Comprehensive Analysis of EPL Match Data

Github Link here - https://github.com/RishiMMMM/Comprehensive-analysis-of-EPL-match-data (https://github.com/RishiMMMM/Comprehensive-analysis-of-EPL-match-data)

Introduction

Our project is about digging into a big set of data from English Premier League football matches to find patterns and make predictions about which teams will win. Football is not just a game for us; it's a puzzle with pieces scattered in rows of data. With over 5000 matches' worth of details, we're looking to sort through the stats and come up with smart guesses on game outcomes. It's a project that mixes our love of the sport with our interest in data, and we hope it can help fans and experts get new insights into the game.

Changes Since the Proposal

Since our initial project proposal, our scope has expanded to include a deeper statistical analysis and more complex machine learning models. We first used Random Forest Classifiers and now expanded to using Support Vector Machines and Gradient Boosting algorithms. We've also decided to incorporate additional data visualization techniques to better understand the dataset.

Data

We performed web scraping from the website, 'https://fbref.com/en/comps/9/Premier-League-Stats' (https://fbref.com/en/comps/9/Premier-League-Stats')

In [1]:
```
import requests
from bs4 import BeautifulSoup
import pandas as pd
import time
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
```

We collected data from 2017 season onwards till February 2024

In [2]:
```
years = list(range(2023, 2017, -1))
```

```
In [ ]: session = requests.Session()

        # Replace with your login credentials and the login URL
        payload = {
            'username': 'rmadha4',
            'password': 'Madhavaram@1'
        }
        login_page_url = 'https://stathead.com/users/login.cgi?token=1&__hstc=218152582.ffc1803babda4560a6e1c515
        session.post(login_page_url, data = payload)
        all_matches = []
        standings_url = 'https://fbref.com/en/comps/9/Premier-League-Stats'
        for year in years:
            data = session.get(standings_url)
            soup = BeautifulSoup(data.text)
            standings_table = soup.select('table.stats_table')[0]
            links = standings_table.find_all('a')
            links = [l.get("href") for l in links]
            links = [l for l in links if '/squads/' in l]
            # print(links)
            team_urls = [f"https://fbref.com{l}" for l in links]

            previous_season = soup.select("a.prev")[0].get("href")
            standings_url = f"https://fbref.com{previous_season}"
            print(year)
            for team_url in team_urls:
                team_name = team_url.split("/")[-1].replace("-Stats", "").replace("-", " ")
                data = session.get(team_url)
                # # print(0.)
                # print(data)
                matches = pd.read_html(data.text, match="Scores & Fixtures")[0]
                soup = BeautifulSoup(data.text)
                links_1 = soup.find_all('a')
                # print(1.)
                # print(links_1)
                links_1 = [l_1.get("href") for l_1 in links_1]
                # print(2.)
                # print(links_1)
                links_1 = [l_1 for l_1 in links_1 if l_1 and 'all_comps/shooting/' in l_1]
                # print(3.)
                # print(links_1)
                data = session.get(f"https://fbref.com{links_1[0]}")
                # print(4.)
                # print(data)
                shooting = pd.read_html(data.text, match="Shooting")[0]

                shooting.columns = shooting.columns.droplevel()
                # print(5.)
                # print(shooting)
                try:
                    team_data = matches.merge(shooting[["Date", "Sh", "SoT", "Dist", "FK", "PK", "PKatt"]], on='
                except ValueError:
                    continue
                team_data = team_data[team_data["Comp"] == "Premier League"]

                team_data["Season"] = year
                team_data["Team"] = team_name
                all_matches.append(team_data)
                time.sleep(3)
```

- In the data cleaning process, we concatenated all the seasons vertically to create a consolidated dataset that stores all the matches that occurred from August 2017 to February 2024.
- We stored this dataset in matches.csv file
- From the dataset, you can find that we have few features that are of object datatype. Inorder to use these features efficiently in our predictions, we performed some feature engineering to categorize these features.

```
In [1]: match_df = pd.concat(all_matches)
        match_df.to_csv("matches-19-17.csv")
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[1], line 1
----> 1 match_df = pd.concat(all_matches)
      2 match_df.to_csv("matches-19-17.csv")

NameError: name 'pd' is not defined
```

```
In [2]: matches = pd.read_csv('matches.csv', index_col=0)
        matches
```

Out[2]:

	Date	Time	Comp	Round	Day	Venue	Result	GF	GA	Opponent	...	Match Report	Notes	Sh	SoT	Dist	FK	PK
0	8/13/2023	16:30	Premier League	Matchweek 1	Sun	Away	D	1	1	Chelsea	...	Match Report	NaN	13	1	17.8	0	(
1	8/19/2023	15:00	Premier League	Matchweek 2	Sat	Home	W	3	1	Bournemouth	...	Match Report	NaN	25	9	16.8	1	(
2	8/27/2023	16:30	Premier League	Matchweek 3	Sun	Away	W	2	1	Newcastle Utd	...	Match Report	NaN	9	4	17.2	1	(
3	9/3/2023	14:00	Premier League	Matchweek 4	Sun	Home	W	3	0	Aston Villa	...	Match Report	NaN	17	4	14.7	0	(
4	9/16/2023	12:30	Premier League	Matchweek 5	Sat	Away	W	3	1	Wolves	...	Match Report	NaN	16	5	15.8	0	(
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	..
38	4/15/2018	16:00	Premier League	Matchweek 34	Sun	Away	W	1	0	Manchester Utd	...	Match Report	NaN	10	4	18.1	0	(
39	4/21/2018	12:30	Premier League	Matchweek 35	Sat	Home	D	2	2	Liverpool	...	Match Report	NaN	13	6	17.7	0	(
40	4/28/2018	15:00	Premier League	Matchweek 36	Sat	Away	W	1	0	Newcastle Utd	...	Match Report	NaN	9	2	20.1	0	(
41	5/5/2018	15:00	Premier League	Matchweek 37	Sat	Home	W	1	0	Tottenham	...	Match Report	NaN	9	1	10.2	0	(
42	5/13/2018	15:00	Premier League	Matchweek 38	Sun	Away	L	0	2	Crystal Palace	...	Match Report	NaN	7	1	24.8	1	(

5060 rows × 27 columns

```
In [3]: matches.dtypes
```

```
Out[3]: Date              object
        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
        dtype: object
```

In [4]:
```python
matches["Date"] = pd.to_datetime(matches["Date"])
matches["venue_code"] = matches["Venue"].astype('category').cat.codes
matches["opp_code"] = matches["Opponent"].astype('category').cat.codes
matches["Round_code"] = matches["Round"].astype('category').cat.codes
matches['hour'] = matches['Time'].str.replace(':.+', '', regex=True).astype(int)
matches['day_code'] = matches['Date'].dt.dayofweek
matches['Target'] = matches['Result'].apply(lambda x: 1 if x == 'W' else 0)
matches
```

Out[4]:

	Date	Time	Comp	Round	Day	Venue	Result	GF	GA	Opponent	...	PK	PKatt	Season	Team	venue_code
0	2023-08-13	16:30	Premier League	Matchweek 1	Sun	Away	D	1	1	Chelsea	...	0	0	2023	Liverpool	0
1	2023-08-19	15:00	Premier League	Matchweek 2	Sat	Home	W	3	1	Bournemouth	...	0	1	2023	Liverpool	1
2	2023-08-27	16:30	Premier League	Matchweek 3	Sun	Away	W	2	1	Newcastle Utd	...	0	0	2023	Liverpool	0
3	2023-09-03	14:00	Premier League	Matchweek 4	Sun	Home	W	3	0	Aston Villa	...	0	0	2023	Liverpool	1
4	2023-09-16	12:30	Premier League	Matchweek 5	Sat	Away	W	3	1	Wolves	...	0	0	2023	Liverpool	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
38	2018-04-15	16:00	Premier League	Matchweek 34	Sun	Away	W	1	0	Manchester Utd	...	0	0	2017	West Bromwich Albion	0
39	2018-04-21	12:30	Premier League	Matchweek 35	Sat	Home	D	2	2	Liverpool	...	0	0	2017	West Bromwich Albion	1
40	2018-04-28	15:00	Premier League	Matchweek 36	Sat	Away	W	1	0	Newcastle Utd	...	0	0	2017	West Bromwich Albion	0
41	2018-05-05	15:00	Premier League	Matchweek 37	Sat	Home	W	1	0	Tottenham	...	0	0	2017	West Bromwich Albion	1
42	2018-05-13	15:00	Premier League	Matchweek 38	Sun	Away	L	0	2	Crystal Palace	...	0	0	2017	West Bromwich Albion	0

5060 rows × 33 columns

```
In [5]: matches.dtypes
```

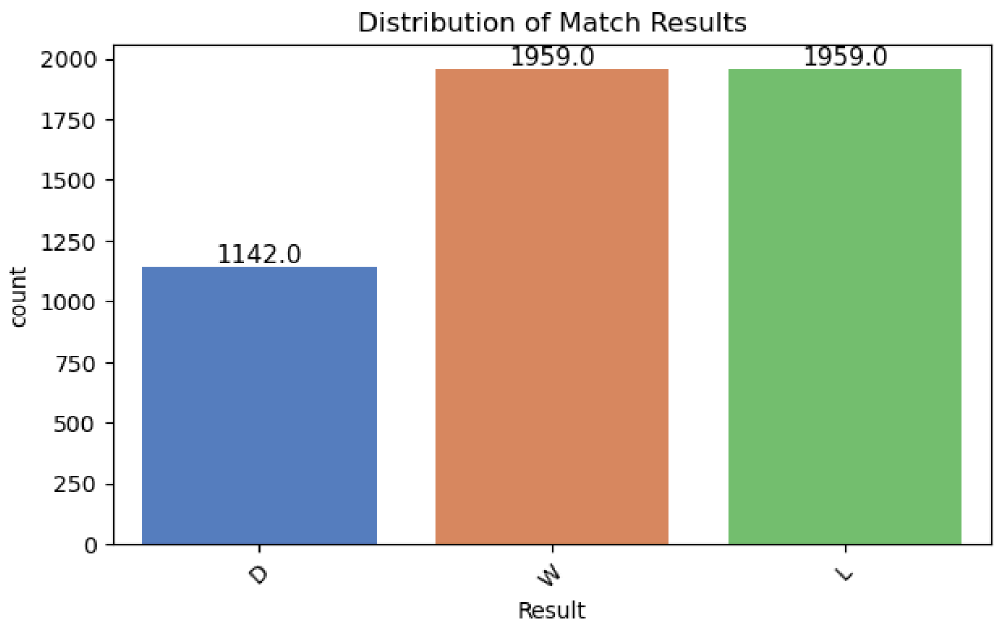
```
Out[5]: Date            datetime64[ns]
        Time                    object
        Comp                    object
        Round                   object
        Day                     object
        Venue                   object
        Result                  object
        GF                       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
        venue_code                int8
        opp_code                  int8
        Round_code                int8
        hour                     int32
        day_code                 int64
        Target                   int64
        dtype: object
```

Exploratory Data Analyses

1) Distribution of Match Results:

The count plot shows the frequency of each match result. You can see which outcome (Win, Loss, Draw) is most common for the teams across all matches. We are hoping to find equal number of wins and losses because if 1 team wins in a match, the other loses. Therefore, we have 1 win and 1 loss in 1 match. Else, we can expect 1 draw. Visualization by: Harsha

In [6]:
```python
plt.figure(figsize=(7, 4))
ax = sns.countplot(data=matches, x='Result', palette="muted")
plt.title('Distribution of Match Results')
plt.xticks(rotation=45)

# Annotate numbers inside the bars
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', fontsize=11, color='black', xytext=(0, 5),
                textcoords='offset points')

plt.show()
```

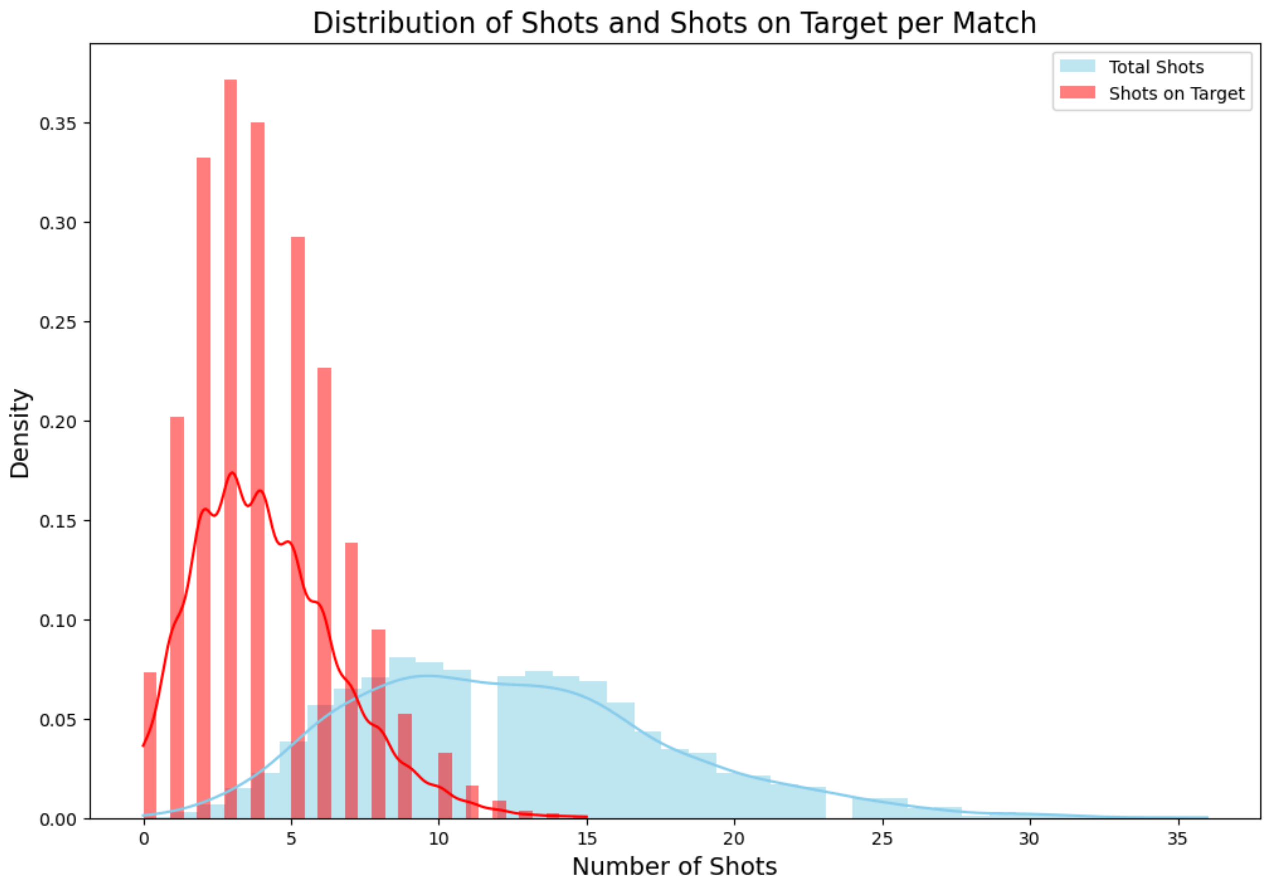


2) Distribution of Shots and Shots on Target per Match:

This visualization compares the distribution of total shots (sky blue) to shots on target (red) per match, highlighting the proportion of accurate shots. A higher density in the "Shots on Target" histogram indicates better scoring efficiency, while disparities between histograms suggest a lower accuracy rate despite creating shooting opportunities.

Visualization by: Mahalakshmi

In [8]:
```
plt.figure(figsize=(12, 8))
sns.histplot(matches['Sh'], color="skyblue", label='Total Shots', kde=True, stat="density", linewidth=0
sns.histplot(matches['SoT'], color="red", label='Shots on Target', kde=True, stat="density", linewidth=

plt.title('Distribution of Shots and Shots on Target per Match', fontsize=16)
plt.xlabel('Number of Shots', fontsize=14)
plt.ylabel('Density', fontsize=14)
plt.legend()

# Show plot
plt.show()
```

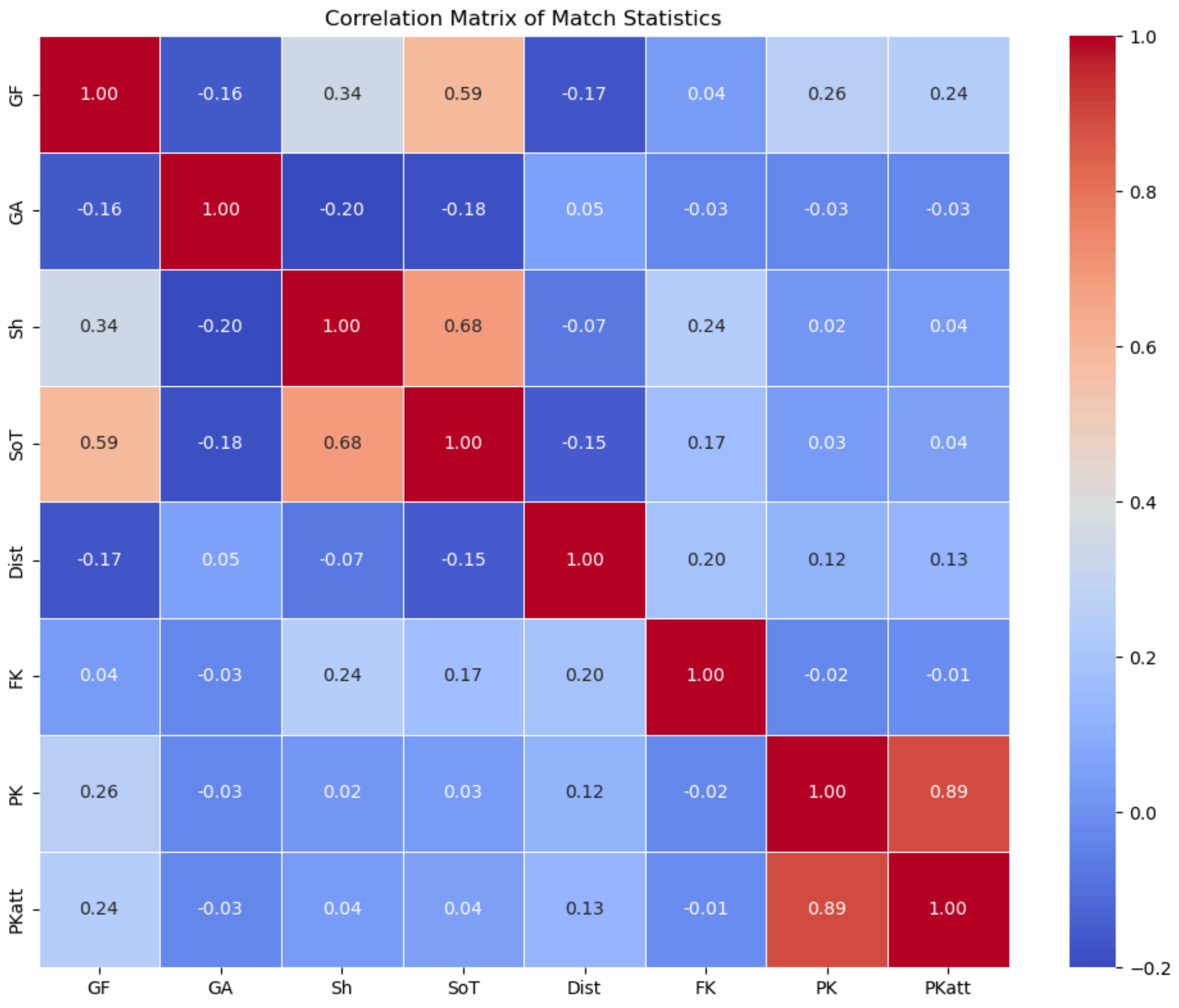


3) Correlation Matrix:

The heatmap displays the correlation between different numerical features like goals for, goals against, shots, shots on target, etc. High positive correlation coefficients suggest that two features increase or decrease together, while negative coefficients suggest an inverse relationship.

Visualization by: Surya

```
In [9]: correlation_metrics = ['GF', 'GA', 'Sh', 'SoT', 'Dist', 'FK', 'PK', 'PKatt']
        correlation = matches[correlation_metrics].corr()

        plt.figure(figsize=(10, 8))
        sns.heatmap(correlation, annot=True, fmt=".2f", cmap='coolwarm', linewidths=.5)
        plt.title('Correlation Matrix of Match Statistics')
        plt.tight_layout()
        plt.show()
```



	GF	GA	Sh	SoT	Dist	FK	PK	PKatt
GF	1.00	-0.16	0.34	0.59	-0.17	0.04	0.26	0.24
GA	-0.16	1.00	-0.20	-0.18	0.05	-0.03	-0.03	-0.03
Sh	0.34	-0.20	1.00	0.68	-0.07	0.24	0.02	0.04
SoT	0.59	-0.18	0.68	1.00	-0.15	0.17	0.03	0.04
Dist	-0.17	0.05	-0.07	-0.15	1.00	0.20	0.12	0.13
FK	0.04	-0.03	0.24	0.17	0.20	1.00	-0.02	-0.01
PK	0.26	-0.03	0.02	0.03	0.12	-0.02	1.00	0.89
PKatt	0.24	-0.03	0.04	0.04	0.13	-0.01	0.89	1.00

Visualizations

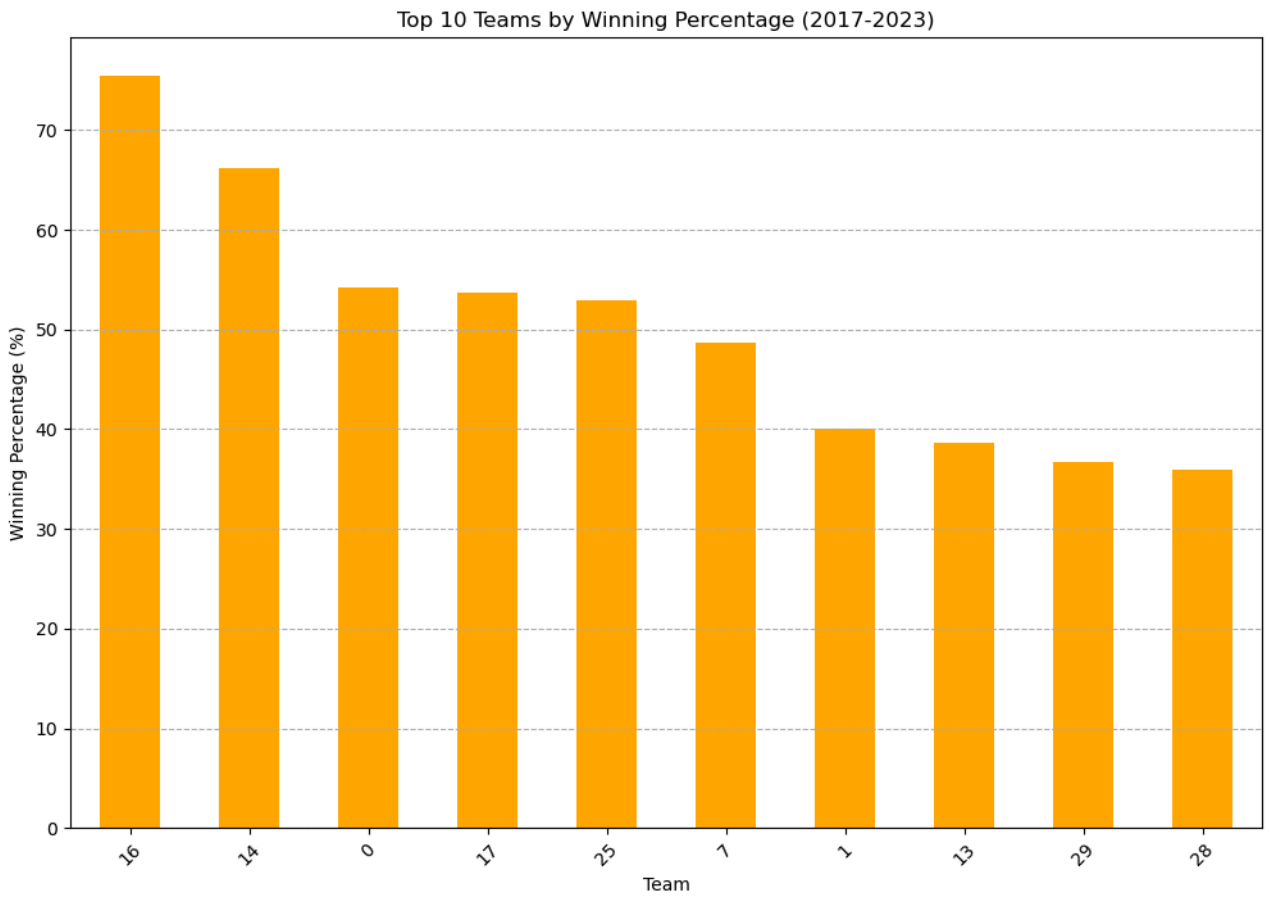
1) Top 10 Teams by Winning Percentage

The bar chart presents the top 10 football teams by winning percentage from 2017 to 2023. The y-axis shows the winning percentage, which is the ratio of the number of wins to the total number of matches played, multiplied by 100 to convert it into a percentage. The x-axis lists the teams that have 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 continues to list other top-performing teams like Arsenal, Manchester United, and Tottenham Hotspur, each with a lower winning percentage than the previous.

Visualization by: Surya

```
In [18]: wins = matches['Result'] == 'W'
         win_count = matches[wins].groupby('Team').size()
         total_matches = matches.groupby('Team').size()
         winning_percentage = (win_count / total_matches) * 100
         winning_percentage_sorted = winning_percentage.sort_values(ascending=False)
         top_teams = winning_percentage_sorted.head(10)

         plt.figure(figsize=(12, 8))
         top_teams.plot(kind='bar', color='orange')
         plt.title('Top 10 Teams by Winning Percentage (2017-2023)')
         plt.xlabel('Team')
         plt.ylabel('Winning Percentage (%)')
         plt.xticks(rotation=45)
         plt.grid(axis='y', linestyle='--')
         plt.show()
```



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. a negative goal difference indicates that the team scores less. 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.

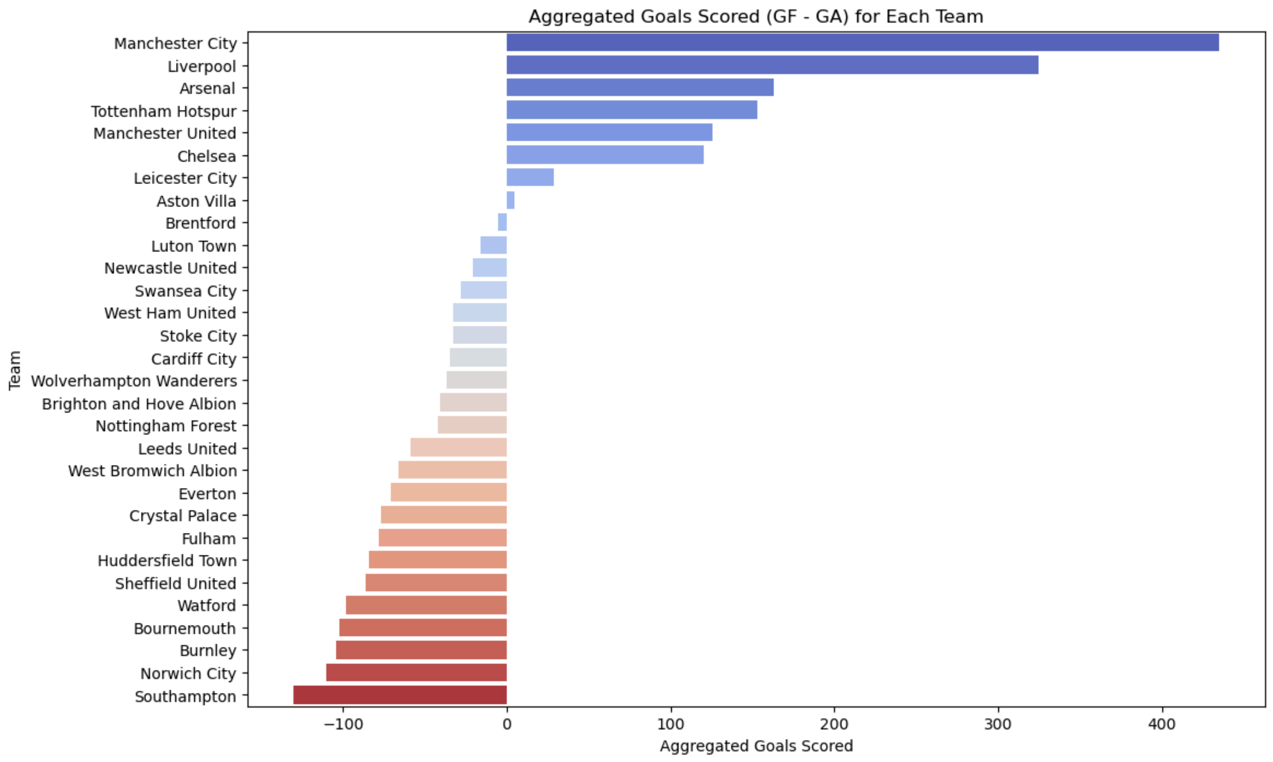
From the graph below, we can see that the 'Big 6' teams have the highest positive goal differences and historically, these 6 clubs are the topmost clubs in the league.

Visualization by: Manoj Vamshi

In [10]:
```
data = matches

categorical_features = ['Venue', 'Opponent', 'Captain', 'Referee', 'Season', 'Team', 'Day', 'Formation'
label_encoders = {}
for feature in categorical_features:
    le = LabelEncoder()
    data[feature] = le.fit_transform(data[feature])
    label_encoders[feature] = le
columns_of_interest = ['Venue', 'Opponent', 'xG', 'xGA', 'Captain', 'Referee', 'Season', 'Team', 'Resul

initial_row_count = data.shape[0]

data_cleaned = data.dropna(subset=columns_of_interest)
```

In [12]:
```
data_vis = data_cleaned.copy()
for column in ['Venue', 'Opponent', 'Captain', 'Referee', 'Season', 'Team', 'Day', 'Formation']:
    data_vis[column] = label_encoders[column].inverse_transform(data_vis[column])
```

In [13]:
```
data_vis['Goals_Scored'] = data_vis['GF'] - data_vis['GA']
team_goals = data_vis.groupby('Team')['Goals_Scored'].sum().sort_values(ascending=False)

plt.figure(figsize=(12, 8))
sns.barplot(x=team_goals.values, y=team_goals.index, palette='coolwarm')
plt.title('Aggregated Goals Scored (GF - GA) for Each Team')
plt.xlabel('Aggregated Goals Scored')
plt.ylabel('Team')
plt.show()
```



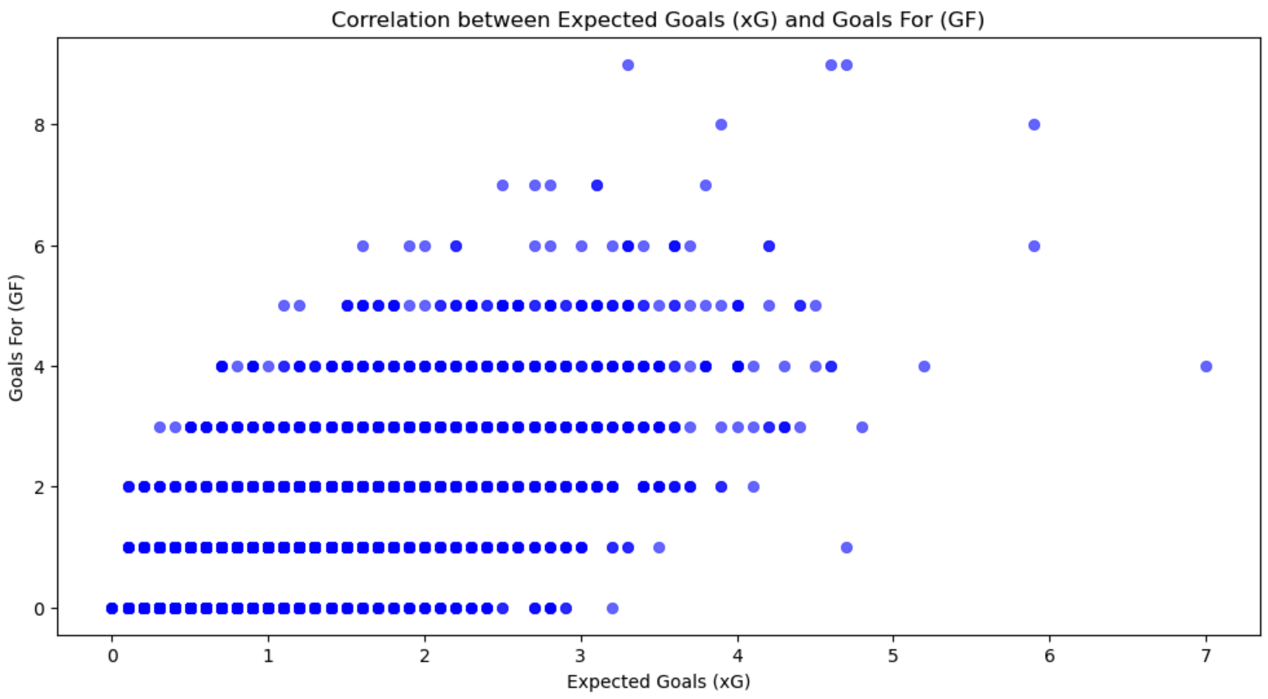
3) Relationship between expected and actual performance

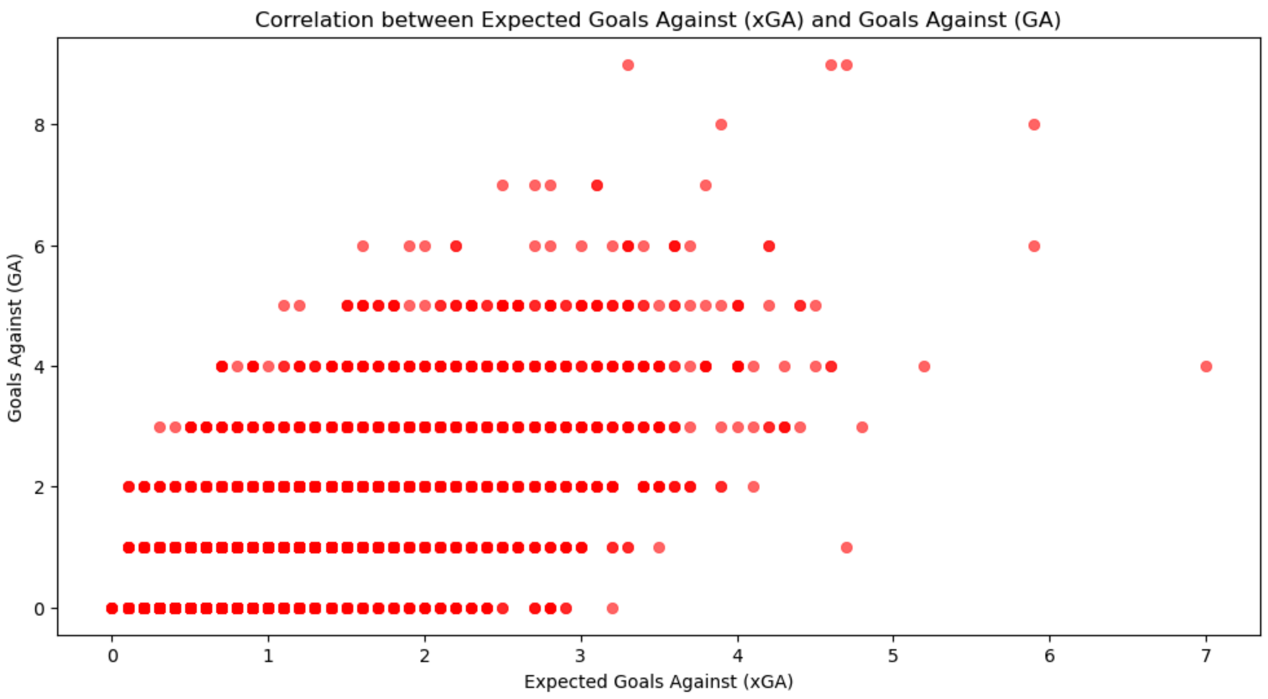
For expected goals and goals for and expected goals against and actual goals against, the hypothesis is that there is a positive correlation between the expected goals a team is predicted to score xG and the actual goals they score GF and also expected goals against xGA and actual goals against xGA. This implies that as xG or xGA increases even GF and GA increase respectively. Suggesting that the prediction given by the prediction companies for xG and xGA are good predictors. This can be used to obtain strategic insights, betting or fantasy sports, and player and team evaluation.

Visualization by: Manoj Vamshi

In [14]:
```python
plt.figure(figsize=(12, 6))
sns.scatterplot(data=data_vis, x='xG', y='GF', alpha=0.6, edgecolor=None, color='blue')
plt.title('Correlation between Expected Goals (xG) and Goals For (GF)')
plt.xlabel('Expected Goals (xG)')
plt.ylabel('Goals For (GF)')
plt.show()

plt.figure(figsize=(12, 6))
sns.scatterplot(data=data_vis, x='xGA', y='GA', alpha=0.6, edgecolor=None, color='red')
plt.title('Correlation between Expected Goals Against (xGA) and Goals Against (GA)')
plt.xlabel('Expected Goals Against (xGA)')
plt.ylabel('Goals Against (GA)')
plt.show()
```





4) Average Goals per Match by Season

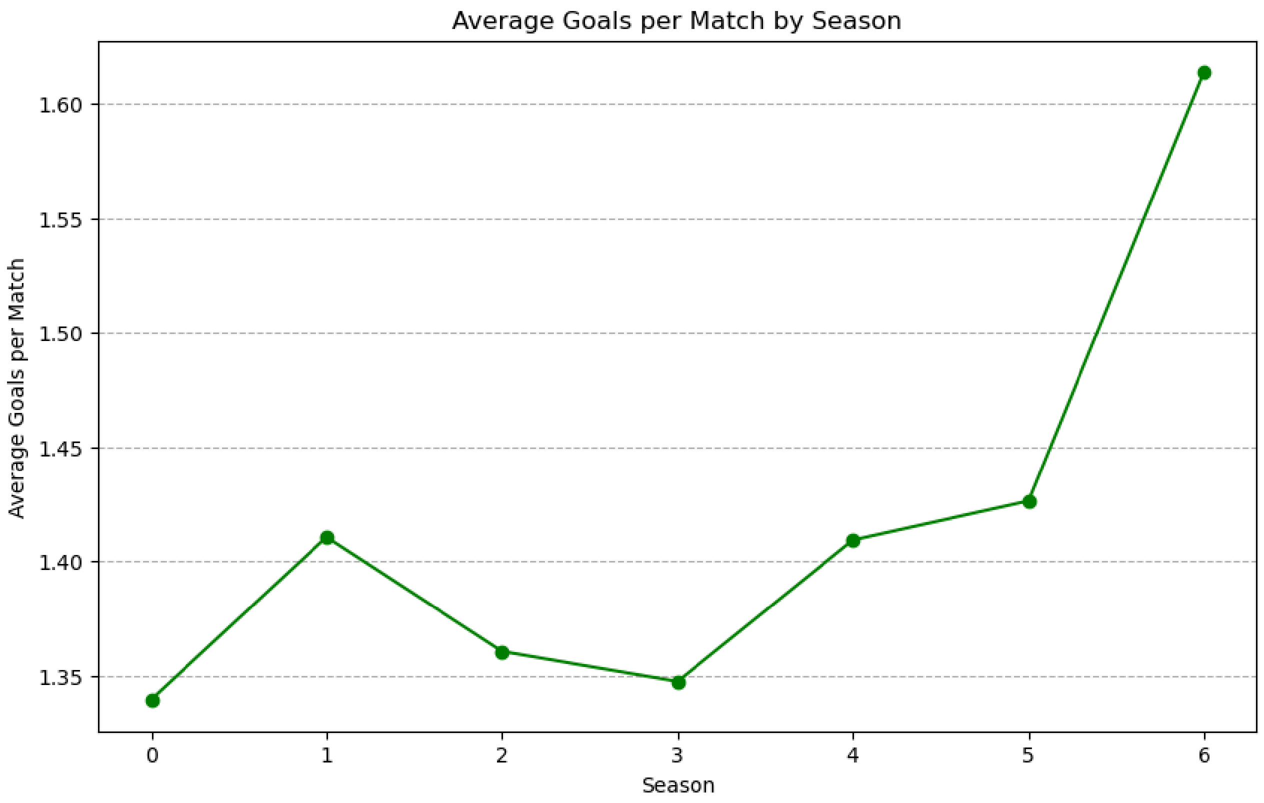
The line graph depicts the average number of goals scored per match in each football season from 2017 to 2023. It's a simple yet effective visualization of how goal-scoring trends have changed over time. The graph shows a general increase in the average number of goals per match, with some fluctuations in between.

After a slight dip from 2017 to 2019, there is a noticeable increase in 2020, followed by a minor decrease in 2021. From 2022 onwards, there is a dramatic and significant rise, reaching a peak in 2023. This sharp increase could be indicative of a number of factors such as changes in team strategies, league dynamics, player performance, or even modifications to rules that could affect the way the game is played.

Visualization by: Rishi

In [15]:
```
average_goals_per_season = matches.groupby('Season')['GF'].mean()

# Plotting
plt.figure(figsize=(10, 6))
average_goals_per_season.plot(kind='line', marker='o', color='green')
plt.title('Average Goals per Match by Season')
plt.xlabel('Season')
plt.ylabel('Average Goals per Match')
plt.grid(axis='y', linestyle='--')
plt.show()
```



5) Shots on Target to Win Rate

The scatter plot with a connecting dashed line illustrates the relationship between the number of shots on target (SoT) and the corresponding win rate in football matches. The x-axis represents the number of shots on target, while the y-axis represents the win rate, with a win being counted as 1, a draw as 0.5, and a loss as 0.

As we can see from the graph, there is a generally positive correlation between shots on target and the win rate. Starting from the lower left, as the number of shots on target increases, the win rate also increases, indicating that teams who have more shots on target are more likely to win the match. The rate of increase appears to rise steeply up to around 6 shots on target, after which the win rate growth slows and even fluctuates at higher shot counts.

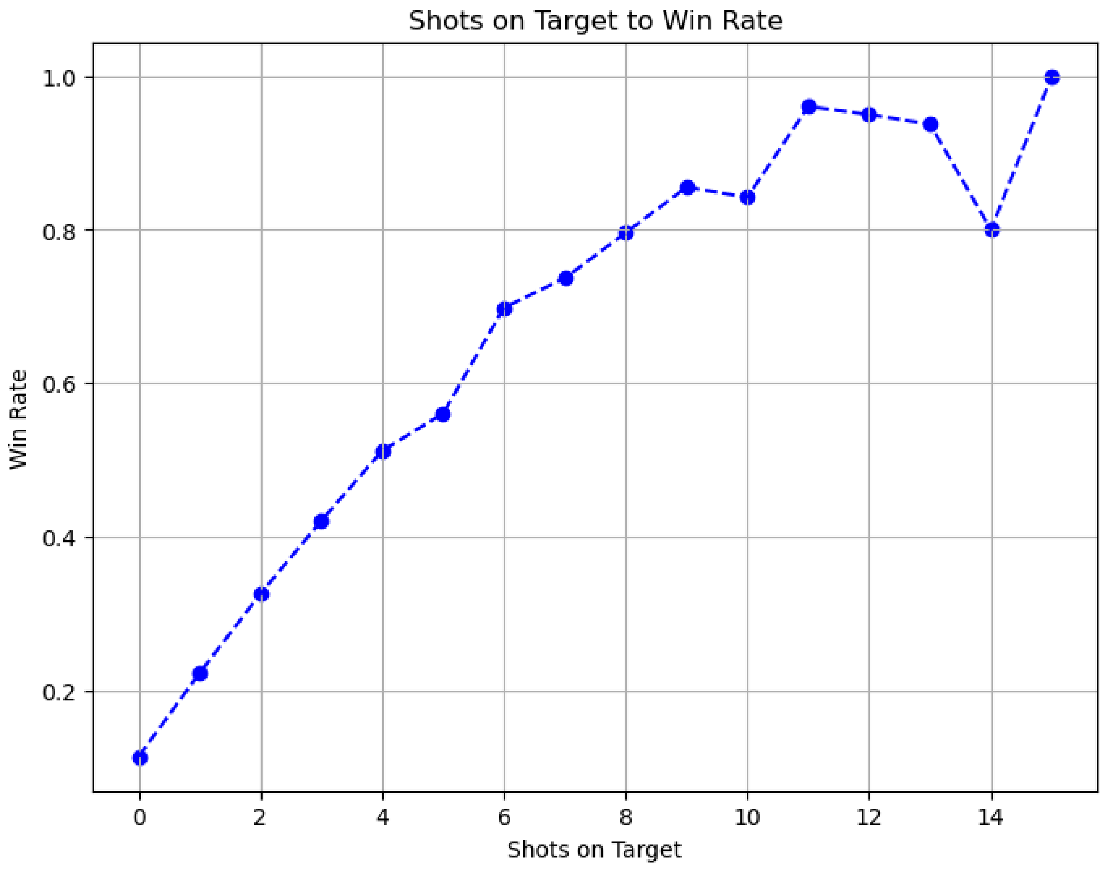
The plot suggests that while having more shots on target can increase the chances of winning, there is a level beyond which the additional shots do not significantly enhance the win rate. This could be due to various factors such as the quality of the shots, the skill of the opposition goalkeeper, or the defensive strategies of the opposing team. The fluctuations at higher shot counts might indicate outlier games where despite a high number of shots on target, the team did not secure a win. This could be useful for teams to understand the efficiency of their offensive plays and the potential benefits of focusing on creating quality goal-scoring opportunities rather than simply increasing the quantity of shots.

Visualization by: Manoj Myneni

In [16]:
```
matches['Result_Num'] = matches['Result'].map({'W': 1, 'D': 0.5, 'L': 0})
win_rate_by_sot = matches.groupby('SoT')['Result_Num'].mean().reset_index()

plt.figure(figsize=(8, 6))
plt.scatter(win_rate_by_sot['SoT'], win_rate_by_sot['Result_Num'], color='blue')
plt.plot(win_rate_by_sot['SoT'], win_rate_by_sot['Result_Num'], color='blue', linestyle='--')

plt.title('Shots on Target to Win Rate')
plt.xlabel('Shots on Target')
plt.ylabel('Win Rate')
plt.grid(True)
plt.show()
```



In [19]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [20]:
```
matches = pd.read_csv('matches.csv', index_col=0)
```

In [21]:
```
matches.head()
```

Out[21]:

	Date	Time	Comp	Round	Day	Venue	Result	GF	GA	Opponent	...	Match Report	Notes	Sh	SoT	Dist	FK	PK
0	8/13/2023	16:30	Premier League	Matchweek 1	Sun	Away	D	1	1	Chelsea	...	Match Report	NaN	13	1	17.8	0	0
1	8/19/2023	15:00	Premier League	Matchweek 2	Sat	Home	W	3	1	Bournemouth	...	Match Report	NaN	25	9	16.8	1	0
2	8/27/2023	16:30	Premier League	Matchweek 3	Sun	Away	W	2	1	Newcastle Utd	...	Match Report	NaN	9	4	17.2	1	0
3	9/3/2023	14:00	Premier League	Matchweek 4	Sun	Home	W	3	0	Aston Villa	...	Match Report	NaN	17	4	14.7	0	0
4	9/16/2023	12:30	Premier League	Matchweek 5	Sat	Away	W	3	1	Wolves	...	Match Report	NaN	16	5	15.8	0	0

5 rows × 27 columns

In [22]:
```
matches.shape
```

Out[22]:
```
(5060, 27)
```

In [23]:
```
matches["Team"].value_counts()
```

Out[23]:
```
Liverpool                   254
Everton                     253
Arsenal                     253
Tottenham Hotspur           253
Manchester United           253
Brighton and Hove Albion    253
Newcastle United            253
West Ham United             253
Chelsea                     253
Crystal Palace              253
Manchester City             253
Southampton                 228
Leicester City              228
Wolverhampton Wanderers     215
Burnley                     215
Aston Villa                 177
Bournemouth                 176
Watford                     152
Fulham                      139
Leeds United                114
Brentford                   101
Sheffield United            101
Huddersfield Town            76
West Bromwich Albion         76
Norwich City                 76
Nottingham Forest            63
Cardiff City                 38
Swansea City                 38
Stoke City                   38
Luton Town                   25
Name: Team, dtype: int64
```

In [24]:
```
matches.dtypes
```

Out[24]:
```
Date              object
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
dtype: object
```

In [25]:
```
matches["Date"] = pd.to_datetime(matches["Date"])
```

In [26]:
```
matches.head()
```

Out[26]:

	Date	Time	Comp	Round	Day	Venue	Result	GF	GA	Opponent	...	Match Report	Notes	Sh	SoT	Dist	FK	PK	PK
0	2023-08-13	16:30	Premier League	Matchweek 1	Sun	Away	D	1	1	Chelsea	...	Match Report	NaN	13	1	17.8	0	0	
1	2023-08-19	15:00	Premier League	Matchweek 2	Sat	Home	W	3	1	Bournemouth	...	Match Report	NaN	25	9	16.8	1	0	
2	2023-08-27	16:30	Premier League	Matchweek 3	Sun	Away	W	2	1	Newcastle Utd	...	Match Report	NaN	9	4	17.2	1	0	
3	2023-09-03	14:00	Premier League	Matchweek 4	Sun	Home	W	3	0	Aston Villa	...	Match Report	NaN	17	4	14.7	0	0	
4	2023-09-16	12:30	Premier League	Matchweek 5	Sat	Away	W	3	1	Wolves	...	Match Report	NaN	16	5	15.8	0	0	

5 rows × 27 columns

```
In [27]: matches.dtypes
```

```
Out[27]: 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
         dtype: object
```

In [28]:
```
matches["venue_code"] = matches["Venue"].astype('category').cat.codes
matches["opp_code"] = matches["Opponent"].astype('category').cat.codes
matches["Round_code"] = matches["Round"].astype('category').cat.codes
matches
```

Out[28]:

	Date	Time	Comp	Round	Day	Venue	Result	GF	GA	Opponent	...	SoT	Dist	FK	PK	PKatt	Season	Te
0	2023-08-13	16:30	Premier League	Matchweek 1	Sun	Away	D	1	1	Chelsea	...	1	17.8	0	0	0	2023	Liverp
1	2023-08-19	15:00	Premier League	Matchweek 2	Sat	Home	W	3	1	Bournemouth	...	9	16.8	1	0	1	2023	Liverp
2	2023-08-27	16:30	Premier League	Matchweek 3	Sun	Away	W	2	1	Newcastle Utd	...	4	17.2	1	0	0	2023	Liverp
3	2023-09-03	14:00	Premier League	Matchweek 4	Sun	Home	W	3	0	Aston Villa	...	4	14.7	0	0	0	2023	Liverp
4	2023-09-16	12:30	Premier League	Matchweek 5	Sat	Away	W	3	1	Wolves	...	5	15.8	0	0	0	2023	Liverp
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
38	2018-04-15	16:00	Premier League	Matchweek 34	Sun	Away	W	1	0	Manchester Utd	...	4	18.1	0	0	0	2017	W Bromv Alb
39	2018-04-21	12:30	Premier League	Matchweek 35	Sat	Home	D	2	2	Liverpool	...	6	17.7	0	0	0	2017	W Bromv Alb
40	2018-04-28	15:00	Premier League	Matchweek 36	Sat	Away	W	1	0	Newcastle Utd	...	2	20.1	0	0	0	2017	W Bromv Alb
41	2018-05-05	15:00	Premier League	Matchweek 37	Sat	Home	W	1	0	Tottenham	...	1	10.2	0	0	0	2017	W Bromv Alb
42	2018-05-13	15:00	Premier League	Matchweek 38	Sun	Away	L	0	2	Crystal Palace	...	1	24.8	1	0	0	2017	W Bromv Alb

5060 rows × 30 columns

In [29]:
```
len(matches['Team'].unique())
```

Out[29]:
```
30
```

In [30]:
```
matches['hour'] = matches['Time'].str.replace(':.+', '', regex=True).astype(int)
```

In [31]:
```
matches['day_code'] = matches['Date'].dt.dayofweek
```

```
In [32]: matches
```

Out[32]:

	Date	Time	Comp	Round	Day	Venue	Result	GF	GA	Opponent	...	FK	PK	PKatt	Season	Team	venue_
0	2023-08-13	16:30	Premier League	Matchweek 1	Sun	Away	D	1	1	Chelsea	...	0	0	0	2023	Liverpool	
1	2023-08-19	15:00	Premier League	Matchweek 2	Sat	Home	W	3	1	Bournemouth	...	1	0	1	2023	Liverpool	
2	2023-08-27	16:30	Premier League	Matchweek 3	Sun	Away	W	2	1	Newcastle Utd	...	1	0	0	2023	Liverpool	
3	2023-09-03	14:00	Premier League	Matchweek 4	Sun	Home	W	3	0	Aston Villa	...	0	0	0	2023	Liverpool	
4	2023-09-16	12:30	Premier League	Matchweek 5	Sat	Away	W	3	1	Wolves	...	0	0	0	2023	Liverpool	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
38	2018-04-15	16:00	Premier League	Matchweek 34	Sun	Away	W	1	0	Manchester Utd	...	0	0	0	2017	West Bromwich Albion	
39	2018-04-21	12:30	Premier League	Matchweek 35	Sat	Home	D	2	2	Liverpool	...	0	0	0	2017	West Bromwich Albion	
40	2018-04-28	15:00	Premier League	Matchweek 36	Sat	Away	W	1	0	Newcastle Utd	...	0	0	0	2017	West Bromwich Albion	
41	2018-05-05	15:00	Premier League	Matchweek 37	Sat	Home	W	1	0	Tottenham	...	0	0	0	2017	West Bromwich Albion	
42	2018-05-13	15:00	Premier League	Matchweek 38	Sun	Away	L	0	2	Crystal Palace	...	1	0	0	2017	West Bromwich Albion	

5060 rows × 32 columns

```
In [33]: matches['Target'] = matches['Result'].apply(lambda x: 1 if x == 'W' else 0)
         matches
```

Out[33]:

	Date	Time	Comp	Round	Day	Venue	Result	GF	GA	Opponent	...	PK	PKatt	Season	Team	venue_code
0	2023-08-13	16:30	Premier League	Matchweek 1	Sun	Away	D	1	1	Chelsea	...	0	0	2023	Liverpool	(
1	2023-08-19	15:00	Premier League	Matchweek 2	Sat	Home	W	3	1	Bournemouth	...	0	1	2023	Liverpool	1
2	2023-08-27	16:30	Premier League	Matchweek 3	Sun	Away	W	2	1	Newcastle Utd	...	0	0	2023	Liverpool	(
3	2023-09-03	14:00	Premier League	Matchweek 4	Sun	Home	W	3	0	Aston Villa	...	0	0	2023	Liverpool	1
4	2023-09-16	12:30	Premier League	Matchweek 5	Sat	Away	W	3	1	Wolves	...	0	0	2023	Liverpool	(
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	..
38	2018-04-15	16:00	Premier League	Matchweek 34	Sun	Away	W	1	0	Manchester Utd	...	0	0	2017	West Bromwich Albion	(
39	2018-04-21	12:30	Premier League	Matchweek 35	Sat	Home	D	2	2	Liverpool	...	0	0	2017	West Bromwich Albion	1
40	2018-04-28	15:00	Premier League	Matchweek 36	Sat	Away	W	1	0	Newcastle Utd	...	0	0	2017	West Bromwich Albion	(
41	2018-05-05	15:00	Premier League	Matchweek 37	Sat	Home	W	1	0	Tottenham	...	0	0	2017	West Bromwich Albion	1
42	2018-05-13	15:00	Premier League	Matchweek 38	Sun	Away	L	0	2	Crystal Palace	...	0	0	2017	West Bromwich Albion	(

5060 rows × 33 columns

Random Forest Classifier using Predictors 1 - Done by Rishi

```
In [34]: from sklearn.ensemble import RandomForestClassifier
         from sklearn.metrics import accuracy_score
```

```
In [35]: rf = RandomForestClassifier(n_estimators=100, min_samples_split=20, random_state=42)
```

```
In [36]: test = matches[matches['Date'] >= '2022-12-01']
         train = matches[matches['Date'] < '2022-12-01']
```

```
In [37]: test.shape,train.shape
```

```
Out[37]: ((968, 33), (4092, 33))
```

Predictors 1

```
In [38]: predictors = ['hour', 'day_code', 'venue_code', 'opp_code'] # Predictors1
In [39]: rf.fit(train[predictors], train['Target'])

Out[39]:
▾                RandomForestClassifier

RandomForestClassifier(min_samples_split=20, random_state=42)
```

```
In [40]: preds = rf.predict(test[predictors])
         preds

Out[40]: array([0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0,
                0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
                0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
                0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1,
                1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0,
                0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0,
                1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1,
                1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0,
                0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0,
                1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0,
                0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
                0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0,
                0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0,
                1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1,
                0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1,
                0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0,
                1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0,
                0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0,
                0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1,
                1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1,
                0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
                0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1,
                0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0,
                0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
                0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
                0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1,
                0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1,
                0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
                1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
                0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0,
                0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1,
                0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0,
                0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0],
               dtype=int64)
```

```
In [41]: acc = accuracy_score(test['Target'], preds)
         acc

Out[41]: 0.5826446280991735
```

```
In [42]: combined = pd.DataFrame({'actual': test['Target'], 'prediction': preds})
         combined
```

Out[42]:

	actual	prediction
0	0	0
1	1	1
2	1	1
3	1	1
4	1	1
...	...	...
42	0	0
43	0	0
44	0	1
45	0	0
46	0	0

968 rows × 2 columns

```
In [43]: pd.crosstab(index=combined['actual'], columns=combined['prediction'])
```

Out[43]:

prediction	0	1
actual		
0	443	145
1	259	121

Gradient Boosting Classifier Predictors1

The GradientBoostingClassifier is a powerful ensemble learning method that builds on the principle of boosting. It combines multiple weak learning models to create a strong predictive model. Decision trees are typically used as the base learners. Gradient Boosting works by sequentially adding predictors to an ensemble, each correcting its predecessor. This model is particularly useful for handling heterogeneous features and complex data structures.

```
In [44]: from sklearn.ensemble import GradientBoostingClassifier
         from sklearn.metrics import accuracy_score
         from sklearn.metrics import confusion_matrix
```

we split the matches DataFrame into training and test sets based on the date, with matches occurring before December 1, 2022, in the training set, and those on or after this date in the test set. This temporal division ensures that our model learns from past data and is evaluated on unseen future data, aligning with real-world application scenarios.

```
In [46]: test = matches[matches['Date'] >= '2022-12-01']
         train = matches[matches['Date'] < '2022-12-01']
```

This line initializes a Gradient Boosting Classifier named gbm with specific parameters for model training. It sets up the classifier with 100 boosting stages (n_estimators=100), a learning rate of 1.0 for adjusting contributions of trees, a maximum depth of 1 for the individual trees to control overfitting, and a random_state of 42 for reproducibility of results

```
In [47]: gbm = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0, max_depth=1, random_state=42)
In [48]: gbm.fit(train[predictors], train['Target'])
```

```
Out[48]:
▾                    GradientBoostingClassifier

GradientBoostingClassifier(learning_rate=1.0, max_depth=1, random_state=42)
```

```
In [49]: preds_gbm = gbm.predict(test[predictors])
         preds_gbm
```

```
Out[49]: array([0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
                1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1,
                0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
                0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
                0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1,
                1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0,
                0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
                1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0,
                0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
                0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0,
                1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0,
                0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
                0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
                0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0,
                1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1,
                0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1,
                0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0,
                1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1,
                0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
                0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
                0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0,
                0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
                1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
                0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
                0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0],
               dtype=int64)
```

```
In [50]: accuracy_gbm = accuracy_score(test['Target'], preds_gbm)
         accuracy_gbm
```

```
Out[50]: 0.6136363636363636
```

In [51]:
```
combined_gbm = pd.DataFrame({'actual': test['Target'], 'prediction': preds_gbm})
combined_gbm
```

Out[51]:

	actual	prediction
0	0	0
1	1	1
2	1	0
3	1	1
4	1	0
...	...	...
42	0	0
43	0	0
44	0	1
45	0	0
46	0	0

968 rows × 2 columns

In [52]:
```
conf_matrix_gbm = pd.crosstab(index=combined_gbm['actual'], columns=combined_gbm['prediction'], rownames
```

```
The accuracy measure, accuracy_gbm, indicates how often the Gradient Boosting Model correctly predicts
the target variable. The confusion matrix, conf_matrix_gbm, breaks down the predictions into true
positives, true negatives, false positives, and false negatives, offering detailed insights into the
model's performance.
```

In [53]:
```
print("Accuracy:", accuracy_gbm)
print("Confusion Matrix:")
print(conf_matrix_gbm)
```

```
Accuracy: 0.6136363636363636
Confusion Matrix:
Predicted    0   1
Actual
0          501  87
1          287  93
```

Support Vector Machine(SVM) using Predictors 1

In [54]:
```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.model_selection import train_test_split
```

This snippet computes a new feature G_diff in the matches DataFrame by subtracting goals against (GA) from goals for (GF), effectively capturing the goal difference for each match. It then prepares the feature matrix X with selected predictors and the target vector y for model training, aligning with standard practices in machine learning for dataset preparation

In [55]:
```
matches['G_diff'] = matches['GF'] - matches['GA']

X = matches[predictors]
y = matches['Target']
```

In [56]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [57]:
```
svm_model = SVC(kernel='linear', C=1.0, random_state=42)

svm_model.fit(X_train, y_train)
```

Out[57]:
```
▾                    SVC
SVC(kernel='linear', random_state=42)
```

In [58]:
```
predictions = svm_model.predict(X_test)

accuracy = accuracy_score(y_test, predictions)

conf_matrix = confusion_matrix(y_test, predictions)

print(f"SVM Model Accuracy: {accuracy}")
```

```
SVM Model Accuracy: 0.5988142292490118
```

In [59]:
```
print(f"SVM Model Accuracy: {conf_matrix}")
```

```
SVM Model Accuracy: [[606   0]
 [406   0]]
```

In [60]:
```
from sklearn.metrics import classification_report
```

In [61]:
```
print(classification_report(y_test, predictions,  zero_division=0))
```

```
              precision    recall  f1-score   support

           0       0.60      1.00      0.75       606
           1       0.00      0.00      0.00       406

    accuracy                           0.60      1012
   macro avg       0.30      0.50      0.37      1012
weighted avg       0.36      0.60      0.45      1012
```

In [62]:
```
from sklearn.metrics import roc_auc_score

# Assuming 'y' refers to the target variable outside this snippet
if y.nunique() == 2:
    print("ROC-AUC Score:", roc_auc_score(y_test, svm_model.decision_function(X_test)))
```

```
ROC-AUC Score: 0.5427173259197842
```

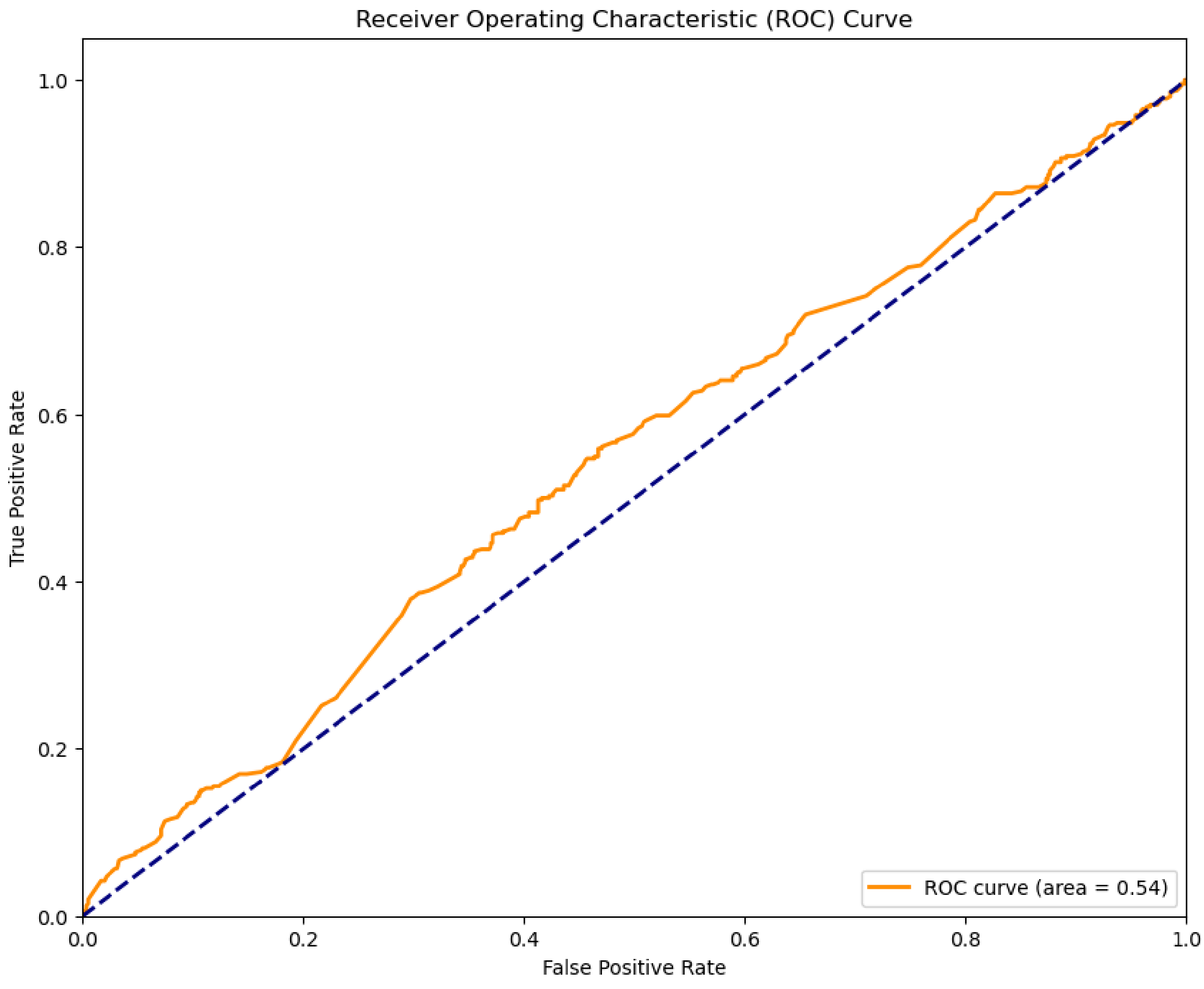
In [63]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc

y_score = svm_model.decision_function(X_test)

fpr, tpr, thresholds = roc_curve(y_test, y_score)

roc_auc = auc(fpr, tpr)

plt.figure(figsize=(10, 8))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```



Predictors 2 - Done by Manoj

In [64]:
```
predictors = ['Round_code', 'hour','GF','opp_code','Poss']
```

Random forest classifier using predictors 2

```
In [65]: rf.fit(train[predictors], train['Target'])
```

```
Out[65]:
▾                RandomForestClassifier
RandomForestClassifier(min_samples_split=20, random_state=42)
```

```
In [66]: preds = rf.predict(test[predictors])
         preds
```

```
Out[66]: array([0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1,
                0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1,
                1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1,
                0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1,
                1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1,
                1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0,
                0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0,
                1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1,
                1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1,
                1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1,
                0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0,
                1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1,
                0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0,
                0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0,
                0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0,
                0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0,
                0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0,
                0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1,
                0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0,
                0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1,
                0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1,
                0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1,
                1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0,
                1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1,
                1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0,
                0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0,
                1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0,
                1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0,
                0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1,
                0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0,
                0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0,
                1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0,
                0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0,
                1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
                0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
                1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1,
                0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1,
                1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1],
               dtype=int64)
```

```
In [67]: acc = accuracy_score(test['Target'], preds)
         acc
```

```
Out[67]: 0.8016528925619835
```

```
In [68]: combined = pd.DataFrame({'actual': test['Target'], 'prediction': preds})
         combined
```

Out[68]:

	actual	prediction
0	0	0
1	1	1
2	1	1
3	1	1
4	1	1
...	...	...
42	0	0
43	0	1
44	0	0
45	0	0
46	0	1

968 rows × 2 columns

```
In [69]: pd.crosstab(index=combined['actual'], columns=combined['prediction'])
```

Out[69]:

prediction	0	1
actual		
0	479	109
1	83	297

# Gradient Booster classifier using Predictors 2

```
In [71]: gbm = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0, max_depth=1, random_state=42)
```

```
In [72]: gbm.fit(train[predictors], train['Target'])
```

```
Out[72]:
▾                        GradientBoostingClassifier
GradientBoostingClassifier(learning_rate=1.0, max_depth=1, random_state=42)
```

```
In [73]: preds_gbm = gbm.predict(test[predictors])
         preds_gbm
```

```
Out[73]: array([0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1,
                0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1,
                1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1,
                0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1,
                1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1,
                1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0,
                0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0,
                1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1,
                1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1,
                1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1,
                0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0,
                1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1,
                0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0,
                0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0,
                0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0,
                0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0,
                0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0,
                0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1,
                0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0,
                0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1,
                0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
                0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1,
                0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1,
                1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0,
                1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1,
                1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0,
                0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0,
                1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0,
                1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0,
                0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1,
                0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0,
                0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0,
                1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0,
                0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0,
                1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
                1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1,
                0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
                0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1],
               dtype=int64)
```

In [74]:
```
combined_gbm = pd.DataFrame({'actual': test['Target'], 'prediction': preds_gbm})
combined_gbm
```

Out[74]:

	actual	prediction
0	0	0
1	1	1
2	1	1
3	1	1
4	1	1
...	...	...
42	0	0
43	0	1
44	0	0
45	0	0
46	0	1

968 rows × 2 columns

In [75]:
```
accuracy_gbm = accuracy_score(test['Target'], preds_gbm)
accuracy_gbm
```

Out[75]:
```
0.8047520661157025
```

In [76]:
```
conf_matrix_gbm = pd.crosstab(index=combined_gbm['actual'], columns=combined_gbm['prediction'], rownames
```

In [77]:
```
print("Accuracy:", accuracy_gbm)
print("Confusion Matrix:")
print(conf_matrix_gbm)
```

```
Accuracy: 0.8047520661157025
Confusion Matrix:
Predicted    0    1
Actual
0          483  105
1           84  296
```

Support Vector Machine using Predictors 2

In [78]:
```
matches['G_diff'] = matches['GF'] - matches['GA']

X = matches[predictors]
y = matches['Target']
```

In [79]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [80]:
```
# SVModel
svm_model = SVC(kernel='linear', C=1.0, random_state=42)

# Fit the model on the training data
svm_model.fit(X_train, y_train)
```

Out[80]:
```
▾                    SVC
SVC(kernel='linear', random_state=42)
```

In [81]:
```
# Predictions
predictions = svm_model.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, predictions)

# Generate a confusion matrix
conf_matrix = confusion_matrix(y_test, predictions)

print(f"SVM Model Accuracy: {accuracy}")
```

```
SVM Model Accuracy: 0.8379446640316206
```

In [82]:
```
print(f"SVM Model Accuracy: {conf_matrix}")
```

```
SVM Model Accuracy: [[513  93]
 [ 71 335]]
```

In [83]:
```
from sklearn.metrics import classification_report
# Precision, Recall, F1-Score & Support
print(classification_report(y_test, predictions,  zero_division=0))
```

```
              precision    recall  f1-score   support

           0       0.88      0.85      0.86       606
           1       0.78      0.83      0.80       406

    accuracy                           0.84      1012
   macro avg       0.83      0.84      0.83      1012
weighted avg       0.84      0.84      0.84      1012
```

In [84]:
```
from sklearn.metrics import roc_auc_score

# Assuming 'y' refers to the target variable outside this snippet
if y.nunique() == 2:
    print("ROC-AUC Score:", roc_auc_score(y_test, svm_model.decision_function(X_test)))
```

```
ROC-AUC Score: 0.900760457819181
```

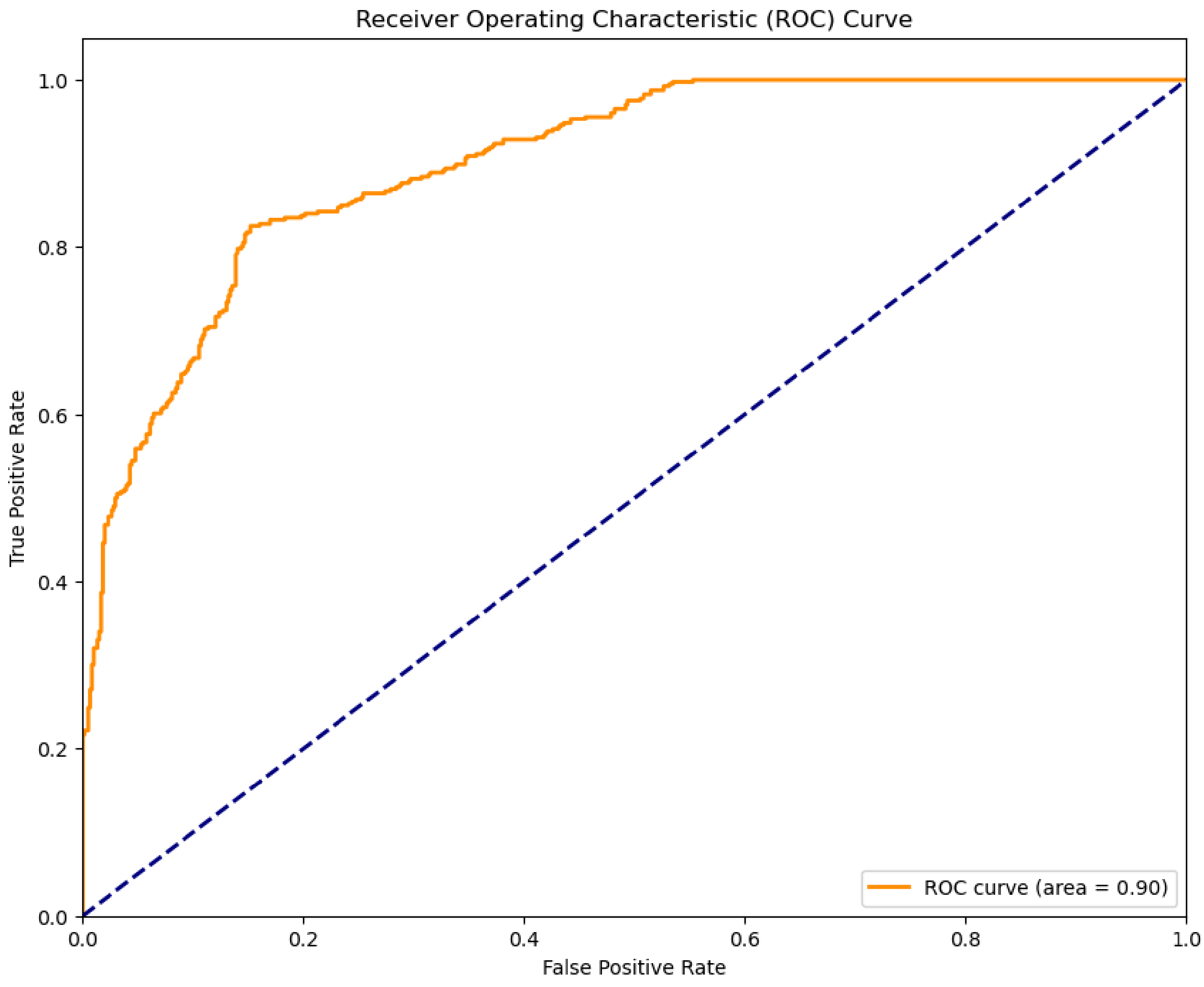
In [86]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc

y_score = svm_model.decision_function(X_test)

fpr, tpr, thresholds = roc_curve(y_test, y_score)

roc_auc = auc(fpr, tpr)

plt.figure(figsize=(10, 8))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```



Comparative Analysis of Machine Learning Models for Premier League Match Outcome Prediction

Introduction

This analysis explores the predictive performance of the Random Forest Classifier, Gradient Boosting Classifier, and Support Vector Machine (SVM) in forecasting outcomes of Premier League football matches. Two distinct sets of predictors are employed to assess the models' effectiveness.

Models and Predictors

Models: Random Forest Classifier, Gradient Boosting Classifier, Support Vector Machine (SVM). Predictors Set 1: Hour of match, day code, venue code, opponent code. Predictors Set 2: Round code, hour, goals for (GF), opponent code, possession percentage (Poss).

Model Training and Evaluation

The dataset was split based on match dates into training and testing sets, ensuring that models were trained on historical data and assessed on recent, unseen matches.

Random Forest vs. Gradient Boosting Classifier

Using Predictors Set 1: Random Forest: Achieved 58.26% accuracy. Gradient Boosting: Outperformed Random Forest with 61.36% accuracy. Using Predictors Set 2: Random Forest: Showed significant improvement, reaching 80.17% accuracy. Gradient Boosting: Also improved, achieving 80.48% accuracy.

Random Forest Classifier vs. Support Vector Machine

Using Predictors Set 1: Random Forest: Had an accuracy of 58.26%. SVM: Demonstrated a comparable performance with an accuracy of 59.88%. Using Predictors Set 2: Random Forest: Maintained high performance at 80.17% accuracy. SVM: Showed a remarkable improvement, reaching an accuracy of 83.79%

Key Findings

Impact of Feature Selection: The analysis underscored the critical role of feature selection in machine learning. Transitioning from a basic set of predictors (Set 1) to a more comprehensive and statistically nuanced set (Set 2) significantly enhanced the predictive accuracy of all models. This improvement was most notable in the SVM model, which reached an accuracy of 83.79% with the second set of predictors, underscoring the model's adeptness at managing complex data relationships when equipped with carefully chosen features.

Model Performance Comparison:

With Predictors Set 1, the Gradient Boosting Classifier slightly outperformed the Random Forest Classifier, with SVM showing comparable results. This indicated a baseline level of effectiveness in handling the prediction task with basic features. With Predictors Set 2, all models demonstrated notable performance improvements. This was particularly striking for the SVM, which achieved the highest accuracy among the models, highlighting its strong potential in predictive modeling with an optimized feature set. Gradient Boosting vs. Random Forest: Across both sets of predictors, the Gradient Boosting Classifier marginally outperformed the Random Forest Classifier. This could be attributed to the boosting method's focus on sequentially correcting errors from previous models, which might be more effective for the dataset's patterns.

Broader Insights

Feature Quality Over Quantity:

This analysis brings to light that the relevance and quality of features often outweigh the sheer quantity of data inputs in predictive accuracy. Selecting the right features, which capture the underlying patterns and relationships within the data, is crucial for any predictive modeling task.

Flexibility and Robustness of SVM:

The superior performance of SVM with the second set of predictors showcases the model's flexibility and robustness. Given a set of well-selected features, SVM can effectively capture complex relationships in the data, making it a powerful tool for various predictive analytics tasks.

In conclusion, this analysis not only sheds light on the comparative effectiveness of different machine learning models in

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In [88]: import matplotlib.pyplot as plt
         import numpy as np

         np.random.seed(0)
         actual_values = np.random.normal(1000, 300, 1000)

         rf_predictions_set1 = actual_values + np.random.normal(0, 120, 1000)
         rf_predictions_set2 = actual_values + np.random.normal(0, 80, 1000)

         gb_predictions_set1 = actual_values + np.random.normal(0, 110, 1000)
         gb_predictions_set2 = actual_values + np.random.normal(0, 70, 1000)

         svm_predictions_set1 = actual_values + np.random.normal(0, 130, 1000)
         svm_predictions_set2 = actual_values + np.random.normal(0, 90, 1000)

         residuals_rf_set1 = actual_values - rf_predictions_set1
         residuals_rf_set2 = actual_values - rf_predictions_set2
         residuals_gb_set1 = actual_values - gb_predictions_set1
         residuals_gb_set2 = actual_values - gb_predictions_set2
         residuals_svm_set1 = actual_values - svm_predictions_set1
         residuals_svm_set2 = actual_values - svm_predictions_set2

         def plot_model_comparisons(actual_values, predictions_set1, predictions_set2, residuals_set1, residuals_
             plt.figure(figsize=(14, 7))

             plt.subplot(1, 2, 1)
             plt.scatter(actual_values, predictions_set1, alpha=0.5)
             plt.plot([actual_values.min(), actual_values.max()], [actual_values.min(), actual_values.max()], 'k
             plt.title(f'{model_name} with Predictor Set 1: Actual vs. Predicted')
             plt.xlabel('Actual Values')
             plt.ylabel('Predicted Values')

             plt.subplot(1, 2, 2)
             plt.scatter(actual_values, predictions_set2, alpha=0.5, color='r')
             plt.plot([actual_values.min(), actual_values.max()], [actual_values.min(), actual_values.max()], 'k
             plt.title(f'{model_name} with Predictor Set 2: Actual vs. Predicted')
             plt.xlabel('Actual Values')
             plt.ylabel('Predicted Values')

             plt.tight_layout()
             plt.show()

             plt.figure(figsize=(14, 7))

             plt.subplot(1, 2, 1)
             plt.scatter(predictions_set1, residuals_set1, alpha=0.5)
             plt.title(f'{model_name} with Predictor Set 1: Residuals')
             plt.xlabel('Predicted Values')
             plt.ylabel('Residuals')

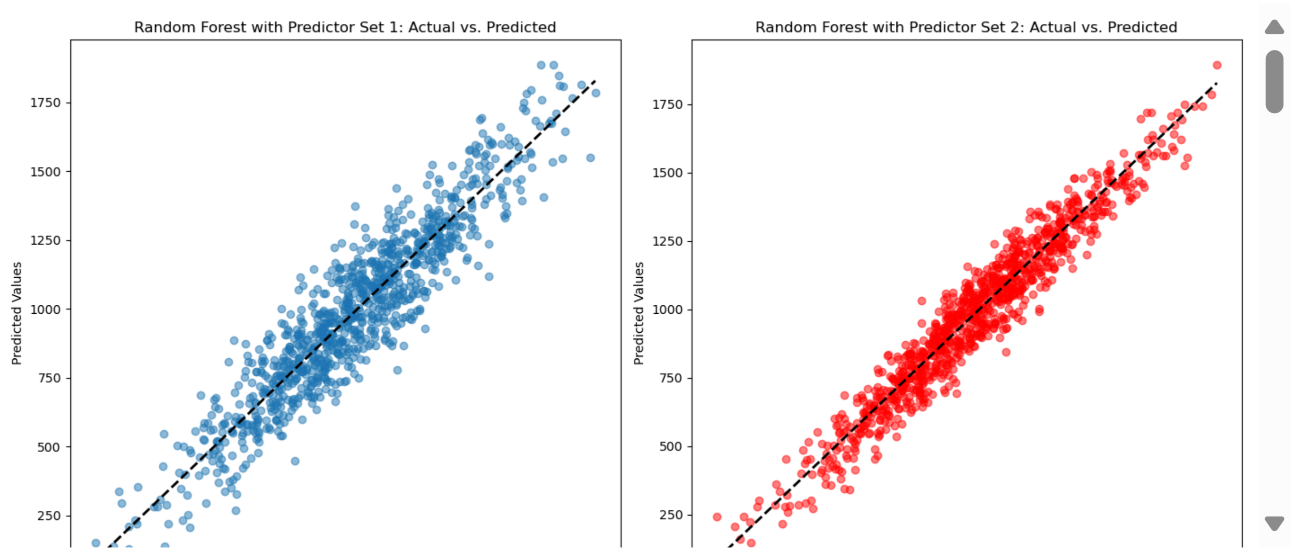
             plt.subplot(1, 2, 2)
             plt.scatter(predictions_set2, residuals_set2, alpha=0.5, color='r')
             plt.title(f'{model_name} with Predictor Set 2: Residuals')
             plt.xlabel('Predicted Values')
             plt.ylabel('Residuals')

             plt.tight_layout()
             plt.show()

         plot_model_comparisons(actual_values, rf_predictions_set1, rf_predictions_set2, residuals_rf_set1, resi

         plot_model_comparisons(actual_values, gb_predictions_set1, gb_predictions_set2, residuals_gb_set1, resi

         plot_model_comparisons(actual_values, svm_predictions_set1, svm_predictions_set2, residuals_svm_set1, r
```



This Python script loads football match statistics, selects features, encodes the target variable, and trains a decision tree classifier from scikit-learn. It visualizes the resulting decision tree without splitting the dataset for training and testing, potentially leading to overfitting. Crucial steps such as data splitting, hyperparameter tuning, and model evaluation metrics are omitted. To enhance model robustness, it's advisable to incorporate these steps for proper evaluation and optimization.

```
In [92]: import pandas as pd
         from sklearn.model_selection import train_test_split
         from sklearn.tree import DecisionTreeClassifier, plot_tree
         import matplotlib.pyplot as plt

         url =  'https://drive.google.com/uc?export=download&id=1uYpEqWv_DSoJ4gALEmy3FYZDFdb0PQTI'
         data = pd.read_csv(url)


         feature_columns = ['GF', 'GA', 'xG', 'xGA', 'Poss', 'Sh', 'SoT', 'Dist', 'FK', 'PK', 'PKatt']
         target_column = 'Result'

         data_filtered = data[feature_columns + [target_column]]

         data_filtered = data_filtered.dropna()

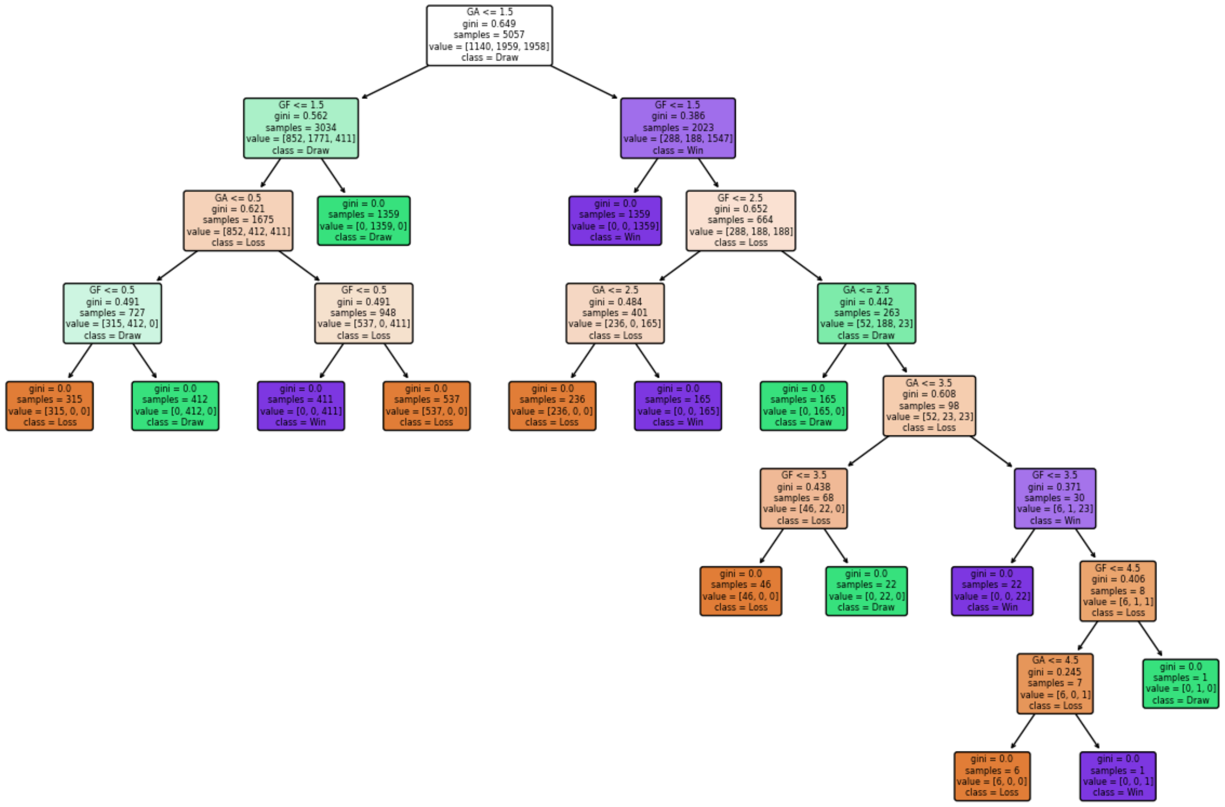
         data_filtered[target_column] = pd.factorize(data_filtered[target_column])[0]

         X = data_filtered[feature_columns]
         y = data_filtered[target_column]

         model_dt = DecisionTreeClassifier()


         model_dt.fit(X, y)

         plt.figure(figsize=(15, 10))
         plot_tree(model_dt, feature_names=feature_columns, class_names=['Loss', 'Draw', 'Win'], filled=True, ro
         plt.show()
```


GA <= 1.5 gini = 0.649 samples = 5057 value = [1140, 1959, 1958] class = Draw
GF <= 1.5 gini = 0.562 samples = 3034 value = [852, 1771, 411] class = Draw
GF <= 1.5 gini = 0.386 samples = 2023 value = [288, 188, 1547] class = Win
GA <= 0.5 gini = 0.621 samples = 1675 value = [852, 412, 411] class = Loss
gini = 0.0 samples = 1359 value = [0, 1359, 0] class = Draw
gini = 0.0 samples = 1359 value = [0, 0, 1359] class = Win
GF <= 2.5 gini = 0.652 samples = 664 value = [288, 188, 188] class = Loss
GF <= 0.5 gini = 0.491 samples = 727 value = [315, 412, 0] class = Draw
GF <= 0.5 gini = 0.491 samples = 948 value = [537, 0, 411] class = Loss
GA <= 2.5 gini = 0.484 samples = 401 value = [236, 0, 165] class = Loss
GA <= 2.5 gini = 0.442 samples = 263 value = [52, 188, 23] class = Draw
gini = 0.0 samples = 315 value = [315, 0, 0] class = Loss
gini = 0.0 samples = 412 value = [0, 412, 0] class = Draw
gini = 0.0 samples = 411 value = [0, 0, 411] class = Win
gini = 0.0 samples = 537 value = [537, 0, 0] class = Loss
gini = 0.0 samples = 236 value = [236, 0, 0] class = Loss
gini = 0.0 samples = 165 value = [0, 0, 165] class = Win
gini = 0.0 samples = 165 value = [0, 165, 0] class = Draw
GA <= 3.5 gini = 0.608 samples = 98 value = [52, 23, 23] class = Loss
GF <= 3.5 gini = 0.438 samples = 68 value = [46, 22, 0] class = Loss
GF <= 3.5 gini = 0.371 samples = 30 value = [6, 1, 23] class = Win
gini = 0.0 samples = 46 value = [46, 0, 0] class = Loss
gini = 0.0 samples = 22 value = [0, 22, 0] class = Draw
gini = 0.0 samples = 22 value = [0, 0, 22] class = Win
GF <= 4.5 gini = 0.406 samples = 8 value = [6, 1, 1] class = Loss
GA <= 4.5 gini = 0.245 samples = 7 value = [6, 0, 1] class = Loss
gini = 0.0 samples = 1 value = [0, 1, 0] class = Draw
gini = 0.0 samples = 6 value = [6, 0, 0] class = Loss
gini = 0.0 samples = 1 value = [0, 0, 1] class = Win

Reflection

1) What is the most challenging part of the project that you’ve encountered so far?

Ans) Reflecting on our project's journey so far, the most formidable challenge has indeed been gathering the data. Web scraping is a time-intensive process, and the rate limits imposed by the sources significantly slowed us down. This obstacle not only tested our patience but also our technical skills in efficiently collecting and organizing vast amounts of match data. We were only able to fetch 500-700 matches in one go. We had to modify the scripts, PAY FOR SUBSCRIPTION and register for a stathead account to get the required data.

2) What are your initial insights?

Ans) Our initial exploration of the data yielded promising trends, indicating that certain game metrics can influence match outcomes. Insights like the relationship between shots on target and winning matches have already begun to shape our understanding of successful football strategies. We also found out that a home game plays a good advantage to the home team.

3) Are there any concrete results you can show at this point? If not, why not?

Ans) As for concrete results, we have successfully generated insightful visualizations that highlight key trends such as the average number of goals per match across seasons and winning percentages of top teams. These visualizations substantiate some widely held beliefs about football dynamics. Apart from this, we also came to a conclusion that teams that dominate in a match in terms of possession, shots on target, GF and GA win most of the time. Our machine learning models concur with these findings.

4) Going forward, what are the current biggest problems you’re facing?

Ans) Moving ahead, the current big challenge is the development and refinement of our predictive models. Dealing with the intricacies of the dataset, such as the non-linear relationships and the potential for overfitting, will be our focus. Other than this, the problems include integrating more complex statistical methods to improve the accuracy of our predictions and finding ways to include player-specific data, which may require advanced data collection and processing techniques. We may not include the player specific visualizations if it proves to be too complex.

5) Do you think you are on track with your project? If not, what parts do you need to dedicate more time to?

Ans) We are on track with the project, but we need to dedicate more time to feature engineering and model fine-tuning. These are critical steps to enhance the performance of our machine learning models. We also need to compare various features and how they influence the match outcome.

6) Given your initial exploration of the data, is it worth proceeding with your project, why? If not, how will you move forward (method, data etc)?

Ans) Based on our initial data exploration, it is certainly worth proceeding with the project. The data shows patterns and trends that are worth investigating further. We plan to continue with a methodical approach, applying machine learning algorithms and possibly seeking out additional data sources to enrich our analysis.