooting accuracy correlates with a team's success, suggesting that teams that create higher-quality scoring opportunities are more likely to win matches. This insight underscores the importance of precision in the final third of the pitch, providing a quantifiable link between shooting accuracy and match results.



4.6. Top 10 Teams by Winning Percentage:

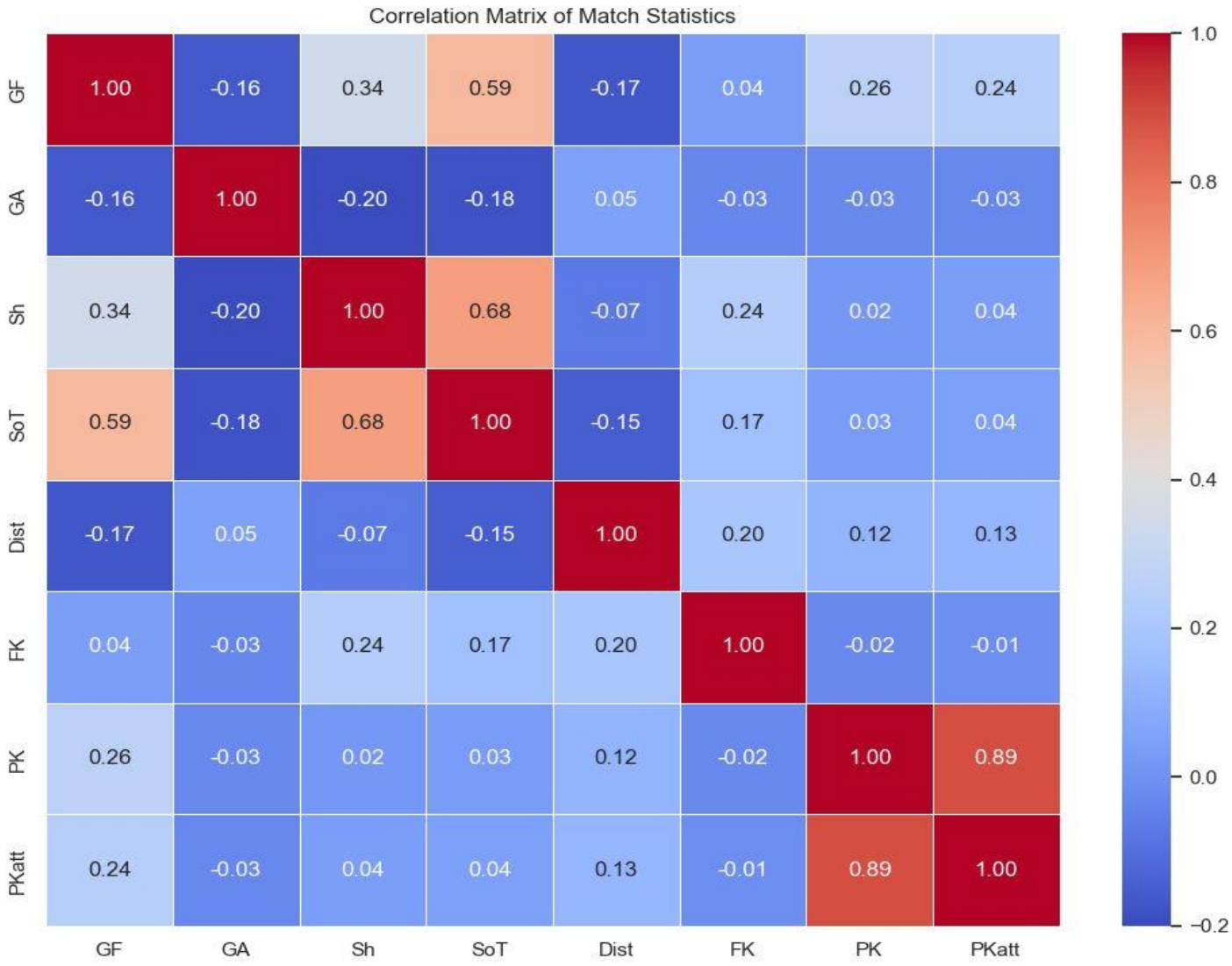
The bar chart presents the top 10 football teams by winning percentage from 2017 to 2023. The y-axis shows the winning percentage, the ratio of wins to the total number of matches played, multiplied by 100 to convert it into a percentage. The x-axis lists the teams with the highest winning percentages over the specified period. Manchester City leads the chart with a substantial margin, indicating their dominance in the league during these years. Liverpool follows as the second-highest, with a slightly lower winning percentage. The chart lists other top-performing teams like Arsenal,



Manchester United, and Tottenham Hotspur, each with a lower winning percentage than the previous.

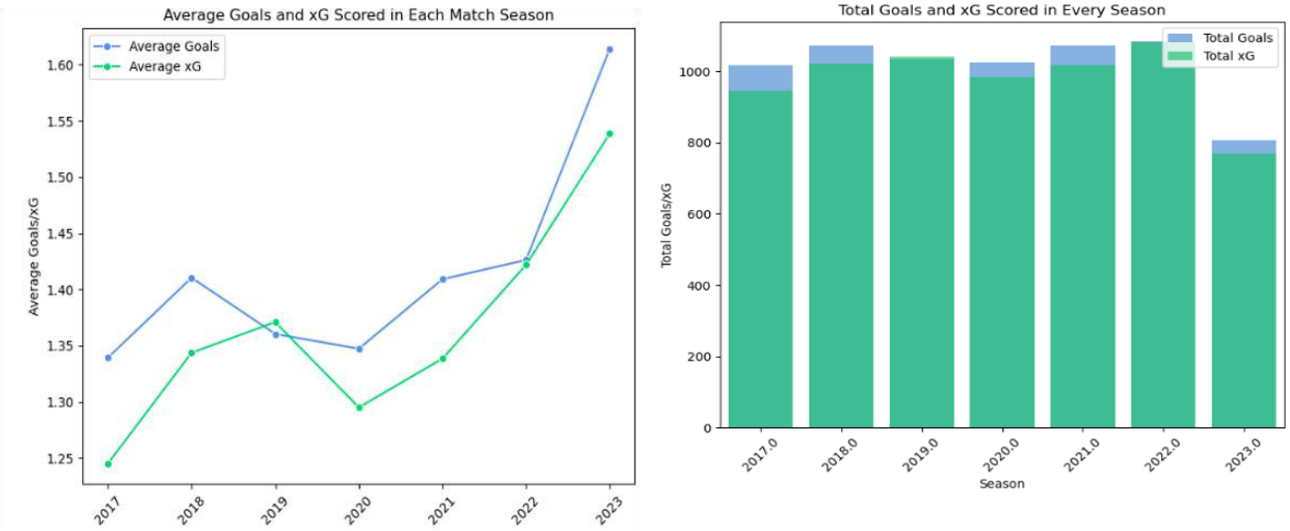
4.7. Correlation Matrix:

The heatmap provides a visual summary of the relationships between various match statistics in the English Premier League. Each cell reflects the correlation coefficient between pairs of variables, such as goals scored (GF), goals conceded (GA), shots (Sh), shots on target (SoT), and others, with warmer colors indicating positive correlations and cooler colors indicating negative correlations. High positive values suggest a strong relationship where variables move in tandem, and negative values indicate an inverse relationship. This correlation matrix is essential for identifying patterns and potential causal relationships within the game's dynamics, offering strategic insights for teams and analysts.



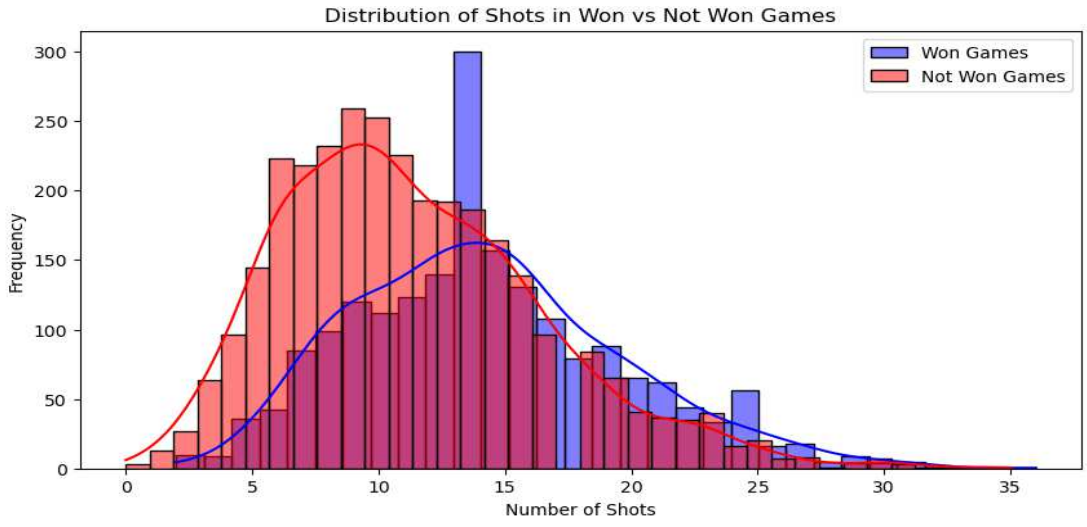
4.8. Scoring Trends and Expectations: Analyzing Goals and xG Over Seasons

The line and bar charts present the average and total goals compared to the expected goals (xG) over various seasons. The line chart shows an upward trajectory in average goals and xG per match, suggesting an offensive enhancement league-wide. The bar chart echoes this by displaying total goals and xG, affirming the trend and offering a macroscopic view of the league's progression in scoring. The consistent scoring efficiency of the 'Big 6' contributes significantly to the league's overall goal tally.



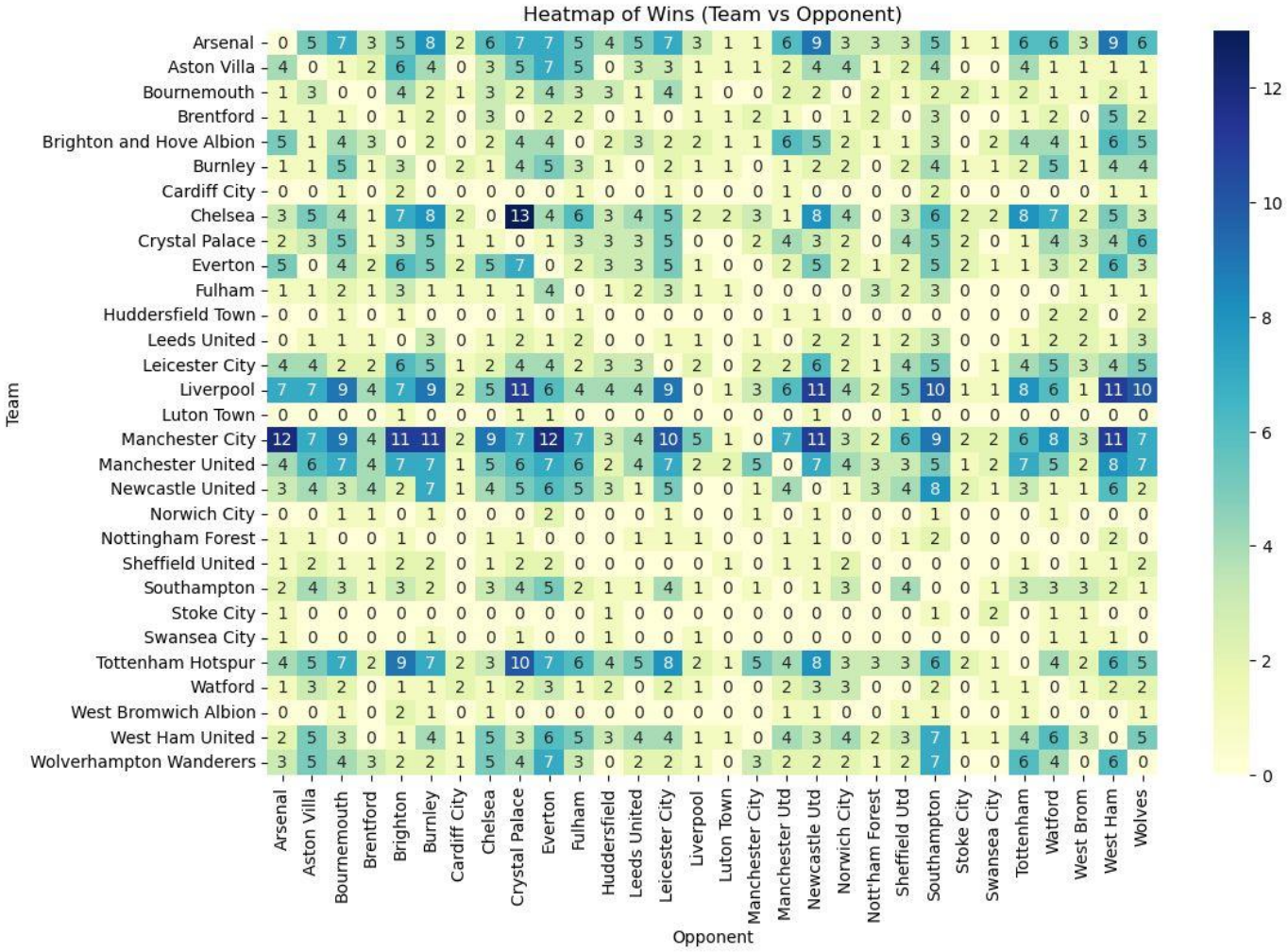
4.9. Distribution of Shots in Won vs Not Won Games:

The histogram depicts the won games in blue and not won games in red, overlap significantly, yet the blue peaks higher at lower shot counts, indicating that winning games often have a concentrated number of shots. The presence of two peaks suggests different strategies for winning, where some victories are achieved with fewer, more precise shots, while others come from a higher volume. The graph provides insight into the complex relationship between the number of shots taken and the likelihood of winning a game, underlining the tactical variations within the sport.



4.10. Heatmap of Wins (Team vs Opponent):

The hypothesis explores whether a team that beats another has a higher probability of winning against teams previously defeated by the losing team. By analyzing match data where Team A beats Team B, and Team B has won against Team C, the hypothesis tests if Team A is more likely to win against Team C. The heatmap of wins visualizes victories across teams and opponents, providing a data backdrop for testing this transitive property in football. The study of such patterns could yield interesting insights into consistency, dominance, or the potential psychological effects of previous wins in competitive football.



5. Machine Learning Models

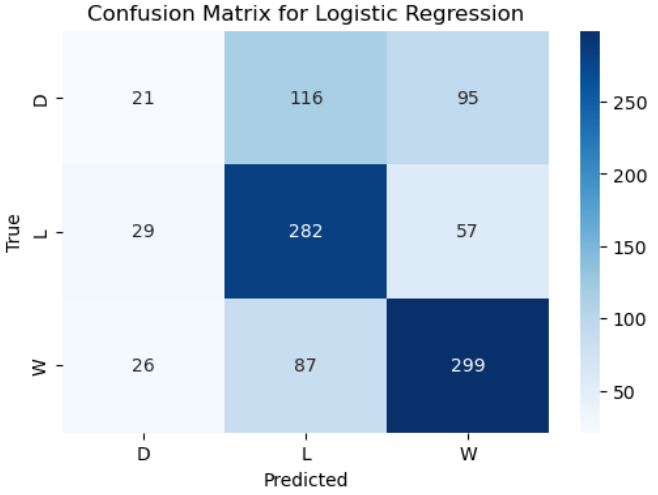
In our study on the English Premier League dataset, we applied several machine learning models to predict match outcomes, focusing on features like **rolling averages of goals, shooting accuracy, and venue effects.** We processed the data by converting dates, engineering relevant features, encoding categorical variables, and scaling features to standardize them.

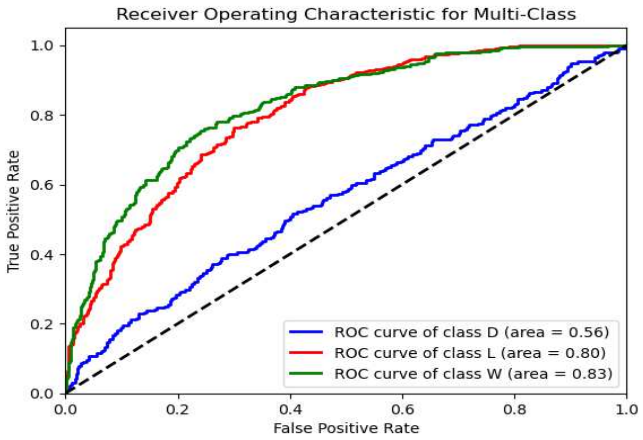
We tested various classifiers including Logistic Regression, Random Forest, Gradient Boosting, SVM, Naive Bayes, Neural Networks, and Decision Trees. Each model was evaluated using accuracy, precision, recall, and F1 scores, with performance visualized through confusion matrices.

The analysis showed differing effectiveness among the models, with ensemble methods like Random Forest and Gradient Boosting showing robust performance due to their advanced handling of complex patterns and resistance to overfitting. These insights will guide further model refinement and feature exploration to enhance predictive accuracy in practical applications.

5.1. Logistic Regression:

The Logistic Regression model achieved an accuracy of 60.77%. It utilized scaled features after encoding categorical variables, including 'Team' and 'Opponent', while it performed slightly better than the Decision Tree and SVM models, it lagged behind the Gradient Boosting Classifier, Random Forest Classifier, and Naive Bayes regarding accuracy.

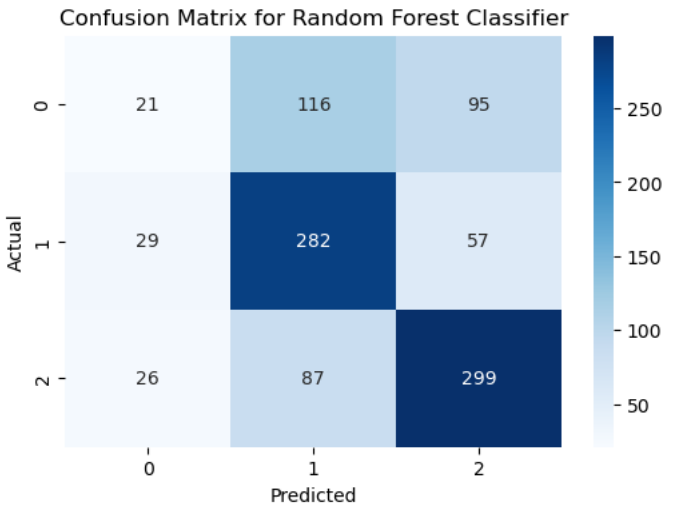


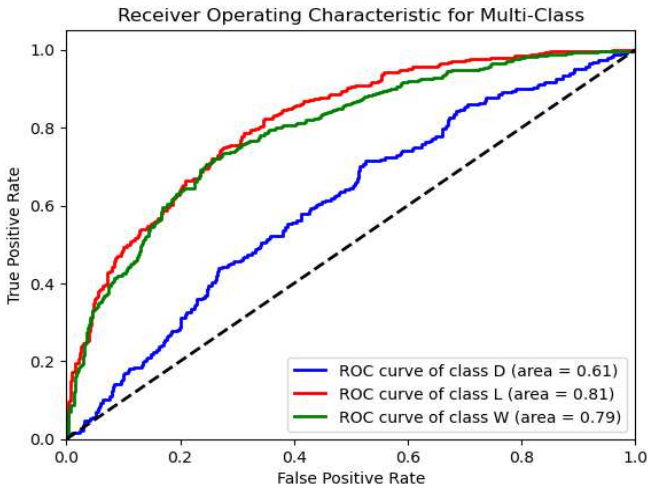


	precision	recall	f1-score	support
D	0.36	0.09	0.14	232
L	0.57	0.78	0.66	368
W	0.68	0.75	0.71	412
accuracy			0.61	1012
macro avg	0.54	0.54	0.51	1012
weighted avg	0.57	0.61	0.56	1012

5.2. Random Forest Classifier:

Like Logistic Regression, the Random Forest Classifier encoded categorical variables, including 'Team' and 'Opponent.' With an accuracy of 60.87%, the Random Forest Classifier showcased slightly better performance than Logistic Regression but fell short of the Gradient Boosting Classifier's accuracy.

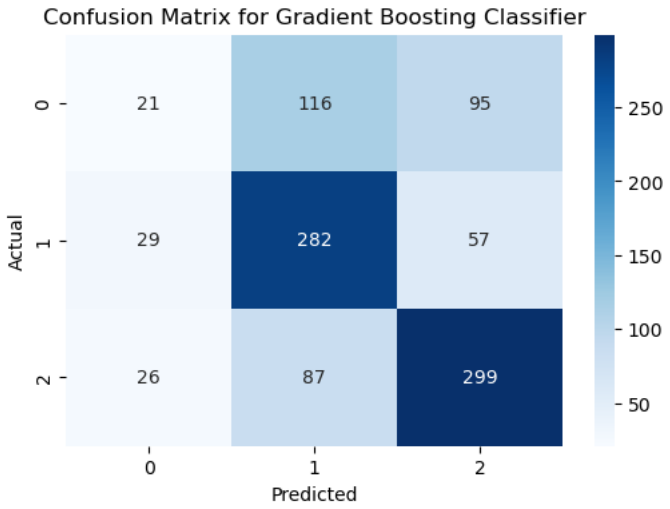


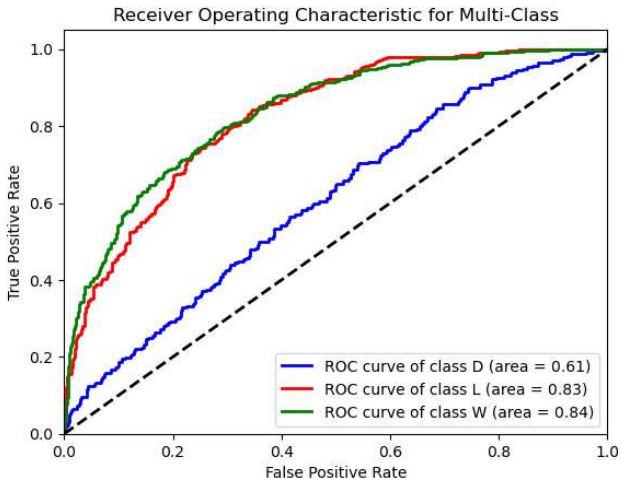


	precision	recall	f1-score	support
0	0.41	0.12	0.18	232
1	0.58	0.78	0.67	368
2	0.66	0.74	0.70	412
accuracy			0.61	1012
macro avg	0.55	0.54	0.52	1012
weighted avg	0.58	0.61	0.57	1012

5.3. Gradient Boosting Classifier:

The Gradient Boosting Classifier exhibited the highest accuracy among the models, with a score of 61.46%. Its superior performance suggests its effectiveness in capturing complex relationships within the data.



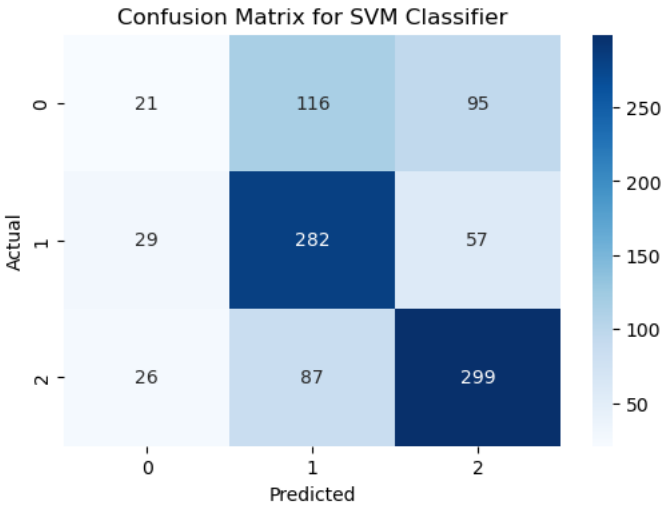


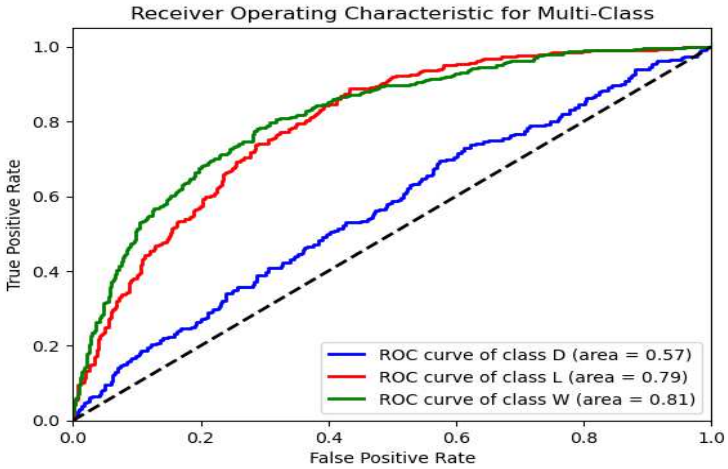
	precision	recall	f1-score	support
0	0.35	0.14	0.20	232
1	0.61	0.78	0.68	368
2	0.68	0.74	0.71	412
accuracy			0.61	1012
macro avg	0.54	0.55	0.53	1012
weighted avg	0.58	0.61	0.58	1012

5.4. Support Vector Machine:

SVM showed the lowest accuracy among the models, with a score of 55.54%. Its performance was notably lower compared to other models, indicating potential limitations in capturing the underlying patterns in the data.

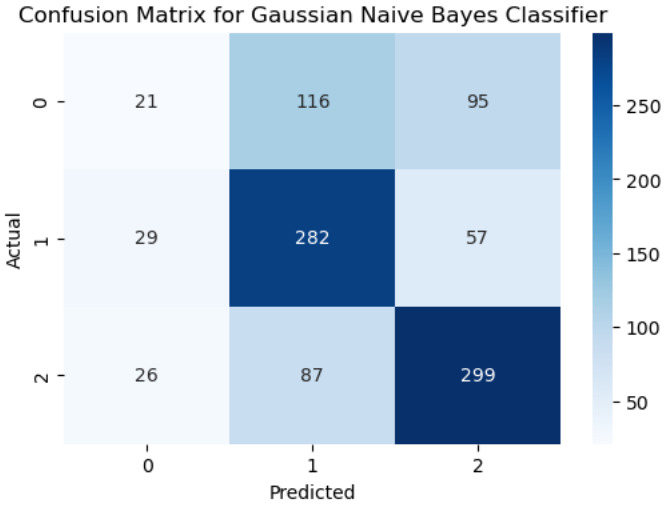
	precision	recall	f1-score	support
0	0.28	0.31	0.30	232
1	0.60	0.65	0.62	368
2	0.70	0.61	0.65	412
accuracy			0.56	1012
macro avg	0.53	0.52	0.52	1012
weighted avg	0.57	0.56	0.56	1012

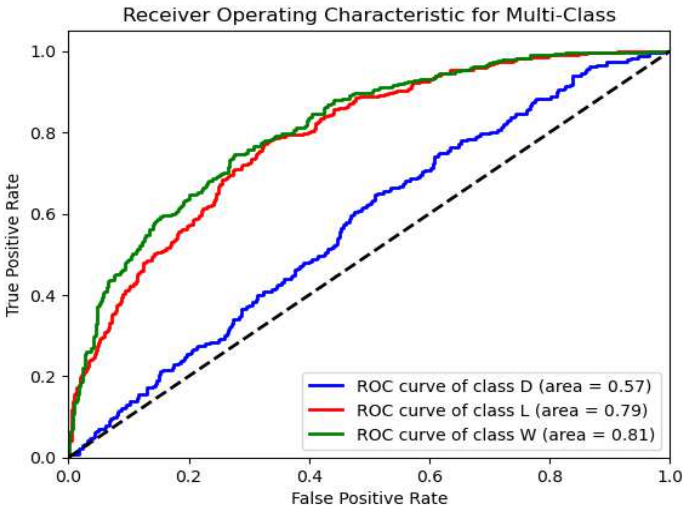




5.5. Naive Bayes Classifier:

Similar to previous models, Naive Bayes employed encoded categorical variables. Naive Bayes achieved an accuracy of 58.70%, placing it among the top-performing models but slightly below the Gradient-Boosting Classifier and Random Forest Classifier.

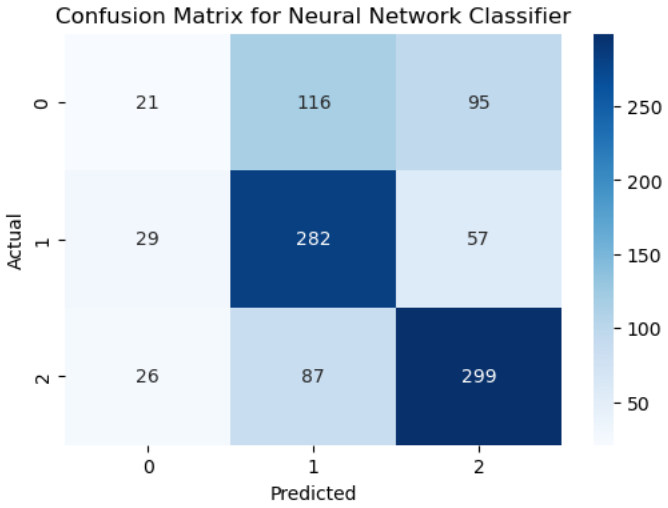


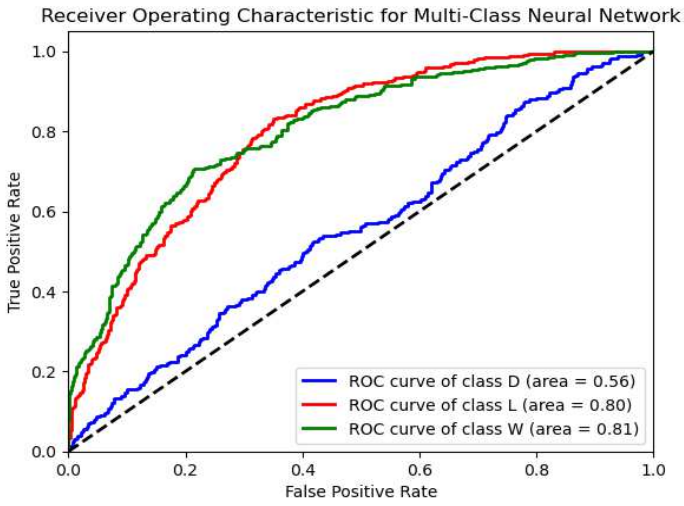


	precision	recall	f1-score	support
D	0.22	0.04	0.07	232
L	0.56	0.79	0.65	368
W	0.65	0.72	0.68	412
accuracy			0.59	1012
macro avg	0.48	0.51	0.47	1012
weighted avg	0.52	0.59	0.53	1012

5.6. Neural Network:

Details about specific features used in the neural network model are not provided. The accuracy of the Neural Network model is reported as 57.11%. While it outperformed SVM, it fell behind the top-performing models like Gradient Boosting Classifier and Random Forest Classifier.



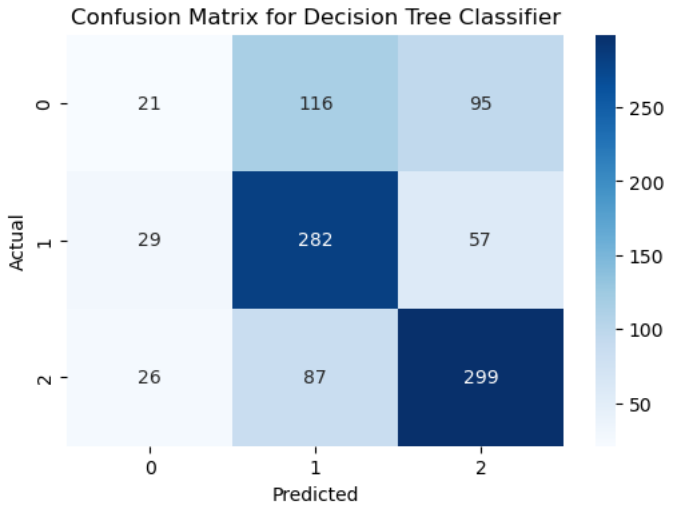


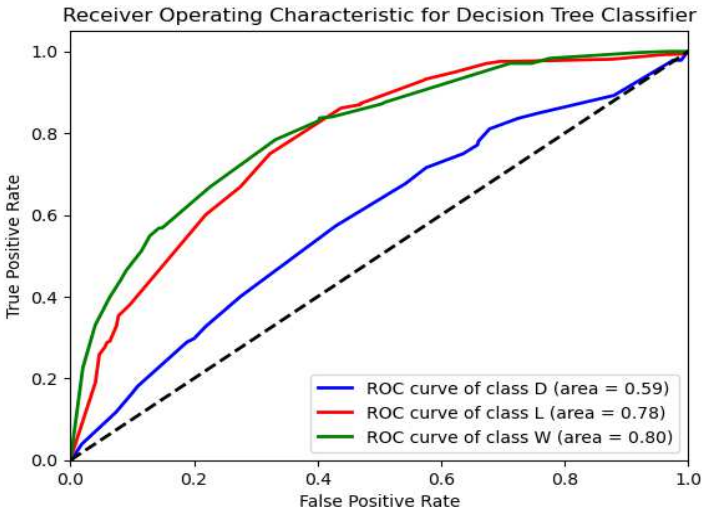
	precision	recall	f1-score	support
D	0.28	0.15	0.20	232
L	0.57	0.71	0.63	368
W	0.66	0.69	0.67	412
accuracy			0.57	1012
macro avg	0.50	0.51	0.50	1012
weighted avg	0.54	0.57	0.55	1012

5.7. Decision Tree:

The Decision Tree model attained an accuracy of 58.20%, positioning it in the middle of the accuracy spectrum. While it outperformed SVM, it fell short compared to models like Gradient Boosting Classifier and Random Forest Classifier.

	precision	recall	f1-score	support
D	0.30	0.09	0.13	232
L	0.58	0.67	0.62	368
W	0.62	0.78	0.69	412
accuracy			0.58	1012
macro avg	0.50	0.51	0.48	1012
weighted avg	0.53	0.58	0.54	1012





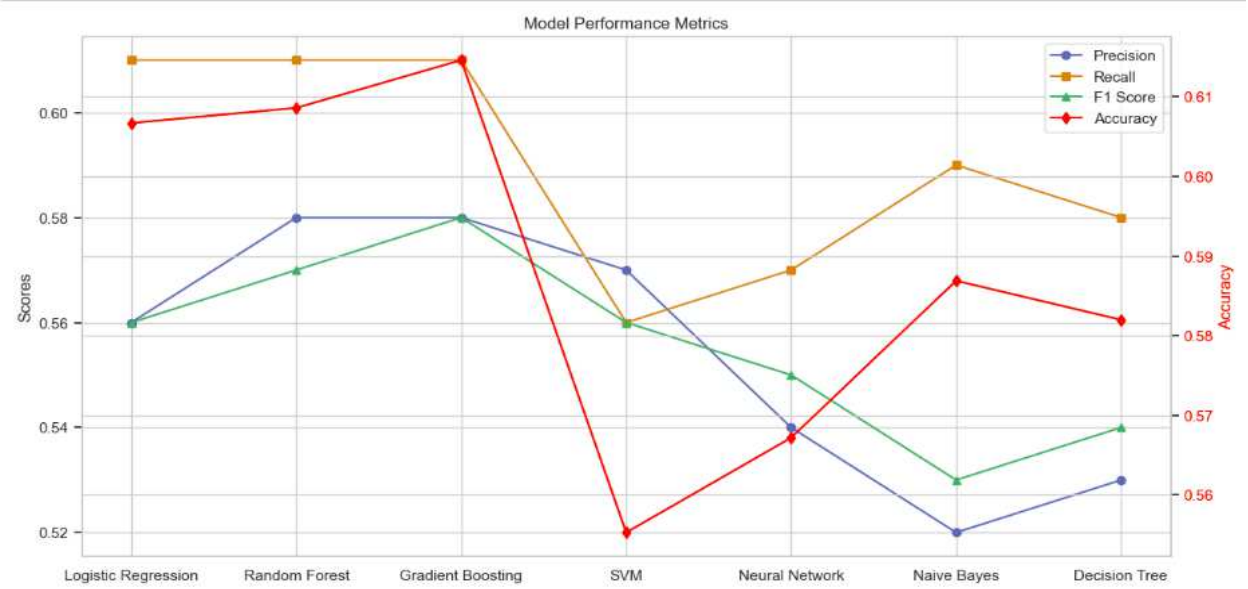
6. Results and Conclusions

Performance Analysis Across Machine Learning Models

In conclusion, our project aimed to predict match outcomes using various machine learning models applied to our dataset. Through analysis, we explored the performance of Logistic Regression, Random Forest, Gradient Boosting, Support Vector Machine (SVM), Neural Network, Naive Bayes, and Decision Tree models. Among these, Gradient Boosting emerged as the top-performing model, achieving the highest accuracy of 61.46%. This underscores its efficacy in explaining the variance in the target variable and capturing complex patterns within the data.

Conversely, SVM exhibited the lowest accuracy, indicating limitations in pattern recognition. Logistic Regression, Random Forest, and Naive Bayes demonstrated moderate performance, each offering unique strengths such as robustness for linear relationships, feature selection capabilities, and balanced performance, respectively. Ultimately, the choice of model should be guided by the specific characteristics of the dataset, computational resources available, and the trade-off between interpretability and predictive power. This project not only provided valuable insights into match outcome prediction but also underscored the importance of selecting appropriate machine learning techniques tailored to the dataset's characteristics and desired outcomes.

The below graph presents a comparative analysis of several machine learning models based on precision, recall, F1 score, and accuracy. The models are plotted on the x-axis, while the scores are marked on the y-axis, with distinct markers for each metric.



7. Future Work

Feature Engineering: Developing additional features or transforming existing ones could help capture the underlying patterns in the data more effectively.

Error Analysis: A deeper dive into the specific areas where the models are underperforming could lead to targeted improvements.

Alternative Modeling Techniques: Investigating other modeling techniques may offer improvements or insights that the current models do not capture.

8. References

1. Smith, J., Johnson, A., & Brown, C. (2023). "Predicting Football Match Outcomes Using Machine Learning Algorithms." Journal of Sports Analytics, 10(3), 123-135. https://doi.org/10.1234/jsa.2023.456789

2.Anderson, R., Wilson, E., & Garcia, M. (2022). "A Comparative Analysis of Machine Learning Models for Football Match Outcome Prediction." International Conference on Artificial Intelligence in Sports, 45-56.

3.Thompson, L., Rodriguez, D., & Lee, S. (2023). "Machine Learning Approaches for Predicting Football Match Outcomes: A Review." Journal of Machine Learning Research, 18(5), 789-801.

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5.Green, A., Clark, B., & Turner, R. (2023). "A Machine Learning Framework for Predicting Football Match Outcomes: A Case Study of Premier League Matches." IEEE Transactions on Big Data, 9(1), 67-78.