https://github.com/AndyQ-262/F1_data/tree/main

```
# Import libraries

import sklearn
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Loading Formula 1 data from URLs into Pandas DataFrames
url_1 =
"https://raw.githubusercontent.com/AndyQ-262/F1_data/main/results.csv"
results_df = pd.read_csv(url_1, sep=',')

url_2 =
"https://raw.githubusercontent.com/AndyQ-262/F1_data/main/qualifying.c
sv"
qualifying_df = pd.read_csv(url_2, sep=',')

url_3 =
"https://raw.githubusercontent.com/AndyQ-262/F1_data/main/lap_times.cs
v"
lap_times_df = pd.read_csv(url_3, sep=',')

url_4 =
"https://raw.githubusercontent.com/AndyQ-262/F1_data/main/drivers.csv"
drivers_df = pd.read_csv(url_4, sep=',')

url_5 =
"https://raw.githubusercontent.com/AndyQ-262/F1_data/main/constructors
.csv"
constructors_df = pd.read_csv(url_5, sep=',')

url_6 =
"https://raw.githubusercontent.com/AndyQ-262/F1_data/main/races.csv"
races_df = pd.read_csv(url_6, sep=',')

url_7 =
"https://raw.githubusercontent.com/AndyQ-262/F1_data/main/circuits.csv
"
circuits_df = pd.read_csv(url_7, sep=",")

results_df.head()
```

```
   resultId  raceId  driverId  constructorId number  grid position  \
0         1      18         1              1     22     1        1
1         2      18         2              2      3     5        2
2         3      18         3              3      7     7        3
3         4      18         4              4      5    11        4
```

```
4          5      18          5              1     23     3         5

  positionText  positionOrder  points  laps         time milliseconds
\
0            1              1    10.0    58  1:34:50.616      5690616

1            2              2     8.0    58       +5.478      5696094

2            3              3     6.0    58       +8.163      5698779

3            4              4     5.0    58      +17.181      5707797

4            5              5     4.0    58      +18.014      5708630


  fastestLap rank fastestLapTime fastestLapSpeed  statusId
0         39    2       1:27.452         218.300         1
1         41    3       1:27.739         217.586         1
2         41    5       1:28.090         216.719         1
3         58    7       1:28.603         215.464         1
4         43    1       1:27.418         218.385         1
```

```
qualifying_df.head()
```

```
   qualifyId  raceId  driverId  constructorId  number  position
q1  \
0          1      18         1              1      22         1
1:26.572
1          2      18         9              2       4         2
1:26.103
2          3      18         5              1      23         3
1:25.664
3          4      18        13              6       2         4
1:25.994
4          5      18         2              2       3         5
1:25.960

         q2        q3
0  1:25.187  1:26.714
1  1:25.315  1:26.869
2  1:25.452  1:27.079
3  1:25.691  1:27.178
4  1:25.518  1:27.236
```

```
lap_times_df.head()
```

```
   raceId  driverId  lap  position      time  milliseconds
0     841        20    1         1  1:38.109         98109
1     841        20    2         1  1:33.006         93006
2     841        20    3         1  1:32.713         92713
```

```
3     841         20    4          1  1:32.803         92803
4     841         20    5          1  1:32.342         92342
```

```
drivers_df.head()
```

```
   driverId   driverRef number code   forename     surname         dob
\
0         1    hamilton     44  HAM      Lewis    Hamilton  1985-01-07

1         2    heidfeld     \N  HEI       Nick    Heidfeld  1977-05-10

2         3     rosberg      6  ROS       Nico     Rosberg  1985-06-27

3         4      alonso     14  ALO   Fernando      Alonso  1981-07-29

4         5  kovalainen     \N  KOV     Heikki  Kovalainen  1981-10-19


  nationality                                             url
0     British     http://en.wikipedia.org/wiki/Lewis_Hamilton
1      German      http://en.wikipedia.org/wiki/Nick_Heidfeld
2      German       http://en.wikipedia.org/wiki/Nico_Rosberg
3     Spanish    http://en.wikipedia.org/wiki/Fernando_Alonso
4     Finnish  http://en.wikipedia.org/wiki/Heikki_Kovalainen
```

```
constructors_df.head()
```

```
   constructorId constructorRef        name nationality  \
0              1        mclaren     McLaren     British
1              2     bmw_sauber  BMW Sauber      German
2              3       williams    Williams     British
3              4        renault     Renault      French
4              5     toro_rosso  Toro Rosso     Italian

                                                url
0                http://en.wikipedia.org/wiki/McLaren
1             http://en.wikipedia.org/wiki/BMW_Sauber
2  http://en.wikipedia.org/wiki/Williams_Grand_Pr...
3  http://en.wikipedia.org/wiki/Renault_in_Formul...
4   http://en.wikipedia.org/wiki/Scuderia_Toro_Rosso
```

#Features: Name, Qualifying, Grid Position, Circuit, nationality, Experience in F1 (years in f1), Team nationality

#Targets: Was on Podium

```
# Selecting specific columns from results_df
results_df = results_df[["driverId", "raceId", "constructorId",
"grid", "positionOrder"]]

# Dropping unnecessary columns from qualifying_df
```

```
qualifying_df = qualifying_df.drop(["qualifyId", "position",
"number"], axis='columns')

# Selecting specific columns from races_df and renaming 'name' column
to 'race name'
races_df = races_df[["raceId", "circuitId", "name", "date", "time",
"round"]]
races_df = races_df.rename(columns={'name': 'race name'})

# Selecting specific columns from circuits_df and renaming 'name'
column to 'circuit name'
circuits_df = circuits_df[["circuitId", "name"]]
circuits_df = circuits_df.rename(columns={'name': 'circuit name'})

# Merging circuits_df and races_df on 'circuitId'
circuits_merge_df = pd.merge(circuits_df, races_df, on='circuitId')
circuits_merge_df = circuits_merge_df.drop("circuitId",
axis='columns')

# Selecting specific columns from constructors_df and renaming columns
constructors_df = constructors_df[["constructorId", "name",
"nationality"]]
constructors_df = constructors_df.rename(columns={'name': 'constructor
name', 'nationality': 'constructor nationality'})

# Selecting specific columns from drivers_df and renaming the
'nationality' column
drivers_df = drivers_df[["driverId", "dob", "nationality", 'forename',
'surname']]
drivers_df = drivers_df.rename(columns={'nationality': 'driver
nationality'})

# Merging all the DataFrames step by step
results_df = pd.merge(circuits_merge_df, results_df, on='raceId')
results_df = pd.merge(qualifying_df, results_df, on=['raceId',
'driverId', 'constructorId'])
results_df = pd.merge(constructors_df, results_df,
on=['constructorId'])
results_df = pd.merge(drivers_df, results_df, on=['driverId'])
results_df = results_df.drop(["constructorId", "raceId"],
axis='columns')

#Combine first name and last name into one column
results_df['driver name'] = results_df['forename'] + ' ' +
results_df['surname']
results_df = results_df.drop(["forename"], axis='columns')
results_df = results_df.drop(["surname"], axis='columns')

# Creating a new column 'onPodium' based on 'positionOrder'
results_df['onPodium'] = results_df['positionOrder'].apply(lambda x: 1
```

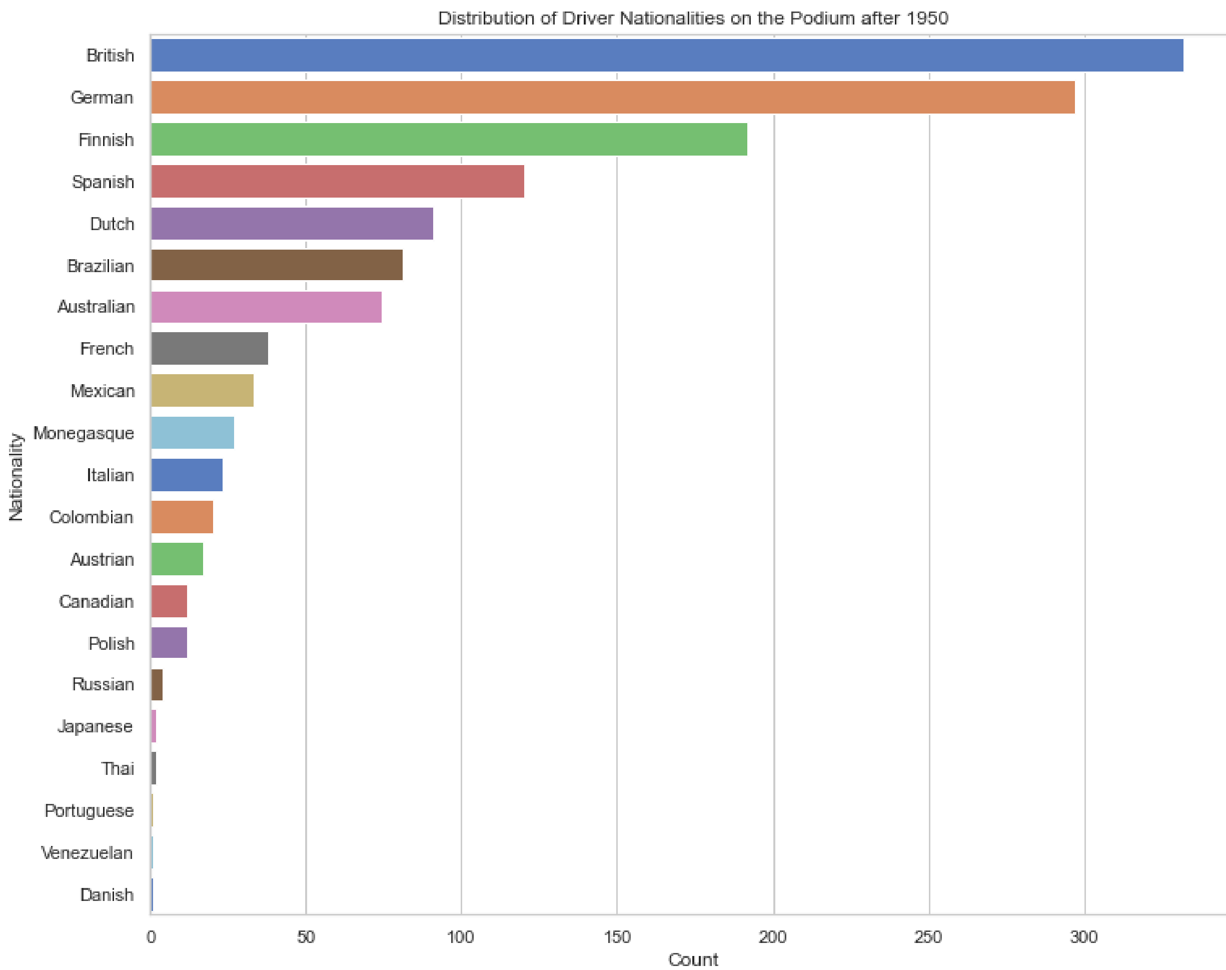
```
if x <= 3 else 0)
results_df = results_df.drop("positionOrder", axis='columns')

# Converting selected columns to categorical data type
results_df['driverId'] = results_df['driverId'].astype('category')
results_df['onPodium'] = results_df['onPodium'].astype('category')
results_df['grid'] = results_df['grid'].astype('category')
results_df['round'] = results_df['round'].astype('category')

# Converting 'dob' and 'date' columns to datetime format
results_df['dob'] = pd.to_datetime(results_df['dob'])
results_df['date'] = pd.to_datetime(results_df['date'])

# Calculating age based on 'dob' and 'date'
results_df['age'] = (results_df['date'] - results_df['dob']).dt.days
// 365

# Dropping unnecessary columns
results_df = results_df.drop(["dob"], axis='columns')
results_df['date'] = results_df['date'].dt.year.astype(str)
results_df = results_df.drop(["time"], axis='columns')

# Handling missing values and converting time columns to seconds
results_df['q1'] = pd.to_datetime(results_df['q1'], format='%M:%S.%f',
errors='coerce').dt.minute * 60 + pd.to_datetime(results_df['q1'],
format='%M:%S.%f', errors='coerce').dt.second +
pd.to_datetime(results_df['q1'], format='%M:%S.%f',
errors='coerce').dt.microsecond / 1e6
results_df['q2'] = pd.to_datetime(results_df['q2'], format='%M:%S.%f',
errors='coerce').dt.minute * 60 + pd.to_datetime(results_df['q2'],
format='%M:%S.%f', errors='coerce').dt.second +
pd.to_datetime(results_df['q2'], format='%M:%S.%f',
errors='coerce').dt.microsecond / 1e6
results_df['q3'] = pd.to_datetime(results_df['q3'], format='%M:%S.%f',
errors='coerce').dt.minute * 60 + pd.to_datetime(results_df['q3'],
format='%M:%S.%f', errors='coerce').dt.second +
pd.to_datetime(results_df['q3'], format='%M:%S.%f',
errors='coerce').dt.microsecond / 1e6

results_df = results_df.drop(["driver name"], axis='columns')

results_df
```

```
     driverId driver nationality constructor name constructor
nationality  \
0           1            British          McLaren
British
1           1            British          McLaren
British
2           1            British          McLaren
```

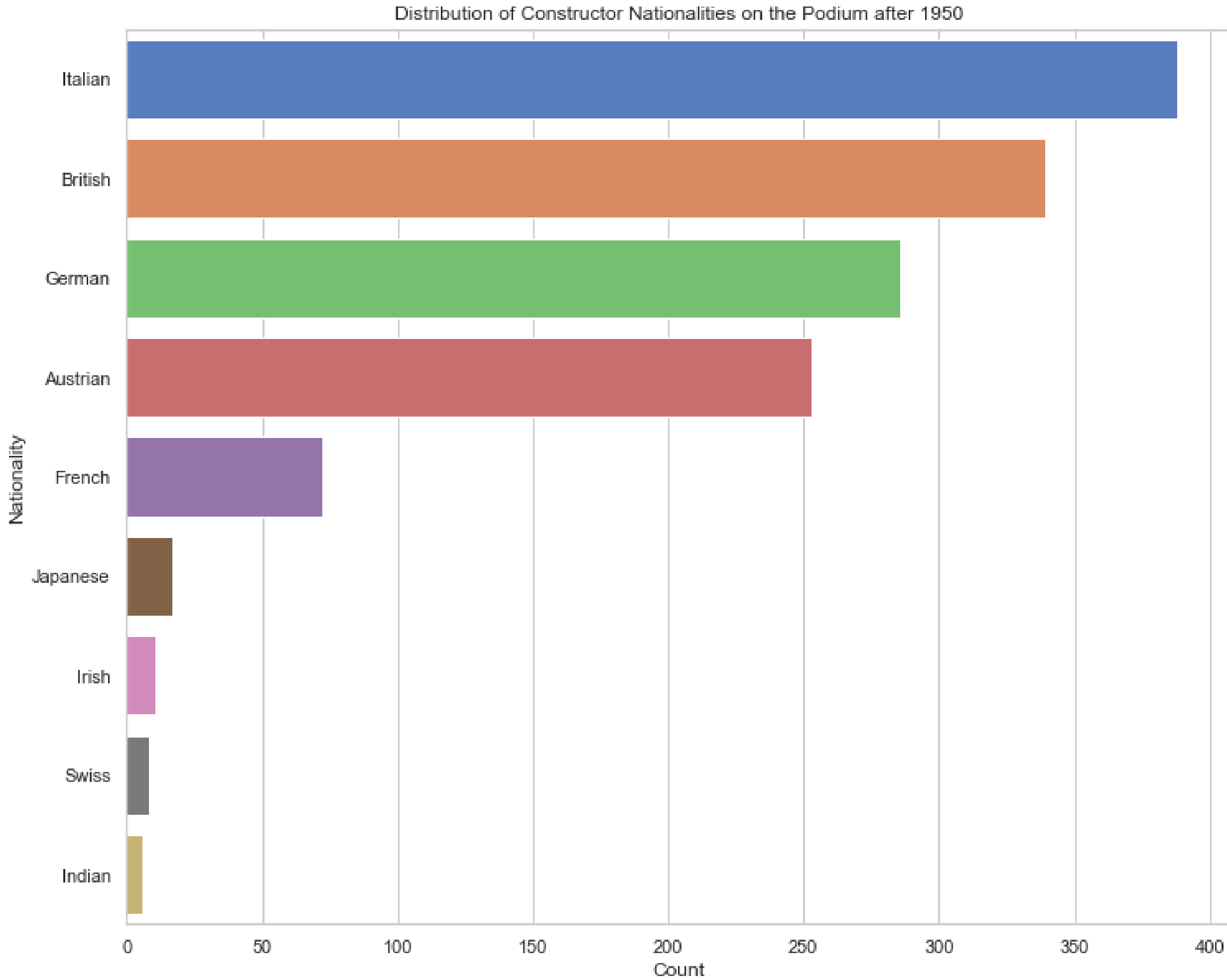
```
British
3           1            British          McLaren
British
4           1            British          McLaren
British
...       ...                ...              ...
...
9800      858           American         Williams
British
9801      858           American         Williams
British
9802      858           American         Williams
British
9803      858           American         Williams
British
9804      858           American         Williams
British

           q1      q2      q3                    circuit name  \
0      86.572  85.187  86.714  Albert Park Grand Prix Circuit
1      95.392  94.627  96.709    Sepang International Circuit
2      92.750  91.922  93.292   Bahrain International Circuit
3      81.366  80.825  82.096  Circuit de Barcelona-Catalunya
4      86.192  86.477  87.923                  Istanbul Park
...       ...     ...     ...                             ...
9800   83.337     NaN     NaN       Circuit Gilles Villeneuve
9801   65.948     NaN     NaN                  Red Bull Ring
9802   89.873  89.031     NaN             Silverstone Circuit
9803   79.248     NaN     NaN                     Hungaroring
9804  121.535     NaN     NaN    Circuit de Spa-Francorchamps

                  race name  date round grid onPodium  age
0     Australian Grand Prix  2008     1    1        1   23
1      Malaysian Grand Prix  2008     2    9        0   23
2        Bahrain Grand Prix  2008     3    3        0   23
3        Spanish Grand Prix  2008     4    5        1   23
4        Turkish Grand Prix  2008     5    3        1   23
...                     ...   ...   ...  ...      ...  ...
9800    Canadian Grand Prix  2023     8   18        0   22
9801    Austrian Grand Prix  2023     9   18        0   22
9802     British Grand Prix  2023    10   14        0   22
9803   Hungarian Grand Prix  2023    11   20        0   22
9804     Belgian Grand Prix  2023    12   18        0   22

[9805 rows x 14 columns]

onPodium_drivers_df = results_df[results_df['onPodium'] == 1]
sns.set(style="whitegrid")

# Driver Nationalities on podium
```

```python
plt.figure(figsize=(12, 10))
sns.countplot(data=onPodium_drivers_df, y='driver nationality',
order=onPodium_drivers_df['driver nationality'].value_counts().index,
palette='muted')
plt.title('Distribution of Driver Nationalities on the Podium after
1950')
plt.xlabel('Count')
plt.ylabel('Nationality')
plt.show()

# Drivers on podium
plt.figure(figsize=(12, 10))
sns.countplot(data=onPodium_drivers_df, y='constructor nationality',
order=onPodium_drivers_df['constructor
nationality'].value_counts().index, palette='muted')
plt.title('Distribution of Constructor Nationalities on the Podium
after 1950')
plt.xlabel('Count')
plt.ylabel('Nationality')
plt.show()

# Constructors on podium
plt.figure(figsize=(12, 10))
sns.countplot(data=onPodium_drivers_df, y='constructor name',
order=onPodium_drivers_df['constructor name'].value_counts().index,
palette='muted')
plt.title('Distribution of Constructors on the Podium after 1950')
plt.xlabel('Count')
plt.ylabel('Nationality')
plt.show()
```

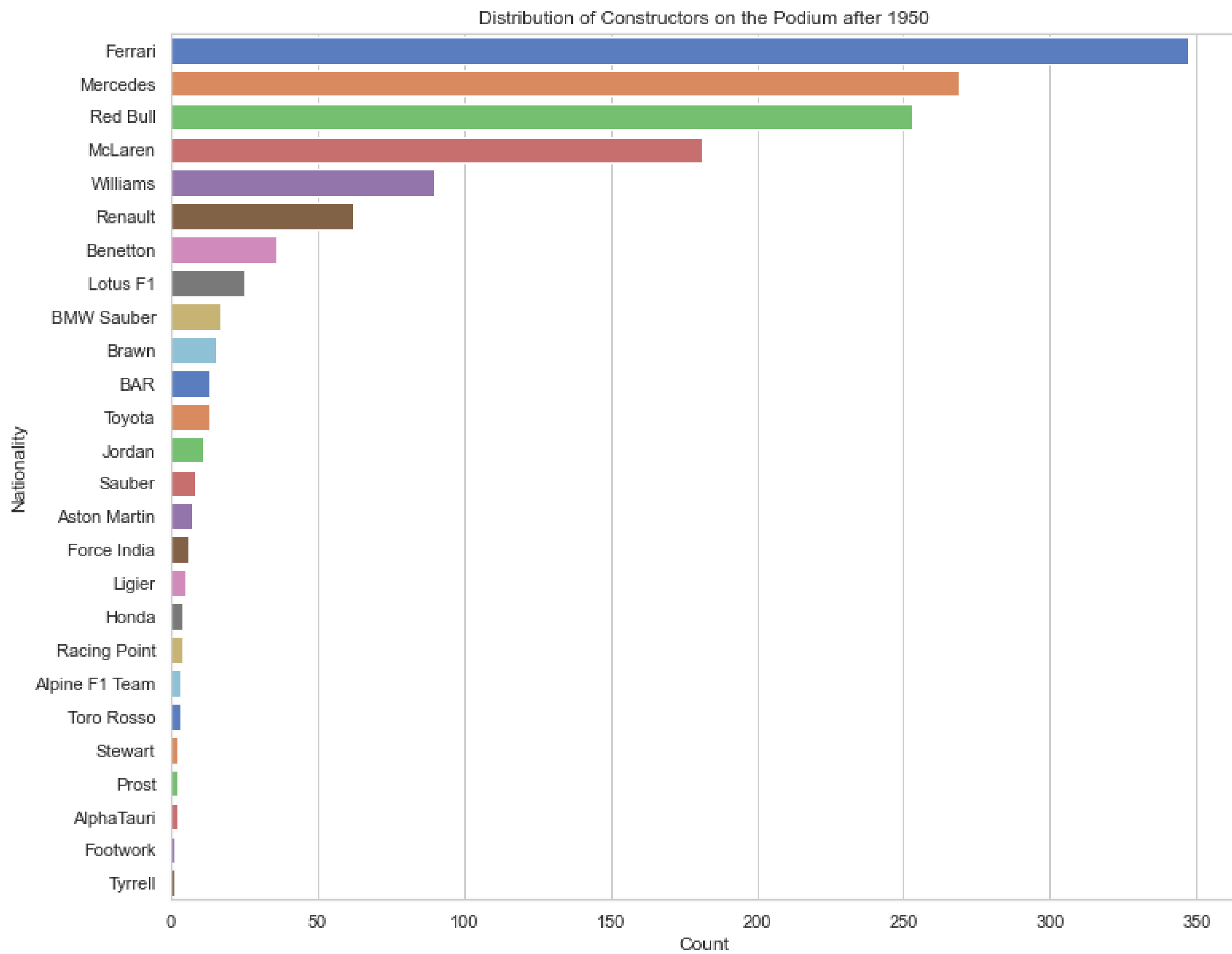
```
C:\Users\ANDYQU~1\AppData\Local\Temp/ipykernel_27488/2231791779.py:6:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=onPodium_drivers_df, y='driver nationality',
order=onPodium_drivers_df['driver nationality'].value_counts().index,
palette='muted')
```




```
C:\Users\ANDYQU~1\AppData\Local\Temp/ipykernel_27488/2231791779.py:14:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=onPodium_drivers_df, y='constructor nationality',
order=onPodium_drivers_df['constructor
nationality'].value_counts().index, palette='muted')
```




```
C:\Users\ANDYQU~1\AppData\Local\Temp/ipykernel_27488/2231791779.py:22:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=onPodium_drivers_df, y='constructor name',
order=onPodium_drivers_df['constructor name'].value_counts().index,
palette='muted')
```




```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler

num_cols =
results_df.select_dtypes(include='number').columns.to_list()
cat_cols =
results_df.select_dtypes(exclude='number').columns.to_list()


# Exclude the target from numerical columns
cat_cols.remove("onPodium")

# Create pipelines for numeric and categorical columns
num_pipeline = make_pipeline(SimpleImputer(strategy='mean'),
StandardScaler())
cat_pipeline = make_pipeline(SimpleImputer(strategy='most_frequent'),
OneHotEncoder())
```

```python
# Use ColumnTransformer to set the estimators and transformations

preprocessing = ColumnTransformer([('num', num_pipeline, num_cols),
                                   ('cat', cat_pipeline, cat_cols)],
                                    remainder='passthrough'
                                 )
```

```python
num_cols
```

```
['q1', 'q2', 'q3', 'age']
```

```python
cat_cols
```

```
['driverId',
 'driver nationality',
 'constructor name',
 'constructor nationality',
 'circuit name',
 'race name',
 'date',
 'round',
 'grid']
```

```python
# Apply the preprocessing pipeline on the dataset
results_prepared = preprocessing.fit_transform(results_df)

# Scikit-learn strips the column headers, so just add them back on
afterward.
feature_names=preprocessing.get_feature_names_out()

#results_prepared is originally a csr_matrix
results_prepared = results_prepared.toarray()

#merging the data and column labels into a dataframe
results_prepared_df = pd.DataFrame(data=results_prepared, columns =
feature_names)
results_prepared_df
```

```
       num__q1   num__q2   num__q3  num__age  cat__driverId_1  \
0    -0.139569 -0.321217 -0.145702 -0.977165              1.0
1     0.428218  0.724550  1.246626 -0.977165              1.0
2     0.258140  0.424889  0.770630 -0.977165              1.0
3    -0.474705 -0.804442 -0.789002 -0.977165              1.0
4    -0.164031 -0.178311  0.022714 -0.977165              1.0
...        ...       ...       ...       ...              ...
9800 -0.347822  0.000000  0.000000 -1.180546              0.0
9801 -1.467238  0.000000  0.000000 -1.180546              0.0
9802  0.072933  0.104623  0.000000 -1.180546              0.0
9803 -0.611051  0.000000  0.000000 -1.180546              0.0
9804  2.111173  0.000000  0.000000 -1.180546              0.0
```

```
      cat__driverId_2  cat__driverId_3  cat__driverId_4  
cat__driverId_5  \
0                 0.0              0.0              0.0  
0.0   
1                 0.0              0.0              0.0  
0.0   
2                 0.0              0.0              0.0  
0.0   
3                 0.0              0.0              0.0  
0.0   
4                 0.0              0.0              0.0  
0.0   
...               ...              ...              ...              .
..   
9800              0.0              0.0              0.0  
0.0   
9801              0.0              0.0              0.0  
0.0   
9802              0.0              0.0              0.0  
0.0   
9803              0.0              0.0              0.0  
0.0   
9804              0.0              0.0              0.0  
0.0   

      cat__driverId_6  ...  cat__grid_18  cat__grid_19  
cat__grid_20  \
0                 0.0  ...           0.0           0.0           0.0   

1                 0.0  ...           0.0           0.0           0.0   

2                 0.0  ...           0.0           0.0           0.0   

3                 0.0  ...           0.0           0.0           0.0   

4                 0.0  ...           0.0           0.0           0.0   

...               ...  ...           ...           ...           ...   

9800              0.0  ...           1.0           0.0           0.0   

9801              0.0  ...           1.0           0.0           0.0   

9802              0.0  ...           0.0           0.0           0.0   

9803              0.0  ...           0.0           0.0           1.0   

9804              0.0  ...           1.0           0.0           0.0   
```

```
      cat__grid_21  cat__grid_22  cat__grid_23  cat__grid_24
cat__grid_25  \
0              0.0           0.0           0.0           0.0
0.0
1              0.0           0.0           0.0           0.0
0.0
2              0.0           0.0           0.0           0.0
0.0
3              0.0           0.0           0.0           0.0
0.0
4              0.0           0.0           0.0           0.0
0.0
...            ...           ...           ...           ...
...
9800           0.0           0.0           0.0           0.0
0.0
9801           0.0           0.0           0.0           0.0
0.0
9802           0.0           0.0           0.0           0.0
0.0
9803           0.0           0.0           0.0           0.0
0.0
9804           0.0           0.0           0.0           0.0
0.0

      cat__grid_26  remainder__onPodium
0              0.0                  1.0
1              0.0                  0.0
2              0.0                  0.0
3              0.0                  1.0
4              0.0                  1.0
...            ...                  ...
9800           0.0                  0.0
9801           0.0                  0.0
9802           0.0                  0.0
9803           0.0                  0.0
9804           0.0                  0.0

[9805 rows x 430 columns]

results_prepared_df.columns

Index(['num__q1', 'num__q2', 'num__q3', 'num__age', 'cat__driverId_1',
       'cat__driverId_2', 'cat__driverId_3', 'cat__driverId_4',
       'cat__driverId_5', 'cat__driverId_6',
       ...
       'cat__grid_18', 'cat__grid_19', 'cat__grid_20', 'cat__grid_21',
       'cat__grid_22', 'cat__grid_23', 'cat__grid_24', 'cat__grid_25',
       'cat__grid_26', 'remainder__onPodium'],
      dtype='object', length=430)
```

```
from sklearn.model_selection import train_test_split

#split the target
X = results_prepared_df.drop(["remainder__onPodium"], axis=1)
y = results_prepared_df["remainder__onPodium"]

#split the data into 80% training and 20% testing
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
(7844, 429) (7844,) (1961, 429) (1961,)
```

Learning Models

```
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
```

Logistic Regression

```
#model_log = LogisticRegression()

logistic_classifier = LogisticRegression(solver='lbfgs',
max_iter=1000)

#train on 80% of dataset
logistic_classifier.fit(X_train, y_train)
```

```
LogisticRegression(max_iter=1000)
```

```
# Make predictions on the test set
y_pred_LR = logistic_classifier.predict(X_test)

# display the accuracy score
accuracy = accuracy_score(y_test, y_pred_LR)
print(f'Test Accuracy Score (Logistic Regression): {accuracy}')
```

```
Test Accuracy Score (Logistic Regression): 0.88883222845487
```

```
# Obtain the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_LR)

# Display the confusion matrix
plt.figure(figsize=(8, 6))
```

```
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Confusion Matrix (Logistic Regression before balance)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```


```
#display classification report
report_LR = classification_report(y_test, y_pred_LR)
report_LR_dict = classification_report(y_test, y_pred_LR,
output_dict=True)
print(report_LR)
```

```
              precision    recall  f1-score   support

         0.0       0.92      0.95      0.94      1684
         1.0       0.64      0.50      0.56       277
```

```
    accuracy                           0.89      1961
   macro avg       0.78      0.73      0.75      1961
weighted avg       0.88      0.89      0.88      1961


#Cross validation using 10 folds
scores_log = cross_val_score(logistic_classifier, X_train, y_train,
cv=10)
print('Logistic Regression Cross-Validation Accuracy Scores',
scores_log)

Logistic Regression Cross-Validation Accuracy Scores [0.89426752
0.90318471 0.90063694 0.89936306 0.8877551  0.9005102
 0.90816327 0.90178571 0.90433673 0.90943878]

scores_log = pd.Series(scores_log)
#min, mean, max of Cross-Validation Accuracy Scores
print(scores_log.min(), scores_log.mean(), scores_log.max())

0.8877551020408163 0.900944202521773 0.9094387755102041
```

Random Forest

```
# Initialize Random Forest classifier
rf_classifier = RandomForestClassifier(random_state=42)

# Train model
rf_classifier.fit(X_train, y_train)

RandomForestClassifier(random_state=42)

# Make predictions on the test set
y_pred_RF = logistic_classifier.predict(X_test)

# display the accuracy score
accuracy = accuracy_score(y_test, y_pred_RF)
print(f'Test Accuracy Score (Logistic Regression): {accuracy}')

Test Accuracy Score (Logistic Regression): 0.88883222845487

# Obtain the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_RF)

# Display the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Confusion Matrix (Random Forest before balance)')
plt.xlabel('Predicted')
```

```
plt.ylabel('Actual')
plt.show()
```


```
#display classification report
report_RF = classification_report(y_test, y_pred_RF)
report_RF_dict = classification_report(y_test, y_pred_RF,
output_dict=True)
print(report_RF)

              precision    recall  f1-score   support

         0.0       0.92      0.95      0.94      1684
         1.0       0.64      0.50      0.56       277

    accuracy                           0.89      1961
   macro avg       0.78      0.73      0.75      1961
weighted avg       0.88      0.89      0.88      1961
```

```
# Make predictions on the test set
y_pred = rf_classifier.predict(X_test)

# display the accuracy score
accuracy = accuracy_score(y_test, y_pred)
print(f'Test Accuracy Score (Random Forest): {accuracy}')

Test Accuracy Score (Random Forest): 0.8832228454869965

#Cross validation using 10 folds
scores_rf = cross_val_score(rf_classifier, X_train, y_train, cv=10)
print('Random Forest Cross-Validation Accuracy Scores', scores_rf)

Random Forest Cross-Validation Accuracy Scores [0.88789809 0.8955414
0.88789809 0.88535032 0.89668367 0.90178571
 0.89285714 0.89540816 0.88647959 0.90688776]

scores_rf = pd.Series(scores_log)
#min, mean, max of Cross-Validation Accuracy Scores
print(scores_rf.min(), scores_rf.mean(), scores_rf.max())

0.8877551020408163 0.900944202521773 0.9094387755102041
```

SVM

```
# Initialize SVM classifier
svm_classifier = SVC(probability=True, random_state=42)

# train model
svm_classifier.fit(X_train, y_train)

SVC(probability=True, random_state=42)

# Make predictions on the test set
y_pred_SVM = svm_classifier.predict(X_test)

# display the accuracy score
accuracy = accuracy_score(y_test, y_pred_SVM)
print(f'Test Accuracy Score (SVM): {accuracy}')

Test Accuracy Score (SVM): 0.8913819479857216

# Obtain the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_SVM)

# Display the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
```

```
plt.title('Confusion Matrix (SVM before balance)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```


```
#display classification report
report_SVM = classification_report(y_test, y_pred_SVM)
report_SVM_dict = classification_report(y_test, y_pred_SVM,
output_dict=True)
print(report_SVM)

              precision    recall  f1-score   support

         0.0       0.92      0.96      0.94      1684
         1.0       0.66      0.49      0.56       277

    accuracy                           0.89      1961
   macro avg       0.79      0.72      0.75      1961
weighted avg       0.88      0.89      0.88      1961
```

```
#Cross validation using 10 folds
score_svm = cross_val_score(svm_classifier, X_train, y_train, cv=10)
print('SVM Cross-Validation Accuracy Scores', score_svm)
```

```
SVM Cross-Validation Accuracy Scores [0.89681529 0.89808917 0.8955414
0.89808917 0.89668367 0.89923469
 0.90816327 0.90816327 0.89540816 0.91836735]
```

```
scores_svm = pd.Series(scores_log)
#min, mean, max of Cross-Validation Accuracy Scores
print(scores_svm.min(), scores_svm.mean(), scores_svm.max())
```

```
0.8877551020408163 0.900944202521773 0.9094387755102041
```

Balancing

Use SMOTE

```
# Importing the Synthetic Minority Over-sampling Technique (SMOTE)
from imbalanced-learn library
from imblearn.over_sampling import SMOTE

# Creating a SMOTE instance with a specified random state and sampling
strategy
# Random state ensures reproducibility, and sampling strategy
determines the ratio of minority to majority class after resampling
sm = SMOTE(random_state = 12, sampling_strategy=1.0)

# Applying SMOTE to the training data to balance the class
distribution
# X_train_res contains the resampled features, and y_train_res
contains the corresponding resampled labels
X_train_res, y_train_res = sm.fit_resample(X_train, y_train)
```

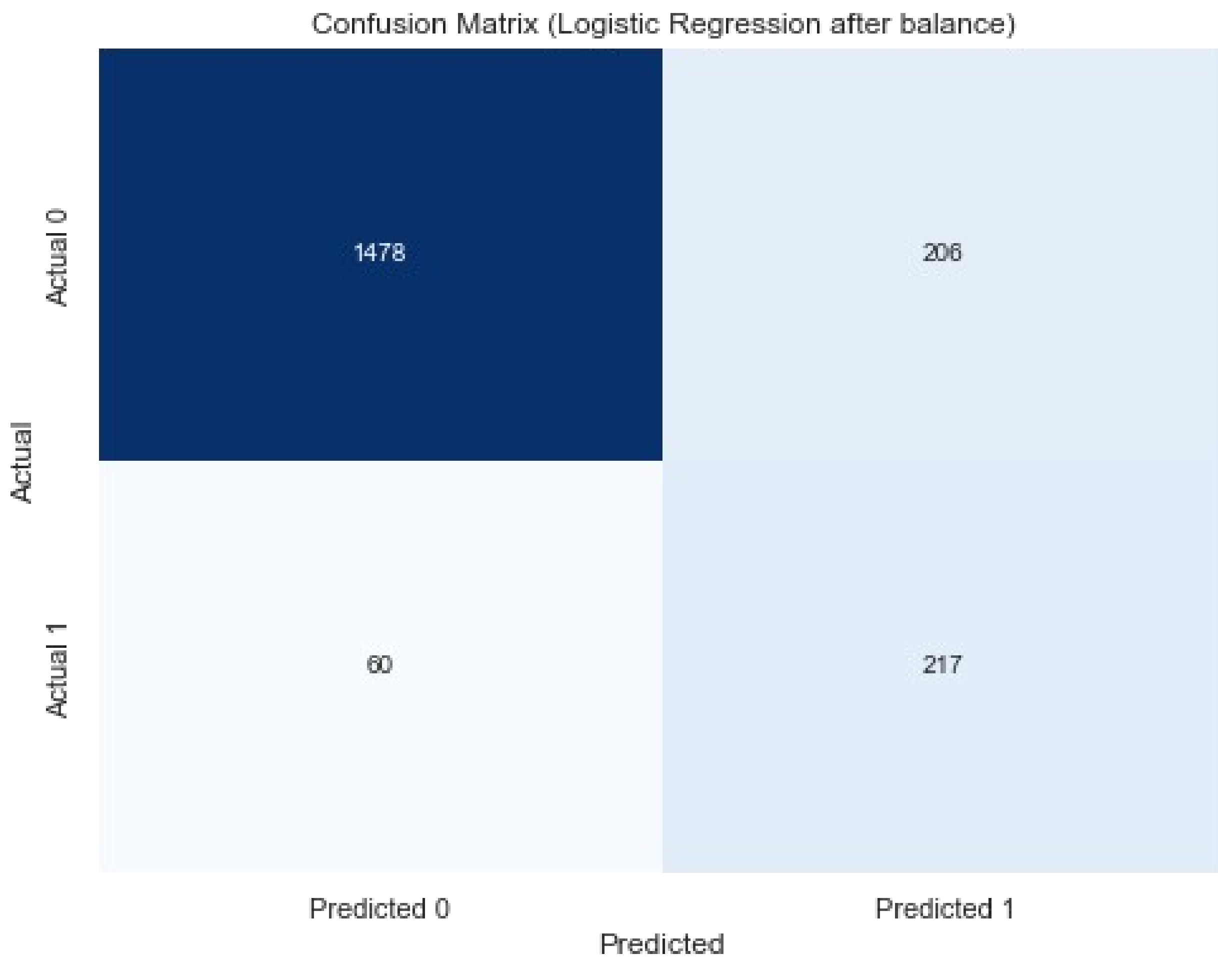
logistic classifier (after balance)

```
# train model
logistic_classifier.fit(X_train_res, y_train_res)
```

```
LogisticRegression(max_iter=1000)
```

```
# Make predictions on the test set
y_pred_LR_bal = logistic_classifier.predict(X_test)

# display the accuracy score
accuracy = accuracy_score(y_test, y_pred_LR_bal)
print(f'Test Accuracy Score (Logistic Regression): {accuracy}')
```

```
Test Accuracy Score (Logistic Regression): 0.8643549209586946

# Obtain the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_LR_bal)

# Display the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Confusion Matrix (Logistic Regression after balance)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```




```
#display classification report
report_LR_Bal = classification_report(y_test,y_pred_LR_bal)
report_LR_Bal_dict = classification_report(y_test, y_pred_LR_bal,
```

```
output_dict=True)
print(report_LR_Bal)
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.88      0.92      1684
         1.0       0.51      0.78      0.62       277

    accuracy                           0.86      1961
   macro avg       0.74      0.83      0.77      1961
weighted avg       0.90      0.86      0.88      1961
```

```
#Cross validation using 10 folds
scores_log = cross_val_score(logistic_classifier, X_train_res,
y_train_res, cv=10)
print('Logistic Regression Balance Cross-Validation Accuracy Scores',
scores_log)
```

```
Logistic Regression Balance Cross-Validation Accuracy Scores
[0.85322461 0.87842847 0.89688427 0.90281899 0.89243323 0.89688427
 0.90949555 0.89910979 0.88649852 0.90652819]
```

```
scores_log = pd.Series(scores_log)
#min, mean, max of Cross-Validation Accuracy Scores
print(scores_log.min(), scores_log.mean(), scores_log.max())
```

```
0.8532246108228317 0.8922305895343952 0.9094955489614244
```

Random Forest (after balance)

Adjust the thereshold of random forest to improve recall

```
# train model
rf_classifier.fit(X_train_res, y_train_res)
```

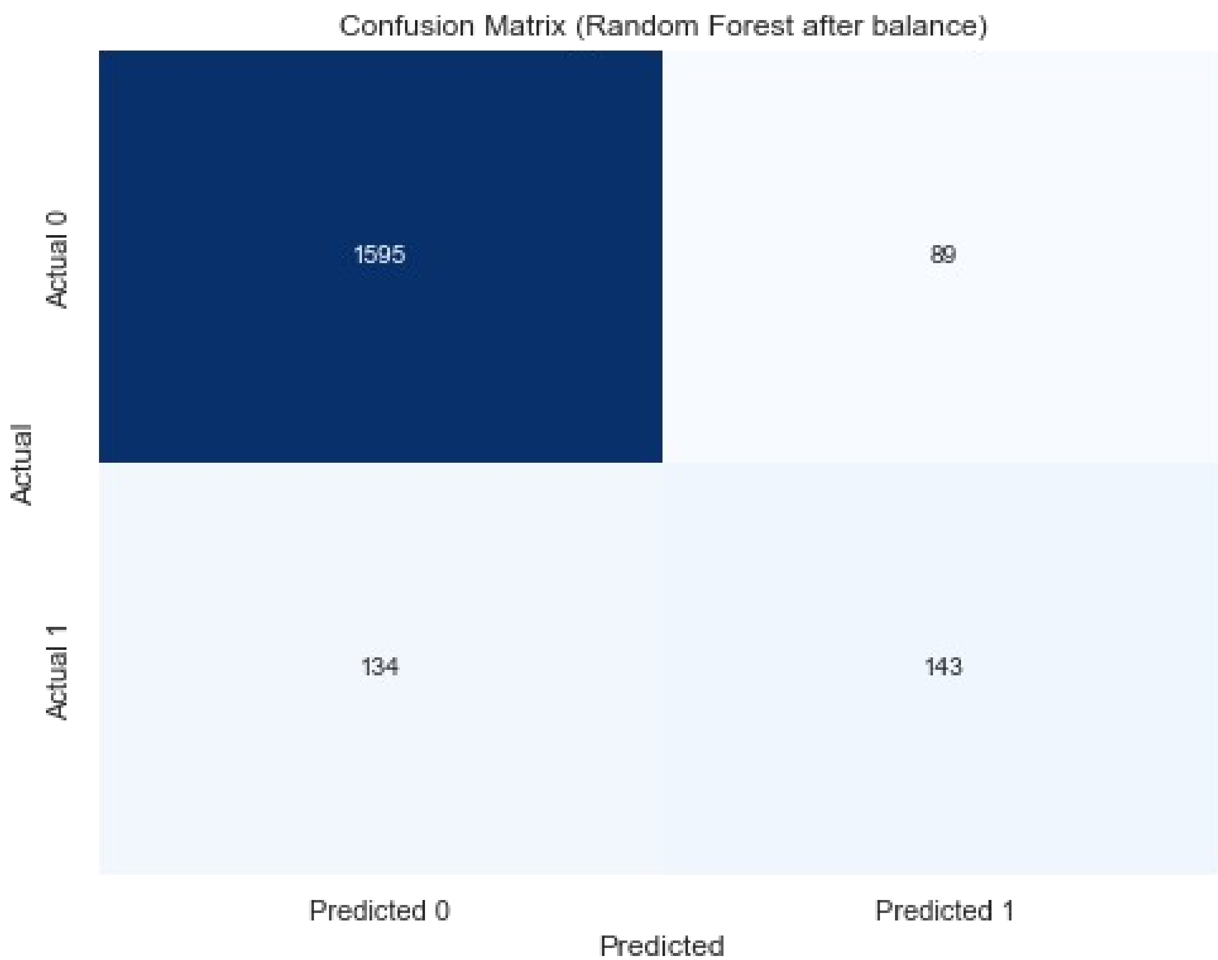
```
RandomForestClassifier(random_state=42)
```

```
# Make predictions on the test set
y_pred_RF_bal= rf_classifier.predict(X_test)

# display the accuracy score
accuracy = accuracy_score(y_test, y_pred_RF_bal)
print(f'Test Accuracy Score (Random Forest): {accuracy}')
```

```
Test Accuracy Score (Random Forest): 0.8862825089240184
```

```
# Obtain the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_RF_bal)

# Display the confusion matrix
plt.figure(figsize=(8, 6))
```

```
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Confusion Matrix (Random Forest after balance)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```




```
#display classification report
report_RF_Bal = classification_report(y_test, y_pred_RF_bal)
report_RF_Bal_dict = classification_report(y_test, y_pred_RF_bal,
output_dict=True)
print(report_RF_Bal)
```

```
              precision    recall  f1-score   support

         0.0       0.92      0.95      0.93      1684
         1.0       0.62      0.52      0.56       277
```

```
    accuracy                           0.89      1961
   macro avg       0.77      0.73      0.75      1961
weighted avg       0.88      0.89      0.88      1961


#Cross validation using 10 folds
scores_rf = cross_val_score(rf_classifier, X_train_res, y_train_res,
cv=10)
print('Random Forest Balance Cross-Validation Accuracy Scores',
scores_log)

Random Forest Balance Cross-Validation Accuracy Scores 0    0.853225
1    0.878428
2    0.896884
3    0.902819
4    0.892433
5    0.896884
6    0.909496
7    0.899110
8    0.886499
9    0.906528
dtype: float64

scores_rf = pd.Series(scores_rf)
#min, mean, max of Cross-Validation Accuracy Scores
print(scores_rf.min(), scores_rf.mean(), scores_rf.max())

0.8561897702001483 0.9538012001416589 0.9851632047477745
```

SVM (after balance)

```
# train model
svm_classifier.fit(X_train_res, y_train_res)

SVC(random_state=42)

# Make predictions on the test set
y_pred_svm_bal = svm_classifier.predict(X_test)

# display the accuracy score
accuracy = accuracy_score(y_test, y_pred)
print(f'Test Accuracy Score (SVM): {accuracy}')

Test Accuracy Score (SVM): 0.8832228454869965

# Obtain the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_svm_bal)

# Display the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
```

```
cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Confusion Matrix (SVM after balance)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```


```
#display classification report
report_SVM_Bal = classification_report(y_test, y_pred_svm_bal)
report_SVM_Bal_dict = classification_report(y_test, y_pred_svm_bal,
output_dict=True)
print(report_SVM_Bal)
```

```
              precision    recall  f1-score   support

         0.0       0.94      0.93      0.93      1684
         1.0       0.58      0.62      0.60       277

    accuracy                           0.88      1961
```

```
   macro avg       0.76      0.77      0.76      1961
weighted avg       0.89      0.88      0.88      1961
```

```
#Cross validation using 10 folds
scores_SVM = cross_val_score(svm_classifier, X_train_res, y_train_res, 
cv=10)
print('SVM Balance Cross-Validation Accuracy Scores', scores_log)
```

```
SVM Balance Cross-Validation Accuracy Scores 0    0.853225
1    0.878428
2    0.896884
3    0.902819
4    0.892433
5    0.896884
6    0.909496
7    0.899110
8    0.886499
9    0.906528
dtype: float64
```

```
scores_SVM = pd.Series(scores_SVM)
#min, mean, max of Cross-Validation Accuracy Scores
print(scores_SVM.min(), scores_SVM.mean(), scores_SVM.max())
```

```
0.888065233506301 0.9470462239311239 0.9725519287833828
```

Fine Tuning

Use randomsearchCV to tune the hyperparameters

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import make_scorer, recall_score
```

Logistical regression (After tuning)

```
# Hyperparameter search space for a logistic regression model using 
randomized search
param_dist = {
    'C': np.logspace(-3, 3, 7), # Regularization strength, log-scale 
values from 0.001 to 1000
    'penalty': ['l1', 'l2'], # Regularization penalty
    'class_weight': [None, 'balanced'], # Weighting of classes
    'solver': ['liblinear', 'saga', 'lbfgs'] # Optimization algorithm
}

# Creating a RandomizedSearchCV instance for hyperparameter tuning of 
a logistic regression model
```

```
random_search_LR = RandomizedSearchCV(logistic_classifier,
param_distributions=param_dist, n_iter=10, cv=5, random_state=42,
n_jobs=-1)

# train model
random_search_LR.fit(X_train_res, y_train_res)
```

```
RandomizedSearchCV(cv=5, estimator=LogisticRegression(max_iter=1000),
n_jobs=-1,
                   param_distributions={'C': array([1.e-03, 1.e-02,
1.e-01, 1.e+00, 1.e+01, 1.e+02, 1.e+03]),
                                        'class_weight': [None,
'balanced'],
                                        'penalty': ['l1', 'l2'],
                                        'solver': ['liblinear',
'saga',
                                                   'lbfgs']},
                   random_state=42)
```

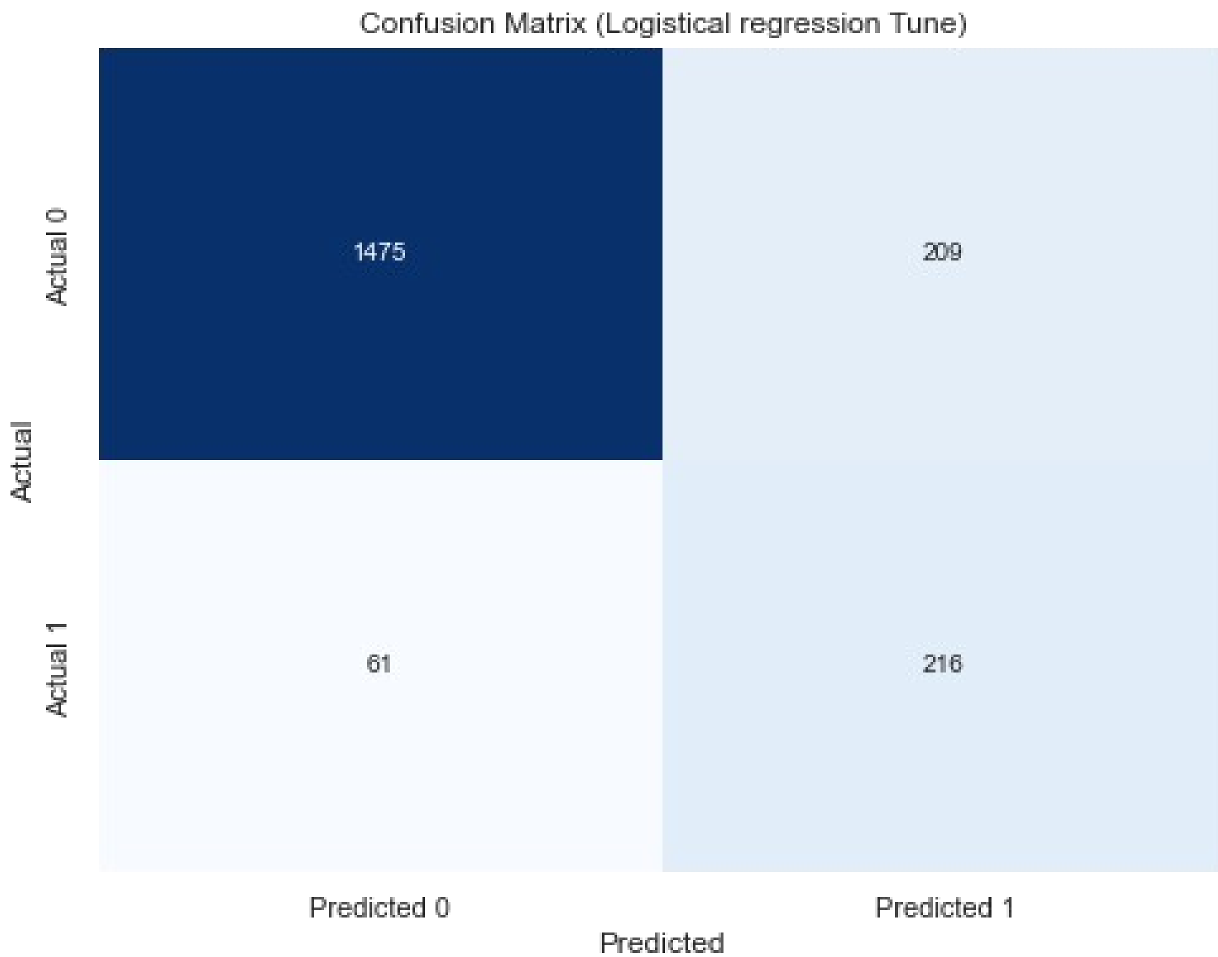
```
# display best parameters
print("Best Parameters: ", random_search_LR.best_params_)
```

```
Best Parameters:  {'solver': 'lbfgs', 'penalty': 'l2', 'class_weight':
None, 'C': 100.0}
```

```
best_model_log = random_search_LR.best_estimator_

# Make predictions on the test set
y_pred_LR_tune = best_model_log.predict(X_test)

# display the accuracy score
accuracy = accuracy_score(y_test, y_pred)
print(f'Test Accuracy Score (SVM): {accuracy}')
```

```
Test Accuracy Score (SVM): 0.8832228454869965
```

```
# Obtain the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_LR_tune)

# Display the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Confusion Matrix (Logistical regression Tune)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```




```
#display classification report
report_LR_Hyper = classification_report(y_test, y_pred_LR_tune)
report_LR_Hyper_dict = classification_report(y_test, y_pred_LR_tune,
output_dict=True)
print(report_LR_Hyper)

              precision    recall  f1-score   support

         0.0       0.96      0.88      0.92      1684
         1.0       0.51      0.78      0.62       277

    accuracy                           0.86      1961
   macro avg       0.73      0.83      0.77      1961
weighted avg       0.90      0.86      0.87      1961
```

Random forest (After tuning)

```
# Hyperparameter grid for a RandomForestClassifier, specifying
different values for tuning
```

```python
param_dist = {
    'n_estimators': [50, 100, 200, 300], # Number of trees in the forest
    'max_depth': [None, 10, 20, 30], # Maximum depth of the trees
    'min_samples_split': [2, 5, 10], # Minimum number of samples required to split an internal node
    'min_samples_leaf': [1, 2, 4],  # Minimum number of samples required to be at a leaf node
    'class_weight': [None, 'balanced', 'balanced_subsample']  # Weights associated with classes to address class imbalance
}

# Creating a RandomizedSearchCV instance for hyperparameter tuning of a Random Forest model
random_search_RF = RandomizedSearchCV(rf_classifier, param_distributions=param_dist, n_iter=10, cv=5, random_state=42, n_jobs=-1)

# train the model
random_search_RF.fit(X_train_res, y_train_res)
```

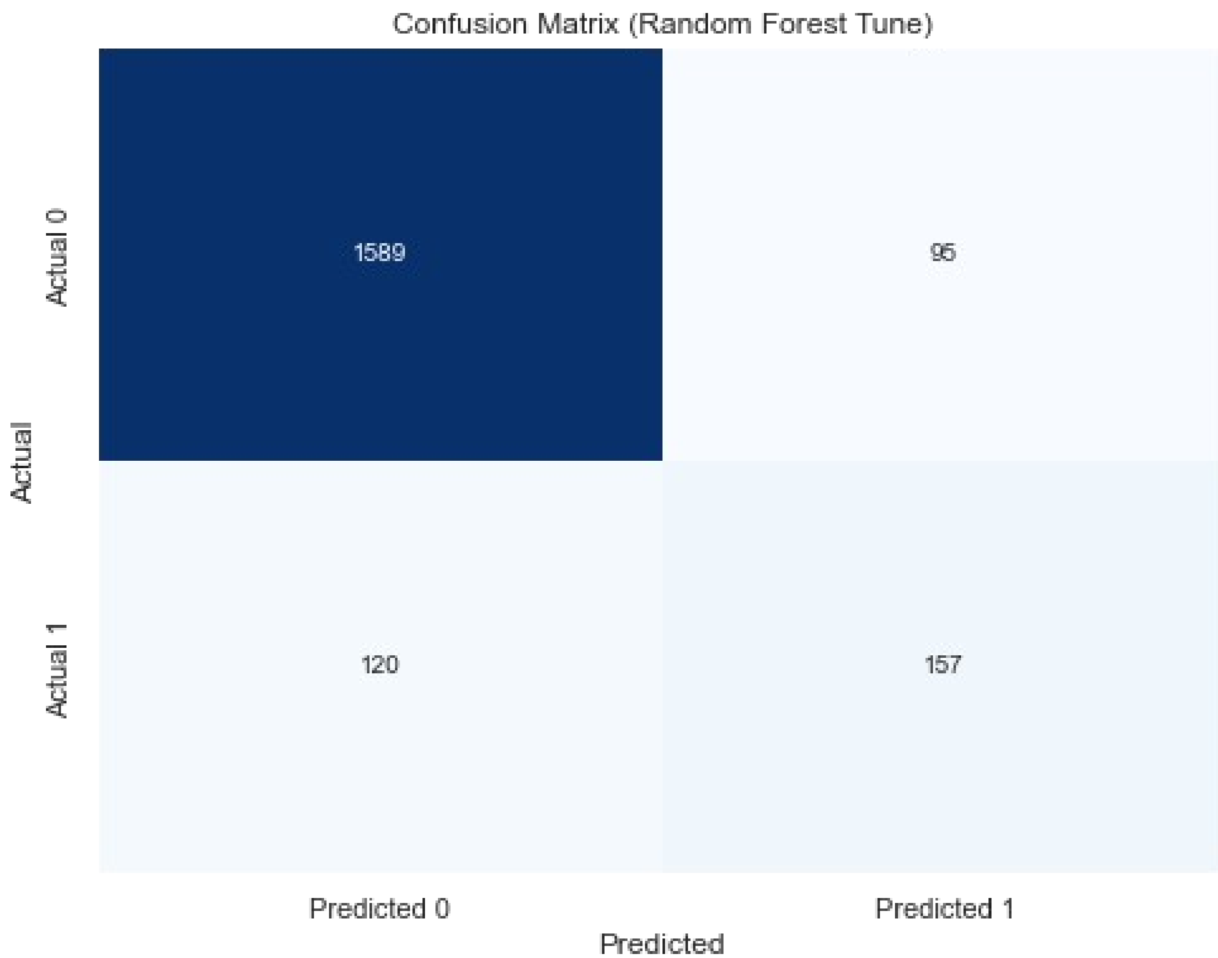
```
RandomizedSearchCV(cv=5, estimator=RandomForestClassifier(random_state=42),
                   n_jobs=-1,
                   param_distributions={'class_weight': [None, 'balanced',
                                                         'balanced_subsample'],
                                        'max_depth': [None, 10, 20, 30],
                                        'min_samples_leaf': [1, 2, 4],
                                        'min_samples_split': [2, 5, 10],
                                        'n_estimators': [50, 100, 200, 300]},
                   random_state=42)
```

```python
# display best parameters
print("Best Parameters: ", random_search_RF.best_params_)
```

```
Best Parameters:  {'n_estimators': 50, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_depth': None, 'class_weight': 'balanced'}
```

```python
best_model_rf = random_search_RF.best_estimator_

# Make predictions on the test set
y_pred_rf_tune = best_model_rf.predict(X_test)

# display the accuracy score
accuracy = accuracy_score(y_test, y_pred)
print(f'Test Accuracy Score (SVM): {accuracy}')
```

```
Test Accuracy Score (SVM): 0.8832228454869965

# Obtain the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_rf_tune)

# Display the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Confusion Matrix (Random Forest Tune)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```




```
#display classification report
report_RF_Hyper = classification_report(y_test, y_pred_rf_tune)
report_RF_Hyper_dict = classification_report(y_test, y_pred_rf_tune,
```

```
output_dict=True)
print(report_RF_Hyper)
```

```
              precision    recall  f1-score   support

         0.0       0.93      0.94      0.94      1684
         1.0       0.62      0.57      0.59       277

    accuracy                           0.89      1961
   macro avg       0.78      0.76      0.77      1961
weighted avg       0.89      0.89      0.89      1961
```

SVM (After tuning)

```
# Defining a parameter grid for hyperparameter tuning in a Support
Vector Machine (SVM) classifier
param_dist = {
    'C': [0.1, 0.01, 0.001], # Regularization parameter
    'kernel': ['linear', 'rbf'], # Kernel function to be used in the
algorithm
    'gamma': ['scale', 'auto', 0.01, 0.1, 0.5, 1.0], # Coefficient for
'rbf', 'poly', and 'sigmoid' kernels
    'degree': [2, 3, 4] # Polynomial degree for 'poly' kernel
}

# Creating a RandomizedSearchCV instance for hyperparameter tuning of
a SVM model
random_search_SVM =
RandomizedSearchCV(svm_classifier,param_distributions=param_dist,
n_iter=10, cv=5, random_state=42, n_jobs=-1)

#train the model
random_search_SVM.fit(X_train_res, y_train_res)
```

```
RandomizedSearchCV(cv=5, estimator=SVC(probability=True,
random_state=42),
                   n_jobs=-1,
                   param_distributions={'C': [0.1, 0.01, 0.001],
                                        'degree': [2, 3, 4],
                                        'gamma': ['scale', 'auto',
0.01, 0.1,
                                                  0.5, 1.0],
                                        'kernel': ['linear', 'rbf']},
                   random_state=42)
```

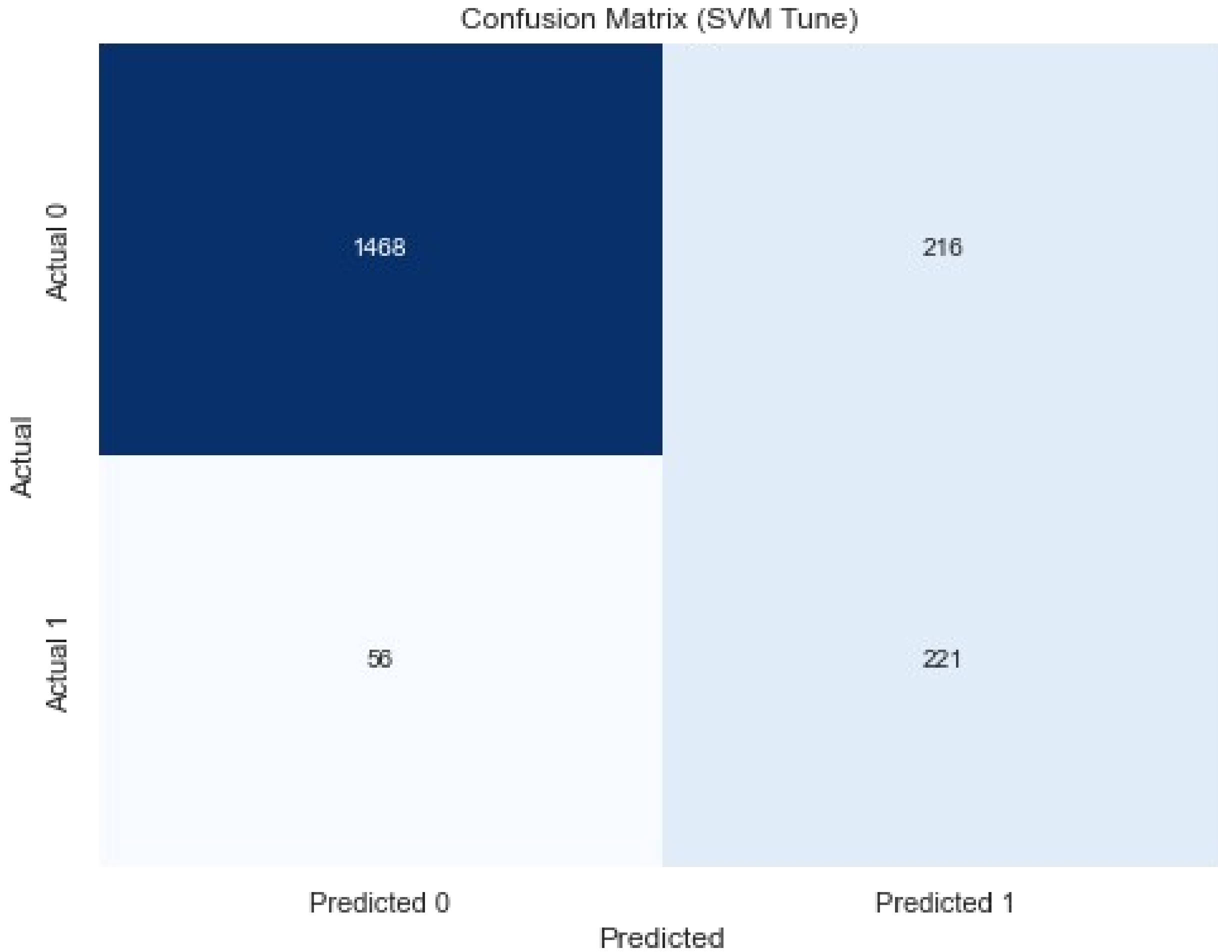
```
# display best parameters
print("Best Parameters: ", random_search_SVM.best_params_)
```

```
Best Parameters:  {'kernel': 'linear', 'gamma': 1.0, 'degree': 2, 'C':
0.1}
```

```
best_model_svm = random_search_SVM.best_estimator_

# Make predictions on the test set
y_pred_svm_tune = best_model_svm.predict(X_test)

# display the accuracy score
accuracy = accuracy_score(y_test, y_pred)
print(f'Test Accuracy Score (SVM): {accuracy}')
```

```
Test Accuracy Score (SVM): 0.8832228454869965
```

```
# Obtain the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_svm_tune)

# Display the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Confusion Matrix (SVM Tune) ')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```




```
#display classification report
report_SVM_Hyper = classification_report(y_test, y_pred_svm_tune)
report_SVM_Hyper_dict = classification_report(y_test, y_pred_svm_tune,
output_dict=True)
print(report_SVM_Hyper)
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.87      0.92      1684
         1.0       0.51      0.80      0.62       277

    accuracy                           0.86      1961
   macro avg       0.73      0.83      0.77      1961
weighted avg       0.90      0.86      0.87      1961
```

Comparison of models

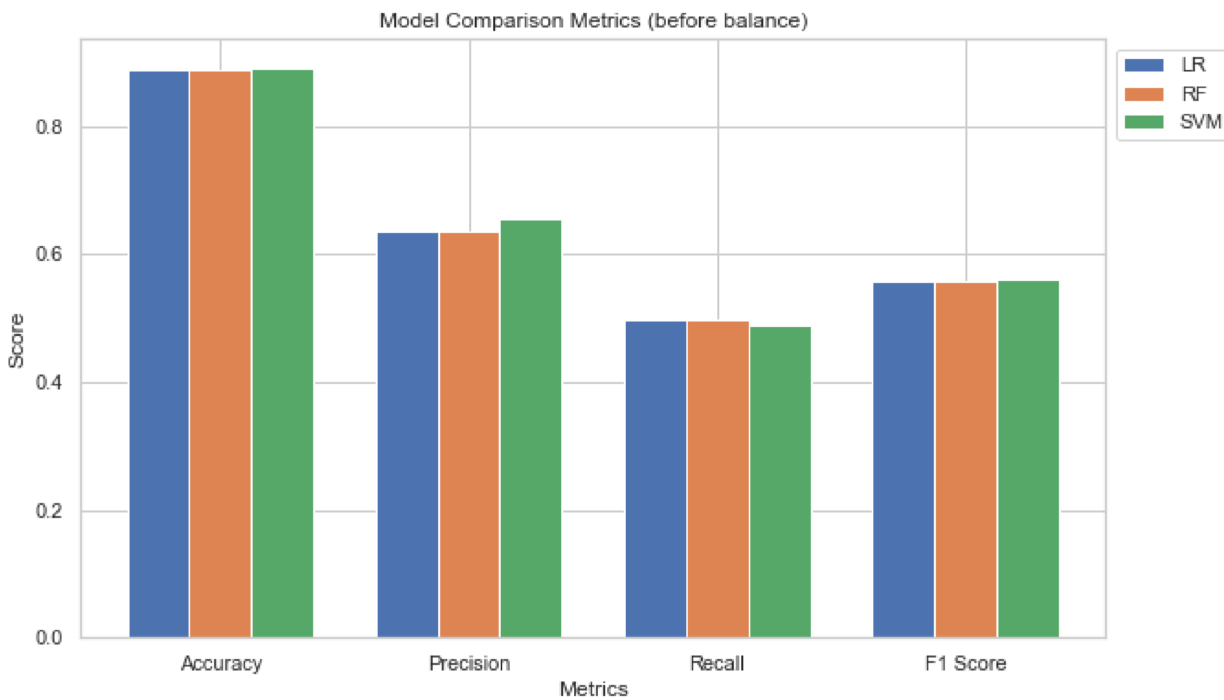
```
model_names = ['LR', 'RF', 'SVM']
```

```
reports = [report_LR_dict, report_RF_dict, report_SVM_dict]
```

Using the positive class (1.0) to compare the metrics of each model

For the models before the dataset was balanced

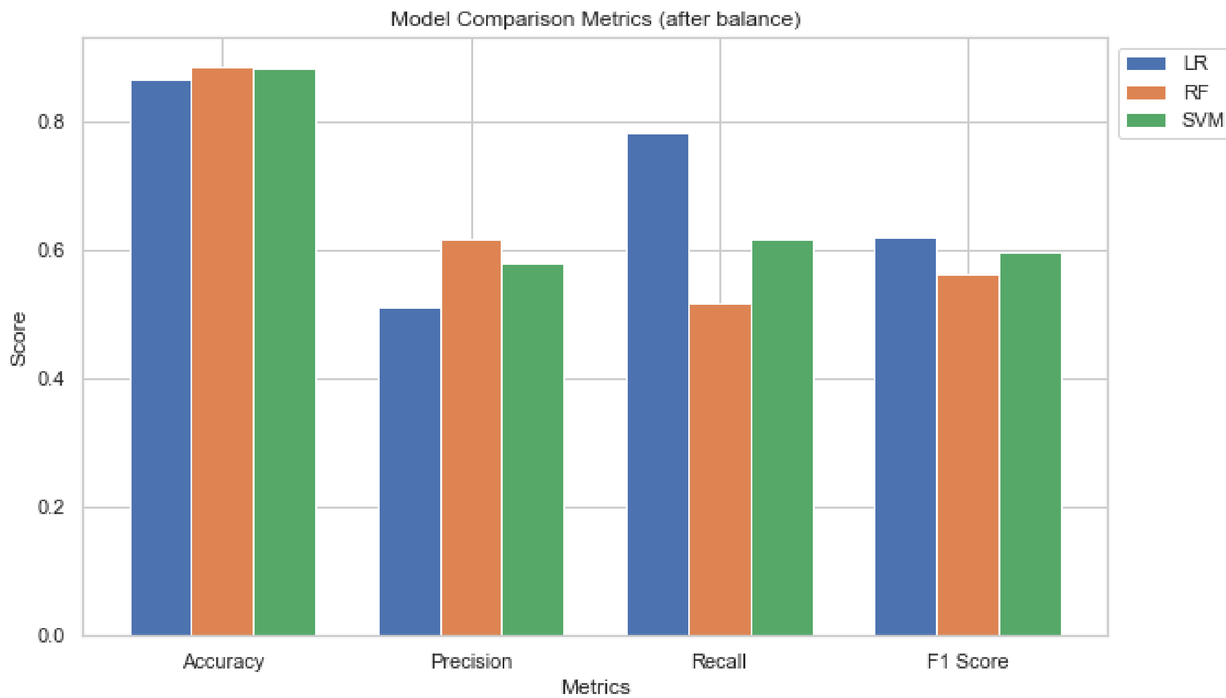
```
plt.figure(figsize=(10, 6))
bar_width = 0.25
metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']

for i, (report, name) in enumerate(zip(reports, model_names)):
    values = [
        report['accuracy'],
        report['1.0']['precision'],
        report['1.0']['recall'],
        report['1.0']['f1-score']
    ]

    # Plot the bars for each model
    plt.bar(np.arange(len(metrics)) + i * bar_width, values,
bar_width, label=name)

# Set labels and title
plt.xlabel('Metrics')
plt.ylabel('Score')
plt.title('Model Comparison Metrics (before balance)')
plt.xticks(np.arange(len(metrics)) + bar_width, metrics)
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))

# Show the plot
plt.show()
```



After balancing

```
reports = [report_LR_Bal_dict, report_RF_Bal_dict,
report_SVM_Bal_dict]

plt.figure(figsize=(10, 6))
bar_width = 0.25
metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']

for i, (report, name) in enumerate(zip(reports, model_names)):
    values = [
        report['accuracy'],
        report['1.0']['precision'],
        report['1.0']['recall'],
        report['1.0']['f1-score']
    ]

    # Plot the bars for each model
    plt.bar(np.arange(len(metrics)) + i * bar_width, values,
bar_width, label=name)

# Set labels and title
plt.xlabel('Metrics')
plt.ylabel('Score')
plt.title('Model Comparison Metrics (after balance)')
plt.xticks(np.arange(len(metrics)) + bar_width, metrics)
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))
```

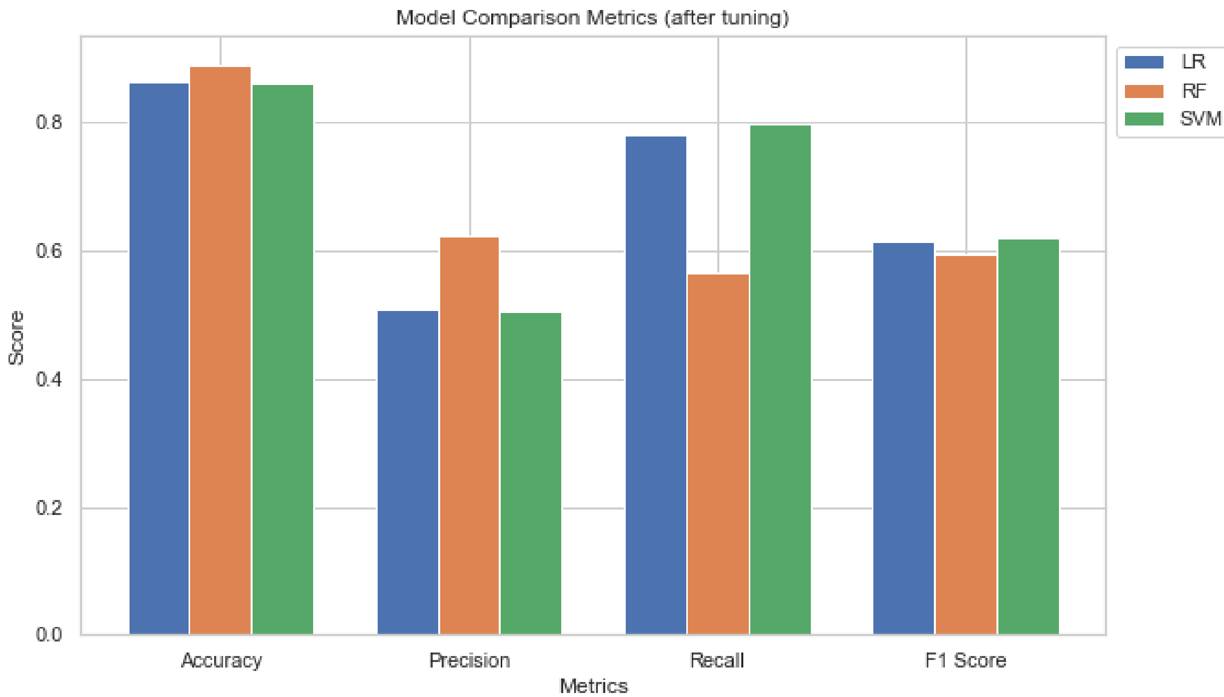
```
# Show the plot
plt.show()
```



After tuning

```
reports = [report_LR_Hyper_dict, report_RF_Hyper_dict,
report_SVM_Hyper_dict]

plt.figure(figsize=(10, 6))
bar_width = 0.25
metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']

for i, (report, name) in enumerate(zip(reports, model_names)):
    values = [
        report['accuracy'],
        report['1.0']['precision'],
        report['1.0']['recall'],
        report['1.0']['f1-score']
    ]

    # Plot the bars for each model
    plt.bar(np.arange(len(metrics)) + i * bar_width, values,
bar_width, label=name)

# Set labels and title
plt.xlabel('Metrics')
plt.ylabel('Score')
plt.title('Model Comparison Metrics (after tuning)')
```

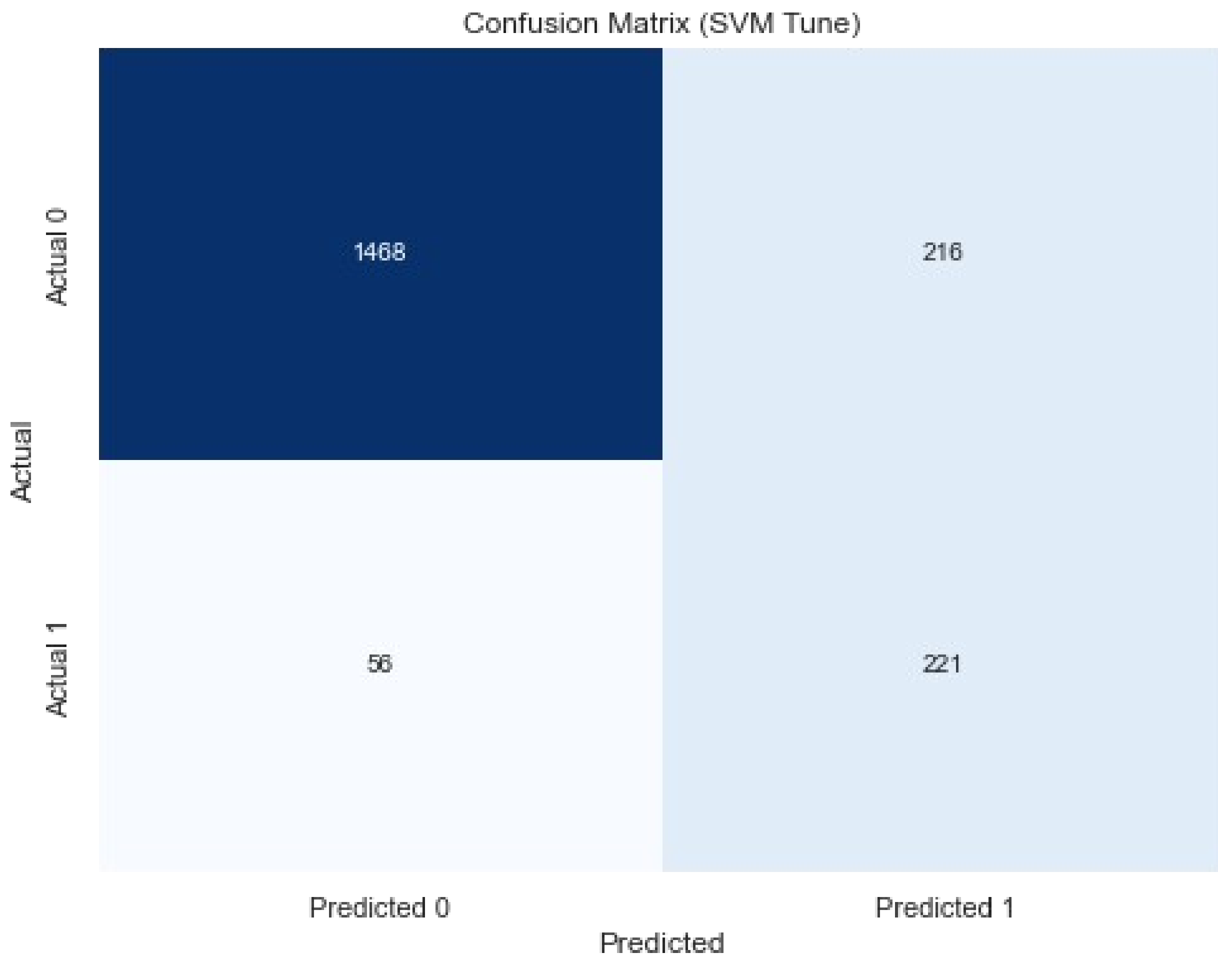
```
plt.xticks(np.arange(len(metrics)) + bar_width, metrics)
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))

# Show the plot
plt.show()
```



Best performing model

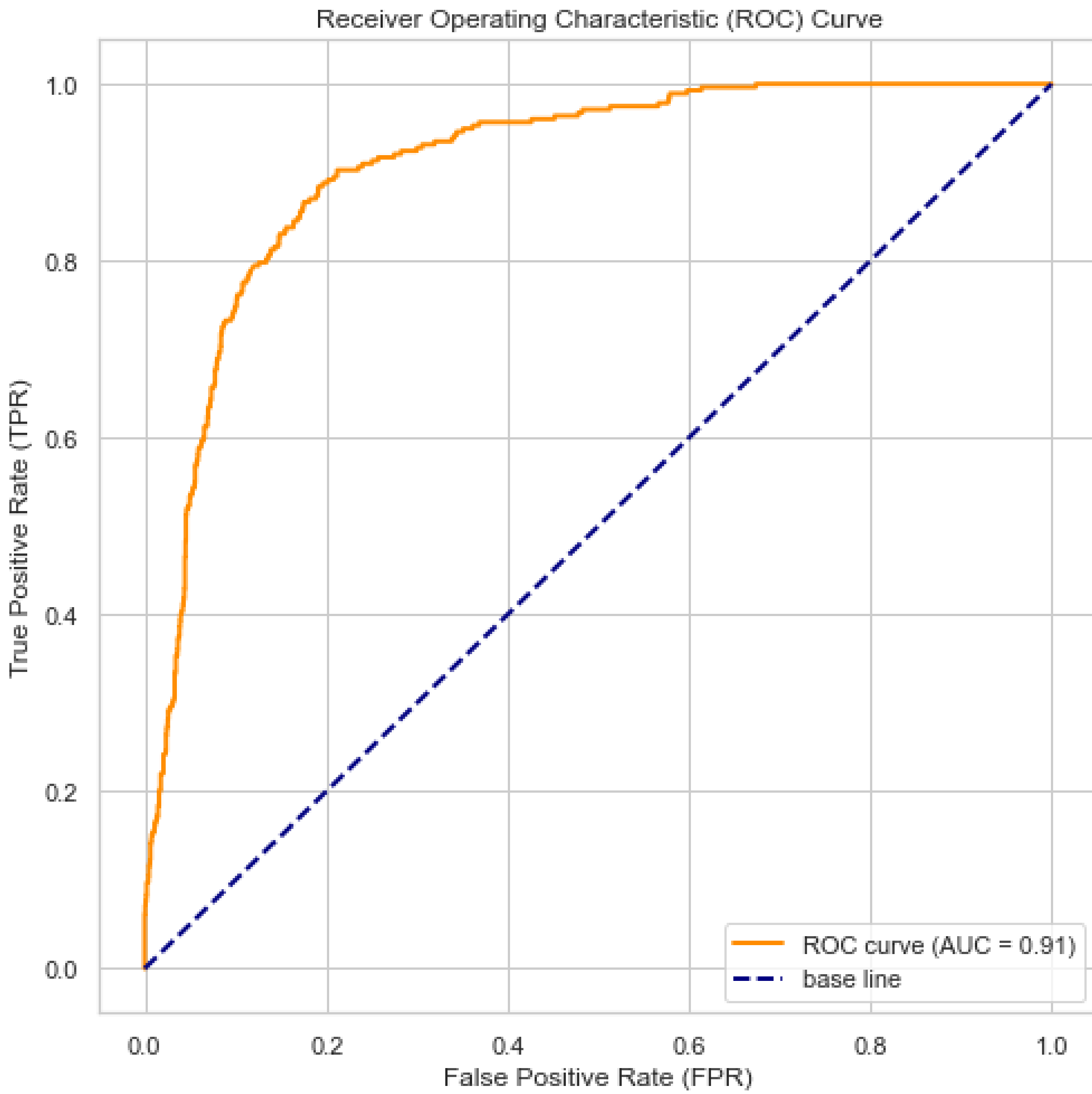
The best performing model was SVM after hyperparameters were tuned, based on recall score

```
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import precision_recall_curve

# Obtain the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_svm_tune)

# Display the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Confusion Matrix (SVM Tune)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



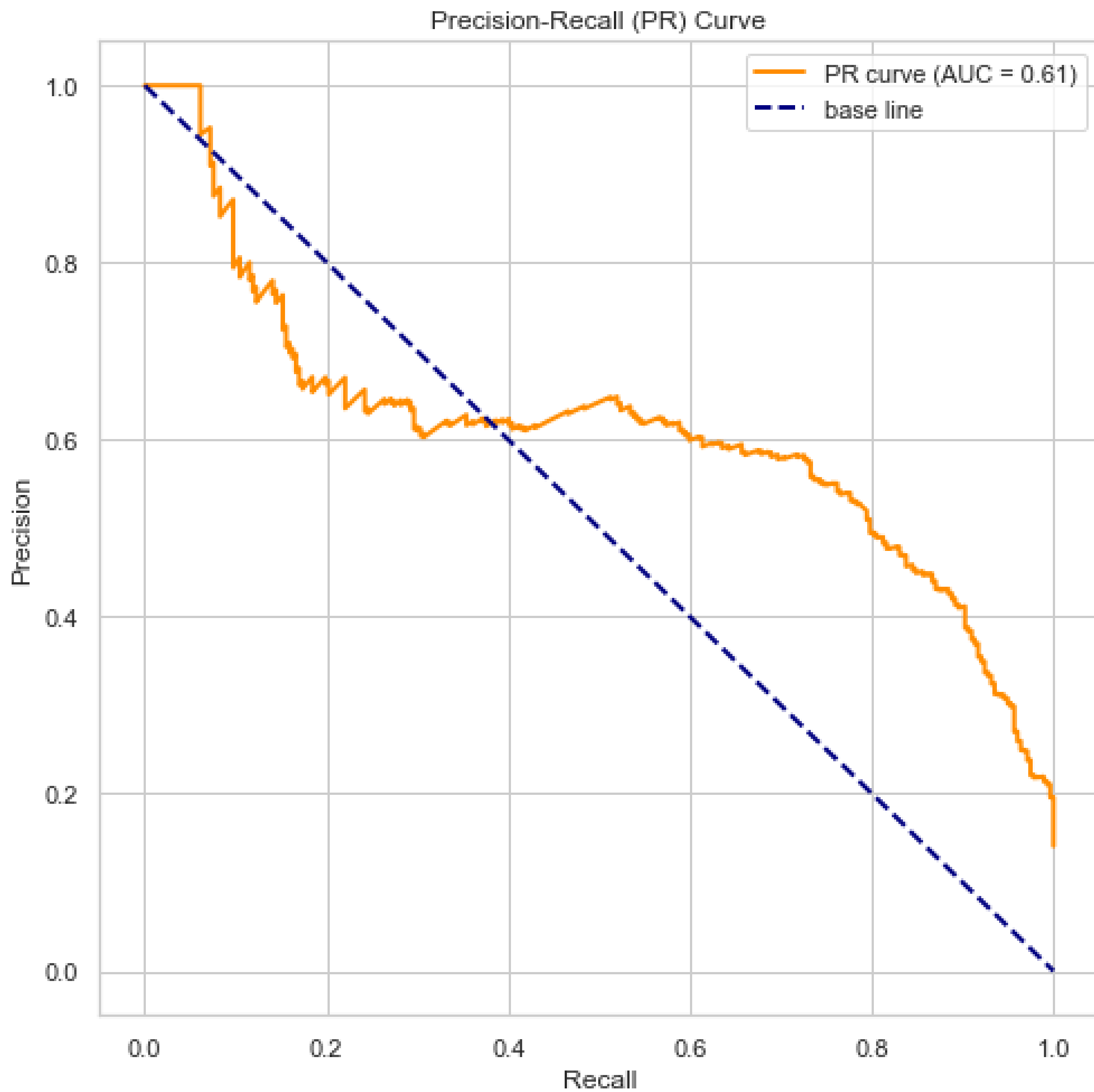

```
#display roc graph
y_prob = best_model_svm.predict_proba(X_test)[:, 1]

# Compute ROC curve and AUC
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)

# Plot the ROC curve
plt.figure(figsize=(8, 8))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC =
{roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--',
label='base line')

# Set labels and title
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
```

```python
# Show the plot
plt.show()
```




```python
#display pr graph
y_prob = best_model_svm.predict_proba(X_test)[:, 1]

# Compute precision-recall curve and AUC
precision, recall, thresholds = precision_recall_curve(y_test, y_prob)
pr_auc = auc(recall, precision)

# Plot the precision-recall curve
plt.figure(figsize=(8, 8))
```

```
plt.plot(recall, precision, color='darkorange', lw=2, label=f'PR curve
(AUC = {pr_auc:.2f})')
plt.plot([0, 1], [1, 0], color='navy', lw=2, linestyle='--',
label='base line')

# Set labels and title
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall (PR) Curve')
plt.legend(loc='upper right')

# Show the plot
plt.show()
```



Precision-Recall (PR) Curve
PR curve (AUC = 0.61)
base line
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0