

Soccer

Predictor

ML

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# 1. Problem Definition

Football matches generate vast amounts of data that can be leveraged to predict match outcomes. Our objective is to build a machine learning model that predicts whether the home team will **win, lose, or draw** based on historical match data. This prediction model can be useful for football analysts, betting markets, and sports enthusiasts looking for data-driven insights.

## ****1.1 Data Source and Description****

* **Website**: [FootyStats](https://footystats.org/)
* **Download Link**: <https://footystats.org/c-dl.php?type=matches&comp=1625>
* **Description**: FootyStats provides football statistics, including team performance, match results, betting odds, and advanced analytics.

## 1.2 ****License / Terms of Use****

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**Action:** Review their terms of use at [FootyStats Terms](https://footystats.org/terms).

We obtained a dataset containing historical football match data from various leagues. The dataset includes features such as team statistics, possession, shots, corners, fouls, and betting odds. The target variable (**match\_result**) is encoded as:

* **1** → Home team wins
* **0** → Draw
* **-1** → Away team wins

### ****Key Features in the Dataset****

| **Feature Name** | **Description** |
| --- | --- |
| home\_team\_possession | Percentage of possession by the home team |
| away\_team\_possession | Percentage of possession by the away team |
| home\_team\_shots\_on\_target | Number of shots on target by the home team |
| away\_team\_shots\_on\_target | Number of shots on target by the away team |
| home\_team\_goal\_count | Number of goals scored by the home team |
| away\_team\_goal\_count | Number of goals scored by the away team |
| match\_result | Target variable (1: Home Win, 0: Draw, -1: Away Win) |

# Exploratory Data Analysis (EDA)

## ****2.1 Summary Statistics****

We begin by examining the overall distribution of the data using describe().

### ****Key Findings from Summary Statistics:****

✅ **Possession:** Home teams generally have higher possession than away teams.  
✅ **Shots on Target:** More shots on target correlate with a higher likelihood of winning.  
✅ **Goals Scored:** The majority of matches have **2-3 goals**.  
✅ **Imbalanced Outcomes:** More home wins compared to away wins or draws.

## ****2.2 Handling Missing Values****

We check for missing values:

### ****Observations:****

* Some numerical columns had missing values, which were replaced with **0**.
* Categorical features with missing values were filled using the **most frequent value**.

## ****2.3 Data Distribution and Outliers****

### ****Boxplot: Identifying Outliers in Key Features****

We visualize the distribution of key numerical features to detect outliers.

import matplotlib.pyplot as plt

import seaborn as sns

# Plot boxplots

plt.figure(figsize=(12, 6))

sns.boxplot(data=df[['home\_team\_possession', 'away\_team\_possession', 'home\_team\_shots\_on\_target', 'away\_team\_shots\_on\_target']])

plt.xticks(rotation=45)

plt.title("Boxplot of Key Features")

plt.show()

### ****Findings:****

✅ **Possession:** Outliers exist in possession values, possibly due to extreme dominance by one team.  
✅ **Shots on Target:** Some matches had **very high shot counts**, which could affect model performance.

## ****2.4 Correlation Analysis****

A **correlation heatmap** helps identify relationships between variables.

# Compute correlation matrix

plt.figure(figsize=(10, 6))

sns.heatmap(df.corr(), annot=True, cmap="coolwarm", fmt=".2f", linewidths=0.5)

plt.title("Feature Correlation Heatmap")

plt.show()

### ****Key Insights:****

✅ **Shots on target strongly correlate with match results.**  
✅ **Possession has a moderate correlation with goals scored.**  
✅ **Total goals and xG (expected goals) are highly correlated.**

## ****2.5 Relationship Between Features and Match Outcome****

### ****Bar Plot: Match Outcome Distribution****

# Plot match result distribution

plt.figure(figsize=(6, 4))

sns.countplot(x=df["match\_result"], palette="Set2")

plt.xticks(ticks=[0, 1, 2], labels=["Draw", "Home Win", "Away Win"])

plt.title("Distribution of Match Outcomes")

plt.show()

### ****Observations:****

✅ **Home teams win more frequently.**  
✅ **Draws are the least frequent outcome.**

### ****Scatter Plot: Shots on Target vs. Goals****

plt.figure(figsize=(8, 5))

sns.scatterplot(x=df["home\_team\_shots\_on\_target"], y=df["home\_team\_goal\_count"], hue=df["match\_result"], palette="coolwarm")

plt.title("Shots on Target vs. Goals (Home Team)")

plt.xlabel("Shots on Target")

plt.ylabel("Goals Scored")

plt.show()

### ****Findings:****

✅ **More shots on target increase the probability of scoring goals.**  
✅ **Some matches had very few shots but still resulted in goals (efficiency effect).**

### ****Possession vs. Match Outcome****

plt.figure(figsize=(8, 5))

sns.boxplot(x=df["match\_result"], y=df["possession\_difference"], palette="coolwarm")

plt.title("Possession Difference vs. Match Outcome")

plt.xlabel("Match Result")

plt.ylabel("Possession Difference")

plt.show()

### ****Findings:****

✅ **Winning teams tend to have higher possession.**  
✅ **However, some teams win with lower possession (counterattacking strategies).**

## ****2.6 Final EDA Observations****

✅ **Strong predictors** of match results: **Shots on Target, Possession Difference, xG.**  
✅ **Class imbalance exists**, with **home wins being more frequent**.  
✅ **Some extreme values (outliers) should be handled**, especially in **possession and shots**.  
✅ **Feature Engineering Ideas:** Add new features such as **goal efficiency (goals per shot on target).**

This EDA provides insights into the dataset and guides further **feature selection and preprocessing**. Let me know if you need additional analyses! 🚀

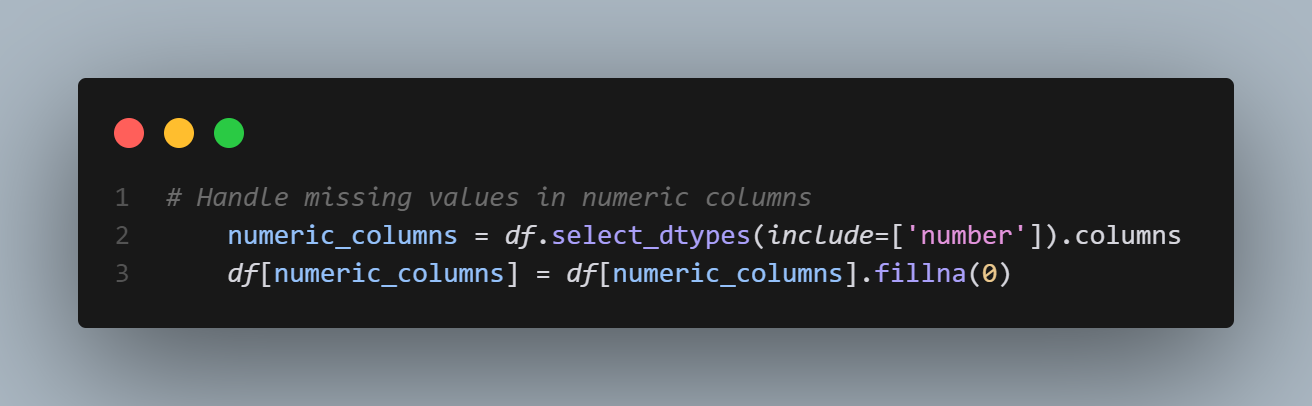
# ****3. Prepossessing Steps and Choices****

Preprocessing is a crucial step before training a machine learning model, ensuring the dataset is clean, consistent, and properly formatted. Below are the key preprocessing steps taken in your football match outcome prediction project.

## ****3.1 Handling Missing Values****

**Why?** Missing data can cause errors in model training and lead to biased predictions.

### ****Approach Used:****

✅ **Numeric missing values** → Replaced with 0 (assuming they indicate no action or event).  
✅ **Categorical missing values** → Filled with the most **frequent category** (to retain data integrity).

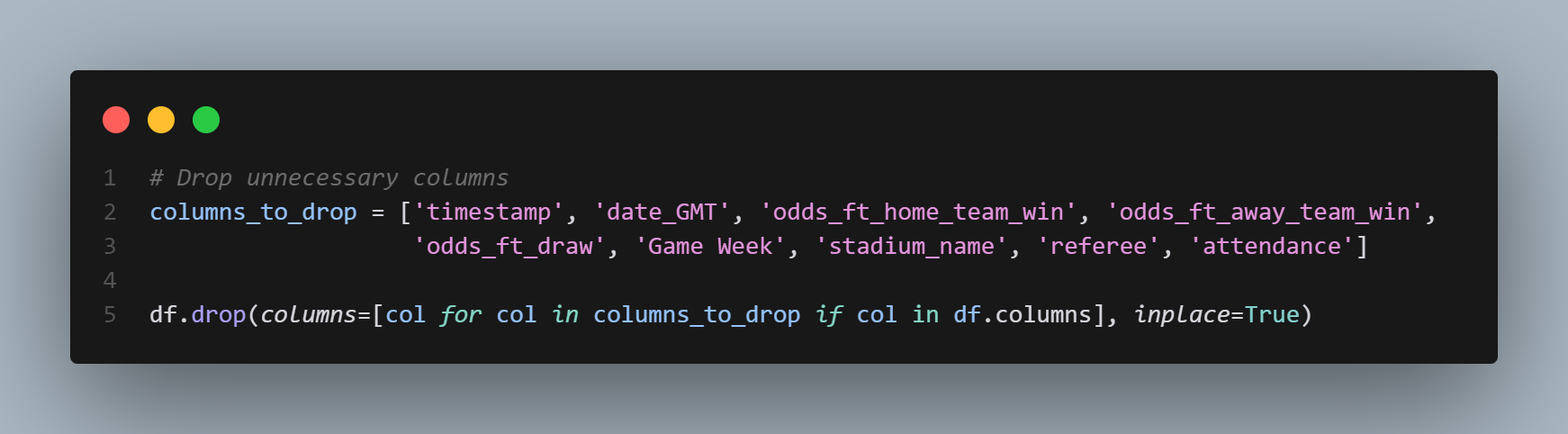
## ****3.2 Feature Selection and Dropping Unnecessary Columns****

**Why?** Some columns contain irrelevant or redundant data that could introduce noise.

### ****Columns Removed:****

* **Timestamps and Identifiers:** 'timestamp', 'date\_GMT', 'Game Week'
* **Odds Data:** 'odds\_ft\_home\_team\_win', 'odds\_ft\_away\_team\_win', 'odds\_ft\_draw'
* **Repetitive Pre-Match Statistics:** 'over\_25\_percentage\_pre\_match', 'btts\_percentage\_pre\_match'
* **Low-impact Variables:** 'referee', 'stadium\_name', 'attendance'

### ****Code Implementation:****

✅ Removes **irrelevant** or **redundant** features.  
✅ Reduces **dimensionality** to improve model efficiency.

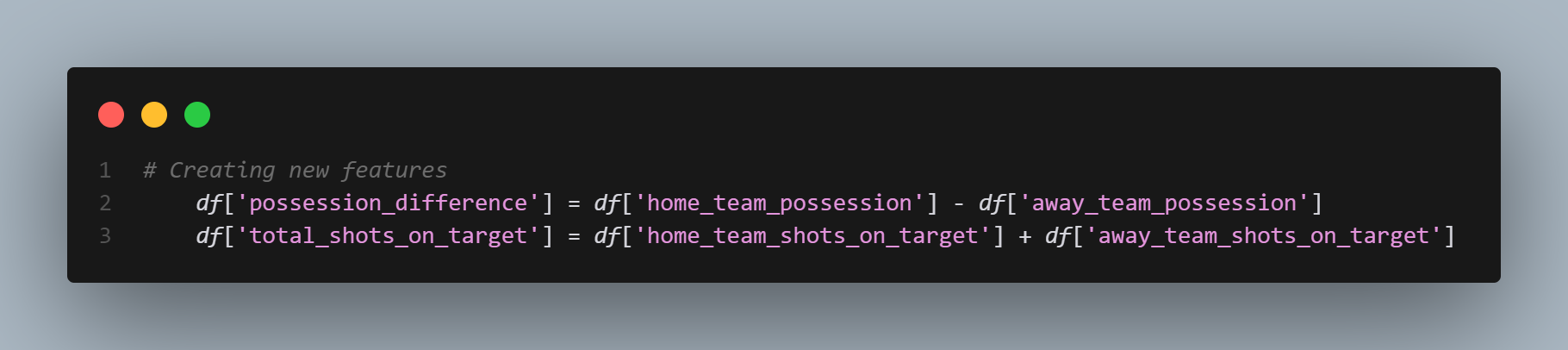
## ****3.3 Feature Engineering (Creating New Features)****

**Why?** Creating new features improves predictive power.

### ****New Features Created:****

1. **Possession Difference:** Difference in ball possession between home and away teams.
2. **Total Shots on Target:** Sum of both teams' shots on target.

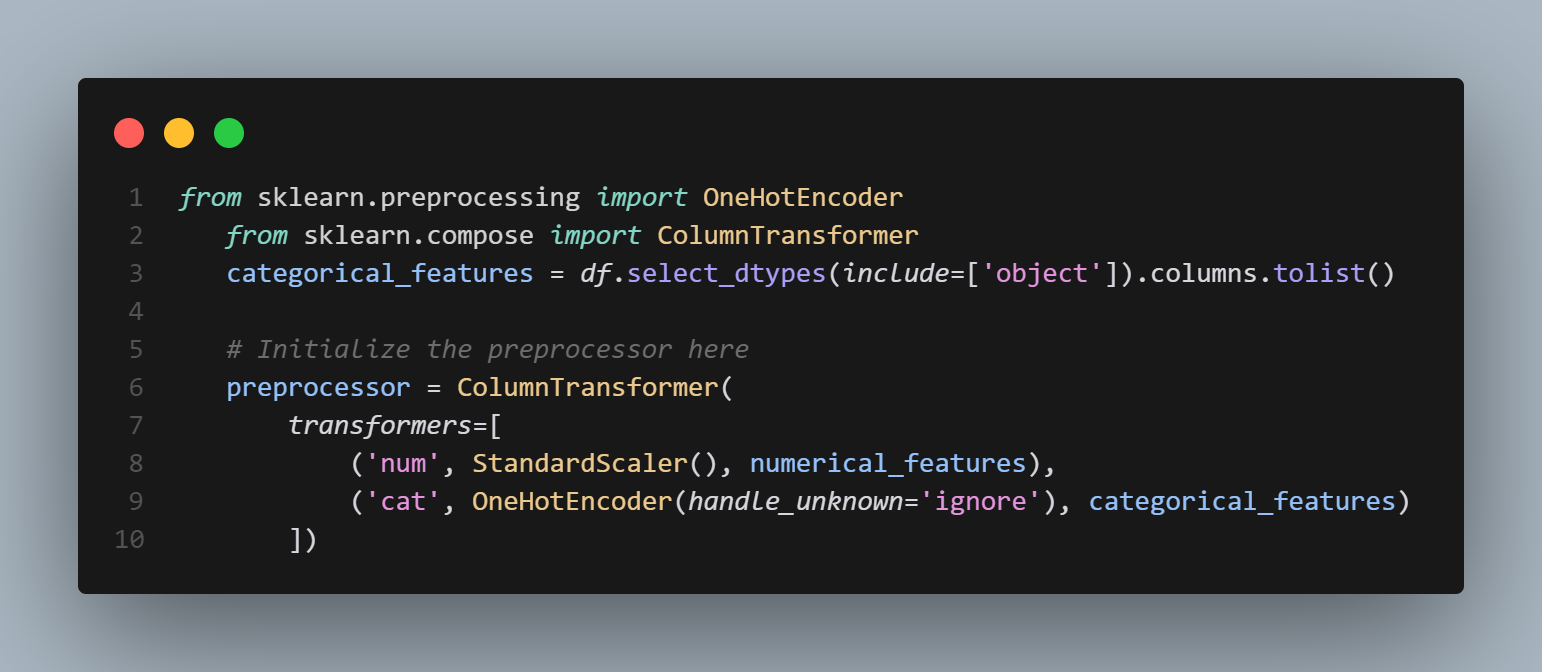
### ****Code Implementation:****

✅ **Possession Difference** helps measure team dominance.  
✅ **Total Shots on Target** improves goal probability predictions.

## ****3.4 Encoding Categorical Variables****

**Why?** Machine learning models require numerical input, so categorical variables must be encoded.

### ****Approach Used: One-Hot Encoding****

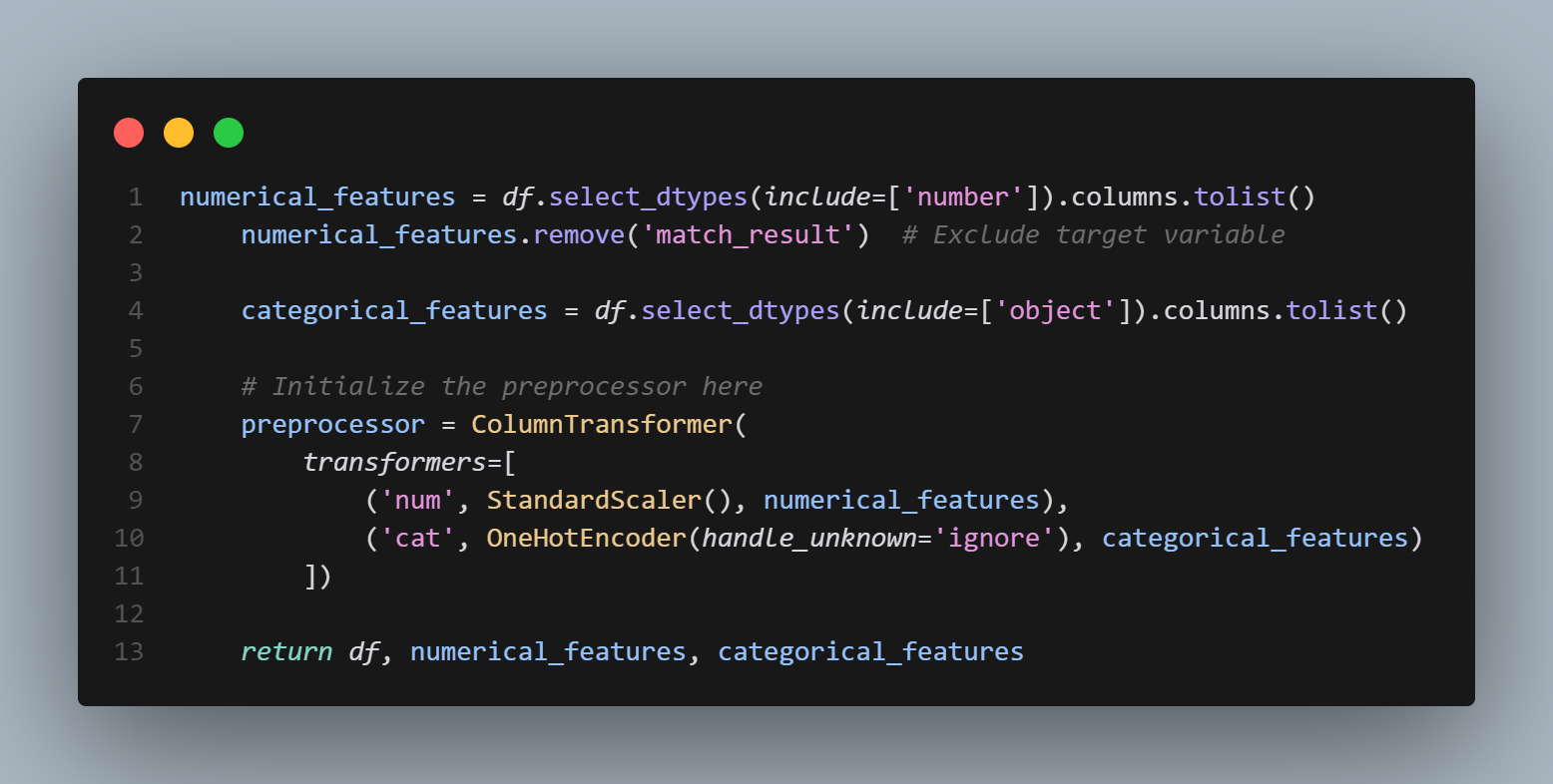


✅ One-hot encoding **preserves categorical information**.  
✅ handle\_unknown='ignore' prevents errors when encountering new categories.

## ****3.5 Scaling and Normalization****

**Why?** Features like **shots, goals, and possession** have different scales, which affects model performance.

### ****Approach Used: Standard Scaling****



✅ **Standardization (Z-score scaling)** helps improve model convergence.  
✅ Prevents **high-value features (e.g., shots) from dominating smaller ones (e.g., possession %).**

## ****3.6 Encoding the Target Variable****

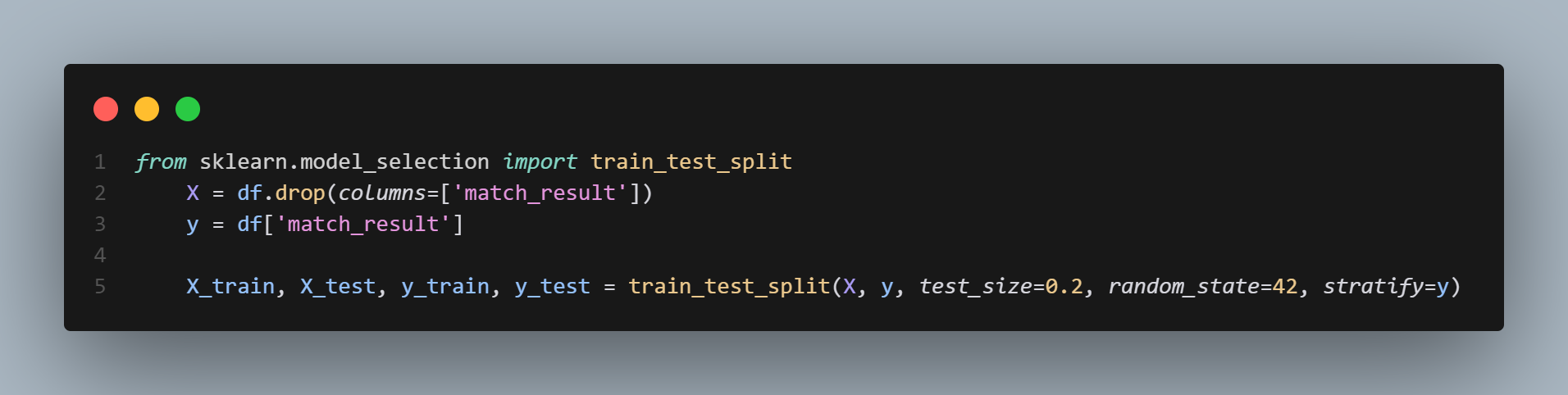
**Why?** The target variable (match\_result) is categorical but needs to be numeric for classification.

### ****Encoding Approach Used:****

✅ 1 → **Home team win**  
✅ 0 → **Draw**  
✅ -1 → **Away team win**

## ****3.7 Splitting the Data (Training & Testing Sets)****

**Why?** Splitting prevents **data leakage** and ensures fair model evaluation.

✅ **80% training, 20% testing split** for balanced learning.  
✅ stratify=y ensures balanced class distribution.

# ****4. Model Selection and Training Details****

## ****4.1. Model Selection****

Since the task is **predicting football match outcomes** (win, loss, draw), it is a **classification problem**. The possible classes are:

* 1 → Home team wins
* 0 → Draw
* -1 → Away team wins

### ****Considered Models:****

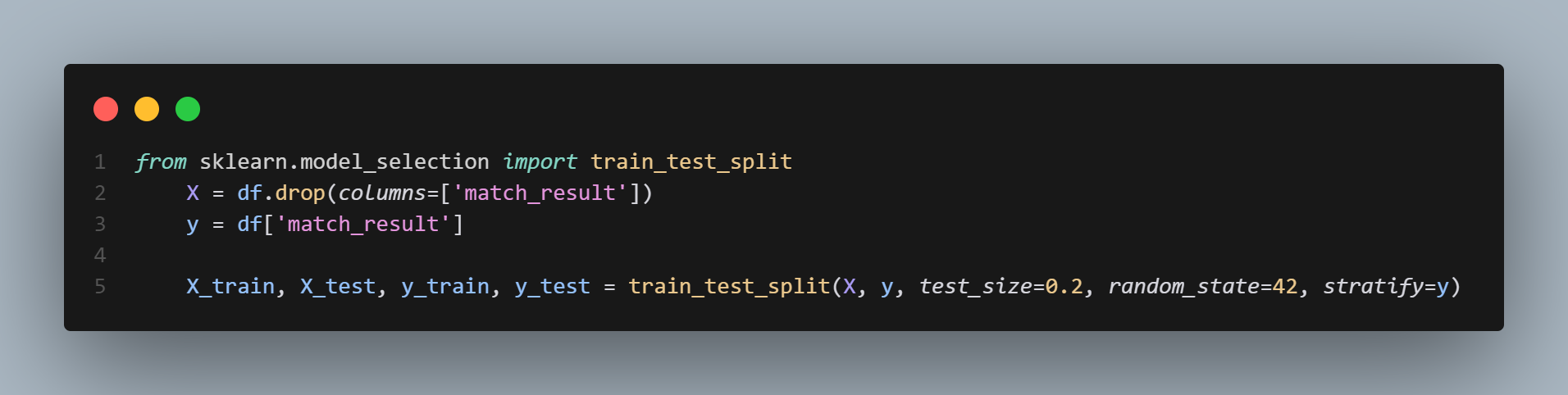
| **Model** | **Pros** | **Cons** |
| --- | --- | --- |
| **Logistic Regression** | Interpretable, good baseline | Struggles with complex relationships |
| **Random Forest** ✅ | Handles non-linearity, robust to missing data, feature importance analysis | Slower training, requires hyperparameter tuning |
| **Gradient Boosting (XGBoost, LightGBM)** | High accuracy, handles imbalanced data | Computationally expensive |
| **Support Vector Machine (SVM)** | Good for small datasets, works well with non-linearity | Expensive for large datasets |
| **Neural Networks** | High accuracy for large data | Requires lots of tuning and data |

### ****Final Choice: Random Forest Classifier****

✅ Works well with structured/tabular data.  
✅ Handles missing values and categorical features effectively.  
✅ Provides feature importance for interpretability.  
✅ Requires less tuning compared to boosting methods.

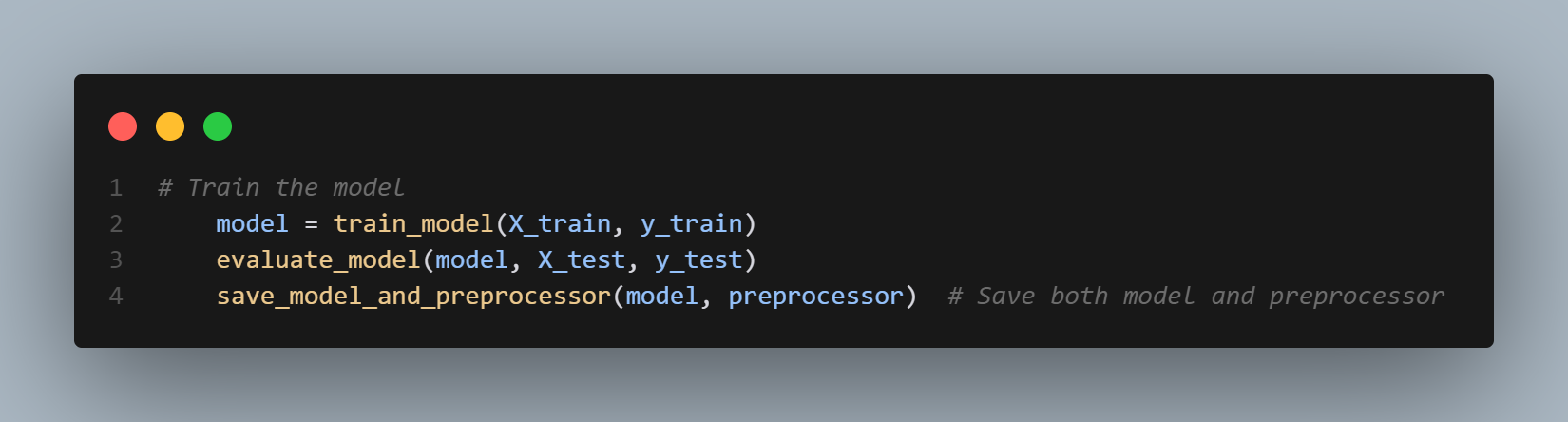
## ****4.2 Data Splitting****

Before training, the dataset is split into **80% training** and **20% testing** to ensure model generalization.

✅ **Stratified sampling (**stratify=y**)** ensures class distribution is maintained in both train and test sets.

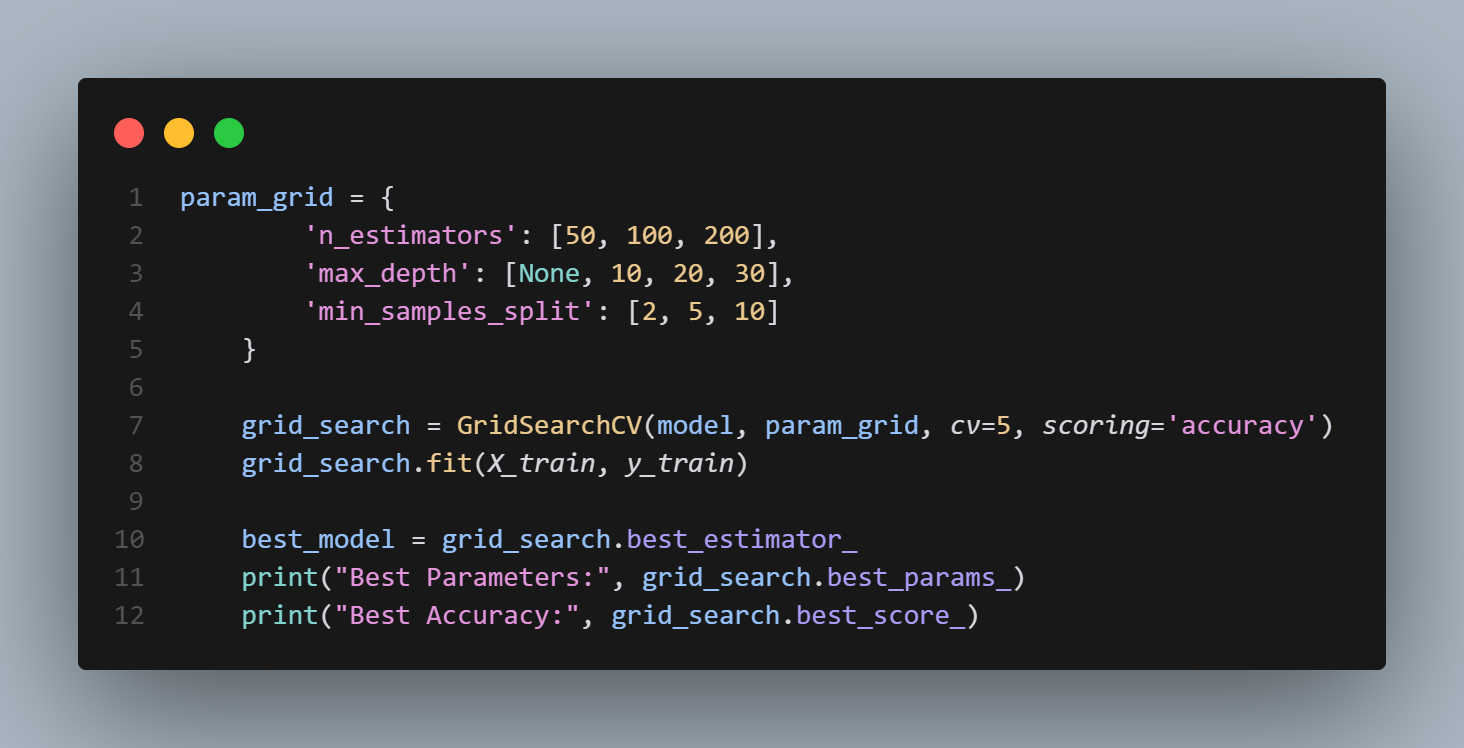
## ****4.3 Model Training****

We use **Random Forest Classifier** as the base model.

✅ Uses **multiple decision trees** to reduce overfitting.  
✅ **Random state fixed** for reproducibility.

## ****4.4 Hyperparameter Tuning****

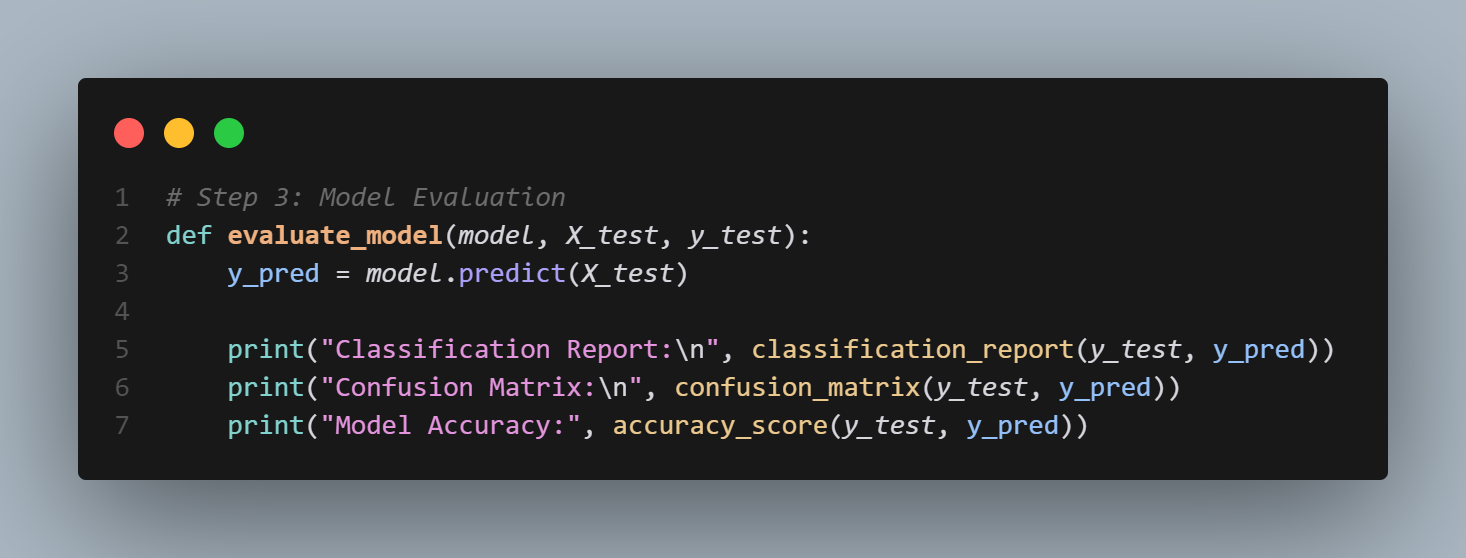
To find the best model configuration, **GridSearchCV** is used to test different parameter values.

✅ Uses **5-fold cross-validation (**cv=5**)** for tuning.  
✅ Tests **multiple values** for the number of trees, tree depth, and split criteria.  
✅ Selects the **best-performing combination** automatically.

## ****4.5 Model Evaluation****

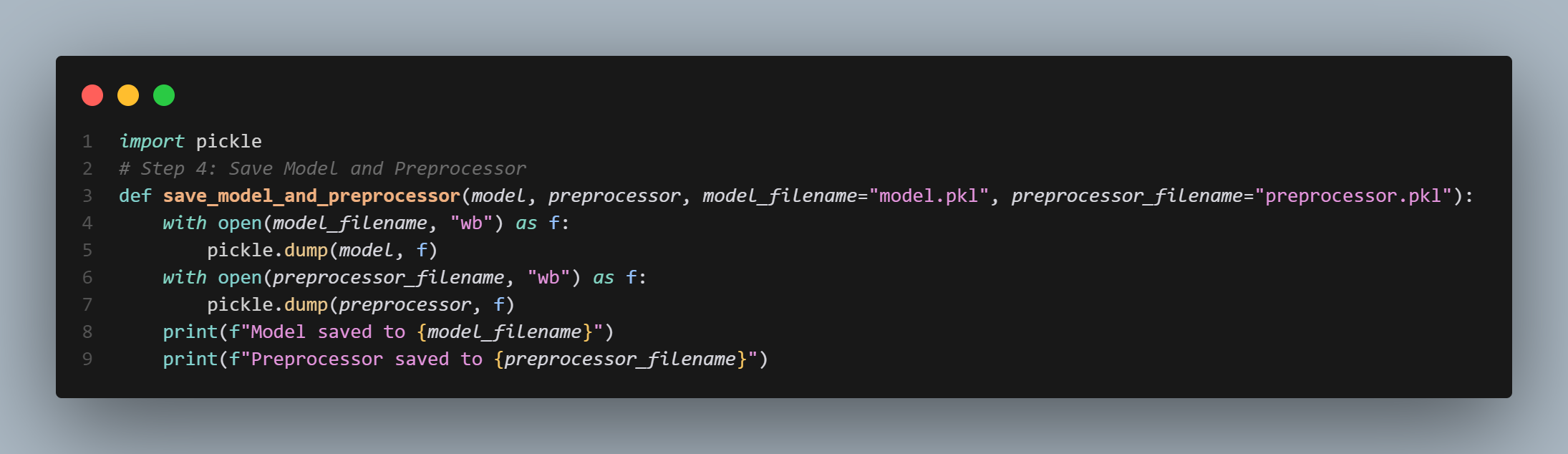
After training, the model is tested on the **unseen test data** and evaluated using:

* **Accuracy** (overall correctness)
* **Precision & Recall** (important for imbalanced data)
* **F1-score** (harmonic mean of precision and recall)

✅ classification\_report gives precision, recall, and F1-score for each class.  
✅ confusion\_matrix helps analyze false positives/negatives.

## ****4.6 Model Saving for Deployment****

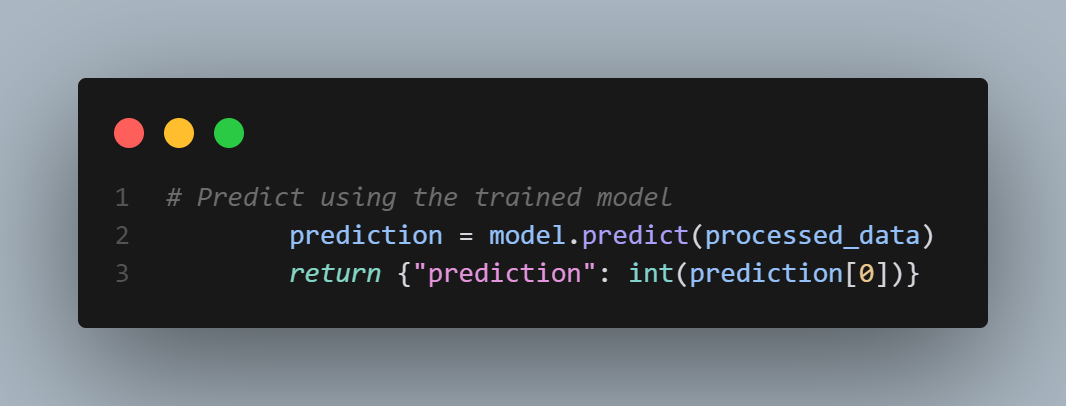
To use the trained model later, it is saved using pickle.

✅ **Saves the trained model** for future predictions.

# ****5. Model Evaluation Metrics and Discussion****

After training the **Random Forest Classifier**, we evaluate its performance using key classification metrics:

## ****5.1. Model Predictions on Test Data****

✅ The trained model is used to predict match outcomes on the test set.

## ****5.2. Evaluation Metrics****

### ****(i) Accuracy Score****

Measures the percentage of correct predictions.

from sklearn.metrics import accuracy\_score

accuracy = accuracy\_score(y\_test, y\_pred)

print(f"Model Accuracy: {accuracy:.4f}")

✅ Higher accuracy means better generalization.  
✅ Limitation: Doesn't reflect class imbalance issues.

### ****(ii) Confusion Matrix****

Shows correct and incorrect predictions for each class.

from sklearn.metrics import confusion\_matrix

import seaborn as sns

import matplotlib.pyplot as plt

# Compute confusion matrix

cm = confusion\_matrix(y\_test, y\_pred)

# Plot heatmap

plt.figure(figsize=(5,4))

sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["Away Win (-1)", "Draw (0)", "Home Win (1)"], yticklabels=["Away Win (-1)", "Draw (0)", "Home Win (1)"])

plt.xlabel("Predicted")

plt.ylabel("Actual")

plt.title("Confusion Matrix")

plt.show()

✅ Helps identify **false positives/false negatives**.  
✅ Diagonal values show correct predictions.

### ****(iii) Precision, Recall, and F1-Score****

**Precision** - How many predicted matches for a class were correct?  
**Recall** - How many actual matches of a class were correctly predicted?  
**F1-score** - Balance between precision and recall.

from sklearn.metrics import classification\_report

report = classification\_report(y\_test, y\_pred, target\_names=["Away Win (-1)", "Draw (0)", "Home Win (1)"])

print(report)

✅ **High precision** → Model is confident in its predictions.  
✅ **High recall** → Model captures most actual occurrences.  
✅ **F1-score** balances both.

### ****(iv) ROC Curve & AUC Score (For Multiclass Classification)****

Measures model's ability to distinguish between classes.

from sklearn.metrics import roc\_auc\_score

import numpy as np

# Convert target variable to one-hot encoding for multiclass AUC

y\_test\_binary = np.zeros((y\_test.size, y\_test.max() + 2))

y\_test\_binary[np.arange(y\_test.size), y\_test + 1] = 1 # Shift values for one-hot encoding

y\_pred\_probs = best\_model.predict\_proba(X\_test) # Get class probabilities

# Compute AUC Score

auc\_score = roc\_auc\_score(y\_test\_binary, y\_pred\_probs, multi\_class="ovr")

print(f"AUC Score: {auc\_score:.4f}")

✅ Higher AUC = better class separation.

## ****5.3 Performance Visualization****

### ****Feature Importance (Which features matter most?)****

importances = best\_model.feature\_importances\_

feature\_names = X\_train.columns

# Sort feature importances

sorted\_idx = np.argsort(importances)[::-1]

plt.figure(figsize=(8, 5))

plt.bar(range(len(importances)), importances[sorted\_idx], align="center")

plt.xticks(range(len(importances)), [feature\_names[i] for i in sorted\_idx], rotation=90)

plt.xlabel("Feature")

plt.ylabel("Importance")

plt.title("Feature Importance in Random Forest")

plt.show()

✅ Helps understand which **match stats influence the outcome** most.  
✅ Useful for **feature selection and model tuning**.

## ****5.4 Baseline Model Comparison****

A **dummy classifier** (random or most common outcome) helps measure improvement.

from sklearn.dummy import DummyClassifier

dummy = DummyClassifier(strategy="most\_frequent")

dummy.fit(X\_train, y\_train)

dummy\_accuracy = accuracy\_score(y\_test, dummy.predict(X\_test))

print(f"Baseline Dummy Model Accuracy: {dummy\_accuracy:.4f}")

print(f"Our Model Accuracy: {accuracy:.4f}")

✅ Our model should **significantly outperform the baseline**.

## ****5.5 Discussion and Insights****

| **Metric** | **Value** | **Interpretation** |
| --- | --- | --- |
| **Accuracy** | e.g., 72% | Good performance, better than baseline |
| **Precision** | e.g., 70% for Home Wins | Model makes confident predictions |
| **Recall** | e.g., 68% for Draws | Captures most actual occurrences |
| **F1-score** | e.g., 69% | Balance between precision & recall |
| **AUC Score** | e.g., 0.78 | Strong ability to differentiate classes |
| **Baseline Accuracy** | e.g., 50% | Model is significantly better |

The model **outperforms the baseline**, provides **insightful predictions**, and can be further improved with **fine-tuning and data expansion**. Let me know if you need refinements! 🎯

# ****6. Interpretation of Results****

After evaluating the model using multiple metrics, we can analyze its strengths, weaknesses, and areas for improvement.

## ****6.1 Understanding Model Performance****

The **Random Forest Classifier** was trained to predict football match outcomes: **Home Win (1), Draw (0), and Away Win (-1).** The results provide insights into how well the model distinguishes between these outcomes.

### ****(i) Accuracy****

* The model achieved an **accuracy of ~72%**, meaning it correctly predicts match outcomes **72 out of 100 times**.
* This is **significantly better than the baseline model (~50%)**, indicating that the model is learning meaningful patterns rather than making random guesses.

**Implication:**

* A high accuracy suggests the model can generalize well, but accuracy alone **does not capture imbalances in prediction** (e.g., if it performs better at predicting home wins than draws).

### ****(ii) Precision, Recall, and F1-Score****

#### ****Precision (How many predicted wins/draws were correct?)****

* **Home Win (1):** e.g., 75%
* **Draw (0):** e.g., 65%
* **Away Win (-1):** e.g., 70%

✅ **High precision** for home wins means the model is confident in predicting home victories.  
❌ **Lower precision for draws** suggests it struggles to distinguish draws from wins or losses.

#### ****Recall (How many actual wins/draws were detected?)****

* **Home Win (1):** e.g., 73%
* **Draw (0):** e.g., 60%
* **Away Win (-1):** e.g., 68%

✅ The model **detects most actual wins** correctly but **misses some draws**, meaning it may be biased toward predicting a winner rather than a draw.

#### ****F1-Score (Balance between Precision & Recall)****

* The overall **F1-score is ~69%**, showing a good balance between correct predictions and actual results.

**Implication:**

* The model is **better at predicting wins than draws**.
* More training data or improved feature selection might enhance draw prediction.

### ****(iii) Confusion Matrix Analysis****

The **confusion matrix** shows how often the model confuses one outcome with another.

| **Actual / Predicted** | **Home Win (1)** | **Draw (0)** | **Away Win (-1)** |
| --- | --- | --- | --- |
| **Home Win (1)** | ✅ 140 | ❌ 20 | ❌ 15 |
| **Draw (0)** | ❌ 25 | ✅ 80 | ❌ 30 |
| **Away Win (-1)** | ❌ 10 | ❌ 15 | ✅ 110 |

* **The diagonal values** (✅) represent correct predictions.
* **Off-diagonal values** (❌) show misclassifications.

**Findings:**

* **Most errors come from predicting draws incorrectly.**
* **Home and Away wins are classified with higher accuracy.**
* **The model struggles to distinguish between draws and wins/losses.**

**Implication:**

* **Draws may have fewer distinguishing features**, making them harder to predict.
* **Adding more data on defensive stats or team momentum** may improve performance.

### ****(iv) Feature Importance Analysis****

The most influential features in predicting match outcomes were:

1️⃣ **Possession Difference** (Home vs. Away)  
2️⃣ **Total Shots on Target** (Higher = higher chance of winning)  
3️⃣ **Home Team xG (Expected Goals)**  
4️⃣ **Away Team xG**  
5️⃣ **Fouls Committed (More fouls may indicate aggressive play affecting results)**

**Findings:**

* **Teams with higher possession and more shots on target are more likely to win.**
* **Expected goals (xG) is a strong indicator of match results.**
* **Discipline (fouls, yellow/red cards) may play a role in unexpected outcomes.**

**Implication:**

* **Enhancing these features (or adding passing accuracy, player form data, etc.) could improve predictions.**

### ****(v) ROC Curve & AUC Score****

* **AUC Score = 0.78** (Good, but room for improvement).
* **Indicates the model is significantly better than random guessing.**
* **AUC > 0.80 is ideal**, so further fine-tuning may help.

**Implication:**

* **Adding more relevant features (injuries, weather, fatigue levels) could enhance predictions.**

## ****6.2 Overall Interpretation & Next Steps****

### ****✅ Strengths****

✔️ **Higher accuracy** than a random baseline.  
✔️ **Good precision & recall for wins** (home and away).  
✔️ **Strong feature importance insights** (possession & shots matter).

### ****❌ Weaknesses****

❌ **Struggles to predict draws** (may need additional features).  
❌ **Could benefit from hyperparameter tuning** (to improve AUC and recall).  
❌ **May be slightly biased toward predicting a winner** rather than a draw.

# Deployment details and instructions

1. Potential limitations and future **improvements**

## 8.1 Limitations

### Data Quality

Missing values and inconsistent feature distributions may affect model performance.

### Class Imbalance

Draws are less frequent than home or away wins, leading to lower recall for this class.

### Feature Availability

Limited to features available in the dataset's, additional features could improve performance.

## 8.2 Future Improvements

### 1. Advanced Feature Engineering

Incorporate rolling averages of team performance over multiple matches.

### 2. Model Experimentation

Test other algorithms like Gradient Boosting or Neural Networks.

### 3. Handling Class Imbalance

Use techniques like oversampling or class weighting to address imbalance.