```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.linear_model import LogisticRegression
import warnings
warnings.filterwarnings("ignore")
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.metrics import accuracy_score, precision_score,roc_auc_score,confusion_matrix

from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
```

```
data=pd.read_csv("titanic_train.csv")
```

```
df=data.copy()
```

EDA

```
df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	F
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

```
df.isnull().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

```
df.shape
```

```
(891, 12)
```

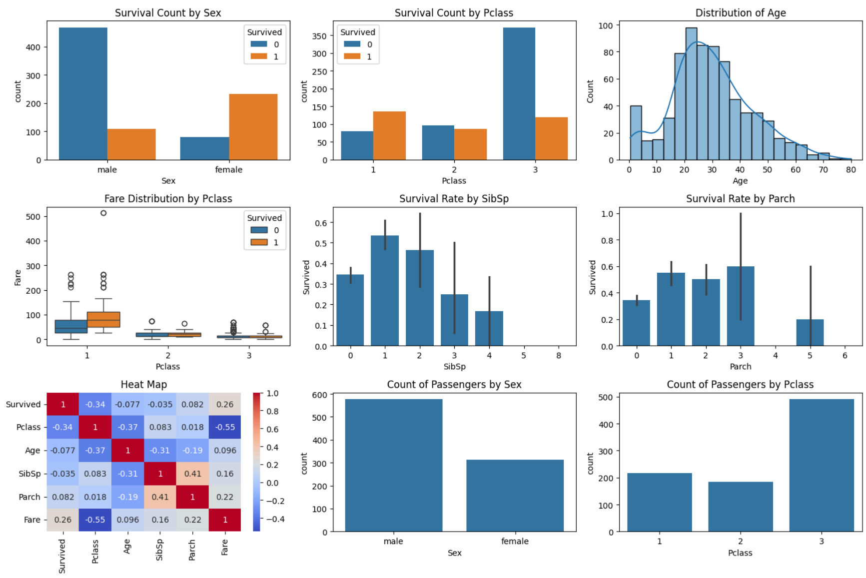
```
df.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fa
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000(
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000(
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000(
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329

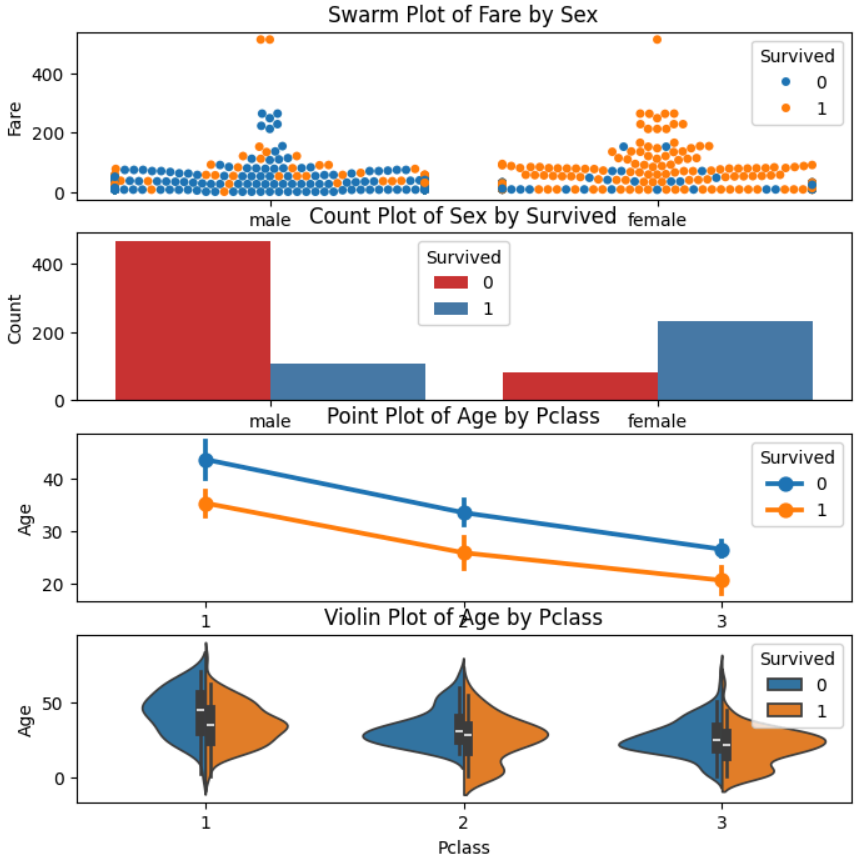
Data Visualization

1. Visualization with Seaborn

```
plt.figure(figsize=(15, 10))

# 1. Sex by Survived
plt.subplot(3, 3, 1)
sns.countplot(x='Sex', hue='Survived', data=df)
plt.title('Survival Count by Sex')

# 2. Pclass by Survived
plt.subplot(3, 3, 2)
sns.countplot(x='Pclass', hue='Survived', data=df)
plt.title('Survival Count by Pclass')

# 3. Age Distribution
plt.subplot(3, 3, 3)
sns.histplot(df['Age'], bins=20, kde=True)
plt.title('Distribution of Age')

# 4. Pclass by Fare
plt.subplot(3, 3, 4)
sns.boxplot(x='Pclass', y='Fare', data=df, hue='Survived')
plt.title('Fare Distribution by Pclass')

# 5. SibSp by Survived
plt.subplot(3, 3, 5)
sns.barplot(x='SibSp', y='Survived', data=df)
plt.title('Survival Rate by SibSp')

# 6. Parch by Survived
plt.subplot(3, 3, 6)
sns.barplot(x='Parch', y='Survived', data=df)
plt.title('Survival Rate by Parch')

# 7. Heatmap
plt.subplot(3, 3, 7)
corr_matrix = df[['Survived', 'Pclass', 'Age', 'SibSp', 'Parch', 'Fare']].corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Heat Map')

# 8. Sex
plt.subplot(3, 3, 8)
sns.countplot(x='Sex', data=df)
plt.title('Count of Passengers by Sex')

# 9. Pclass
plt.subplot(3, 3, 9)
sns.countplot(x='Pclass', data=df)
plt.title('Count of Passengers by Pclass')

plt.tight_layout()
plt.show()
```

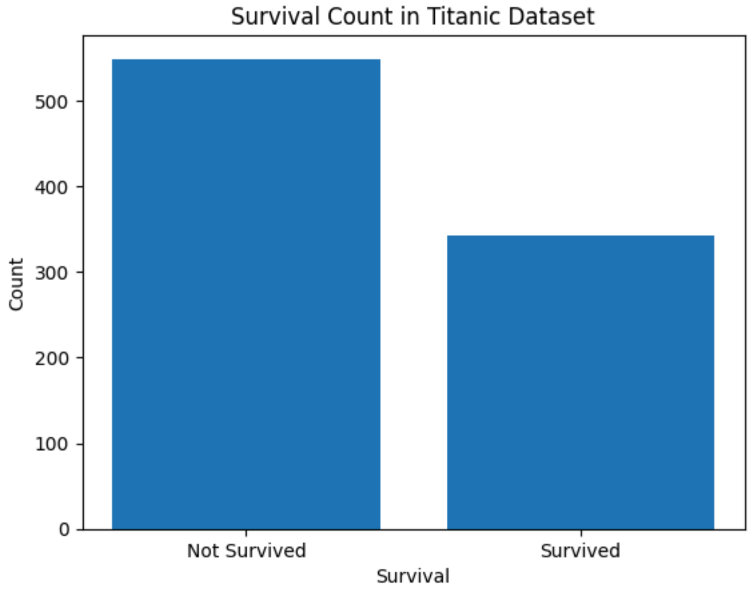



```
plt.figure(figsize=(8, 8))


# 1. Sex by Fare
plt.subplot(4, 1, 1)
sns.swarmplot(x='Sex', y='Fare', data=df, hue='Survived')
plt.title('Swarm Plot of Fare by Sex')

# 2. Sex by Survived

plt.subplot(4, 1, 2)
sns.countplot(x='Sex', hue='Survived', data=df, palette='Set1')

plt.title('Survival Count by Sex')
plt.xlabel('Sex')
plt.ylabel('Count')
plt.title('Count Plot of Sex by Survived')


# 3. Pclass by Age
plt.subplot(4, 1, 3)
sns.pointplot(x='Pclass', y='Age', data=df, hue='Survived')
plt.title('Point Plot of Age by Pclass')

# 4. Pclass by Age
plt.subplot(4, 1, 4)
sns.violinplot(x='Pclass', y='Age', data=df, hue='Survived', split=True)
plt.title('Violin Plot of Age by Pclass')


plt.show()
```



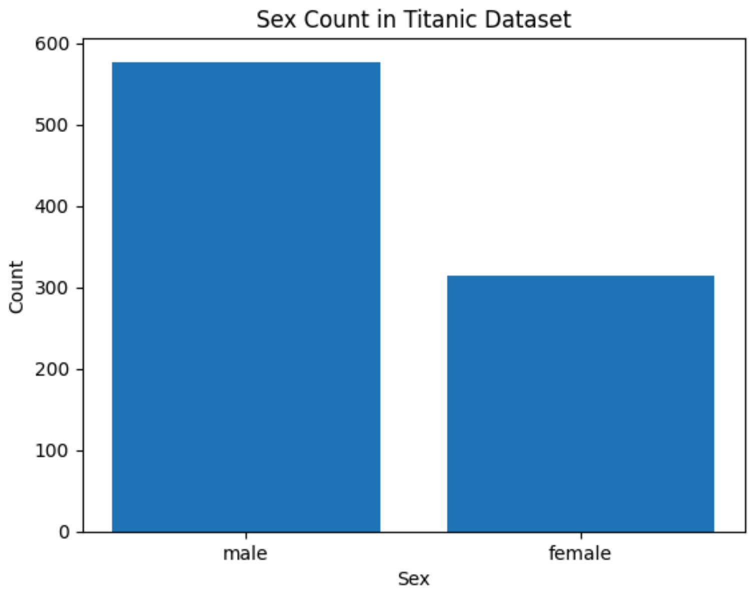
2. Visualization with matplotlib

```
survived_count = df['Survived'].value_counts()

# Defining Categories
categories = ['Not Survived', 'Survived']
values = [survived_count[0], survived_count[1]]

# Creating Bar plot
plt.bar(categories, values)

plt.xlabel('Survival')
plt.ylabel('Count')
plt.title('Survival Count in Titanic Dataset')
plt.show()

print(f"Number of who did not survive: {survived_count[0]}")
print(f"Number of survived: {survived_count[1]}")
```



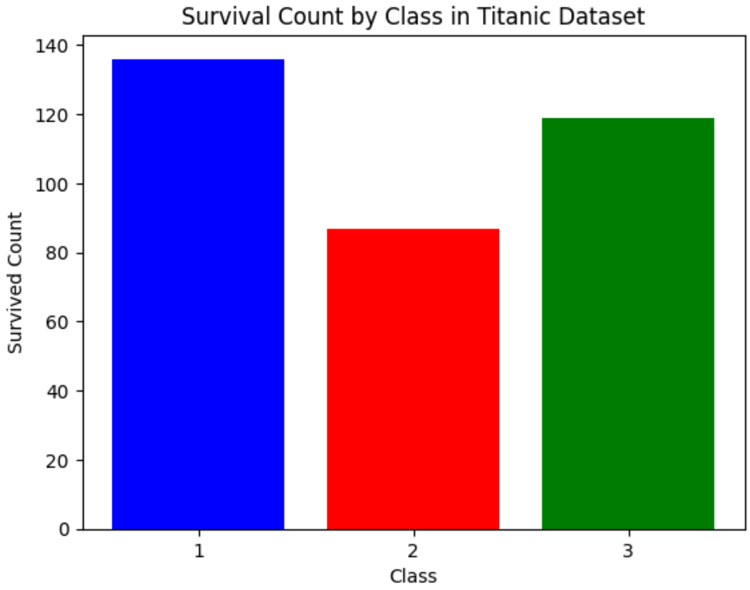

```
Number of who did not survive: 549
Number of survived: 342
```

```
sex_count = df['Sex'].value_counts()

plt.bar(sex_count.index, sex_count.values)

plt.xlabel('Sex')
plt.ylabel('Count')
plt.title('Sex Count in Titanic Dataset')


plt.show()

print(f"Number of Male: {sex_count['male']}")
print(f"Number of Female: {sex_count['female']}")
```

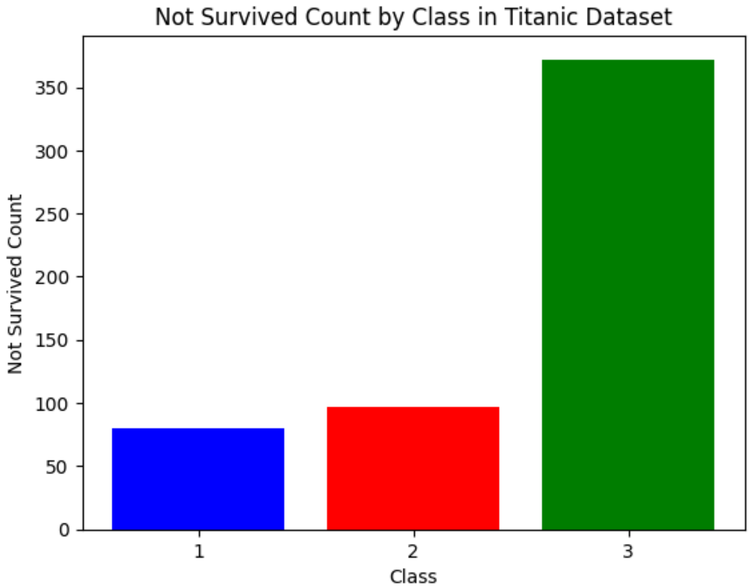



```
Number of Male: 577
Number of Female: 314
```

```
survived_count = df[df['Survived'] == 1]['Pclass'].value_counts()

not_survived_count = df[df['Survived'] == 0]['Pclass'].value_counts()

categories = ['1', '2', '3']

#Shows count of survivors for each passenger class, assigning a default value of 0 if there are no survivors in that class.
values = [survived_count[1], survived_count[2], survived_count[3]]

not_survived_values = [not_survived_count[1], not_survived_count[2], not_survived_count[3]]

plt.bar(categories, values, color=['blue', 'red', 'green'])

plt.xlabel('Class')
plt.ylabel('Survived Count')
plt.title('Survival Count by Class in Titanic Dataset')
plt.show()

print(f"Number of Survived in first Class: {values[0]}")
print(f"Number of Survived in second Class: {values[1]}")
print(f"Number of Survived in third Class: {values[2]}")

plt.bar(categories, not_survived_values, color=['blue', 'red', 'green'])

plt.xlabel('Class')
plt.ylabel('Not Survived Count')
plt.title('Not Survived Count by Class in Titanic Dataset')
plt.show()

print(f"Number of Not Survived in first Class: {not_survived_values[0]}")
print(f"Number of Not Survived in second Class: {not_survived_values[1]}")
print(f"Number of Not Survived in third Class: {not_survived_values[2]}")
```




```
Number of Survived in first Class: 136
Number of Survived in second Class: 87
Number of Survived in third Class: 119
```




```
Number of Not Survived in first Class: 80
Number of Not Survived in second Class: 97
Number of Not Survived in third Class: 372
```

Preprocessing

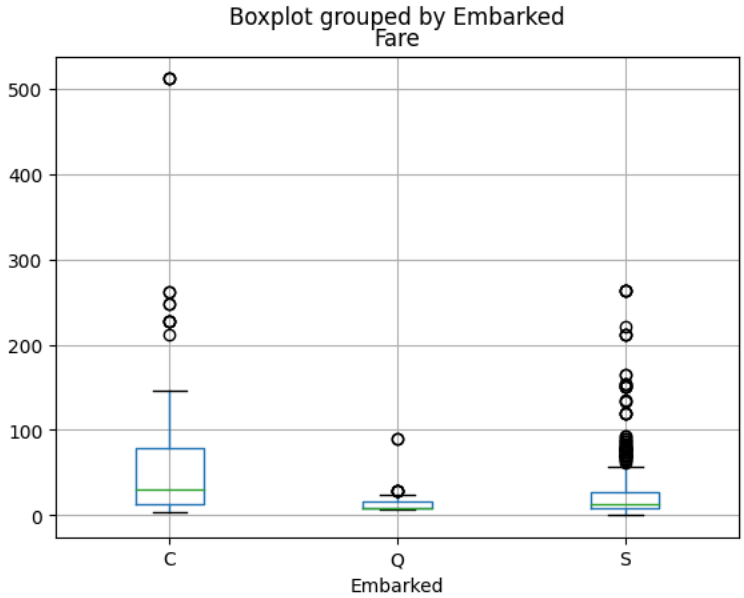
```
#checking for missing values
df.isnull().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

```
df[df["Embarked"].isnull()]
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
61	62	1	1	Icard, Miss. Amelie	female	38.0	0	0	113572	80.0

```
df.boxplot(column="Fare",by = "Embarked")
plt.show()
```




```
# Drop rows where 'Embarked' is missing
df = df.dropna(subset=['Embarked'])
```

```
# List of columns to drop
columns_to_drop = ['Cabin', 'Ticket']  # Example columns; adjust based on your analysis

# Drop the specified columns
df = df.drop(columns=columns_to_drop)

# Separate features and target variable
X = df.drop('Survived', axis=1)
Y = df['Survived']

# Define numerical and categorical columns
numerical_cols = ['Age', 'Fare']
categorical_cols = ['Pclass', 'Sex', 'Embarked']

# Preprocessing for numerical data: impute missing values and scale features
numerical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

# Preprocessing for categorical data: impute missing values and apply one-hot encoding
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Combine preprocessing steps
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_cols),
        ('cat', categorical_transformer, categorical_cols)
    ])

# Apply preprocessing
X_preprocessed = preprocessor.fit_transform(X)

# Split the preprocessed dataset into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(X_preprocessed, Y, test_size=0.3, random_state=101)

# Output the shapes of the splits to verify
print("Training set features shape:", X_train.shape)
print("Test set features shape:", X_test.shape)
print("Training set labels shape:", Y_train.shape)
print("Test set labels shape:", Y_test.shape)
```

```
Training set features shape: (622, 10)
Test set features shape: (267, 10)
Training set labels shape: (622,)
Test set labels shape: (267,)
```

Logistic Regression

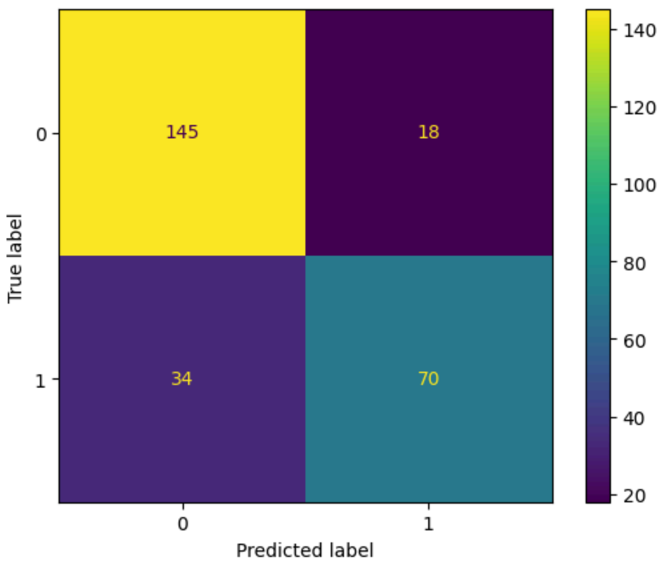
```
logreg = LogisticRegression()

# Train the model
logreg.fit(X_train, Y_train)

# Make predictions
y_pred_logreg = logreg.predict(X_test)
```

```
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score, confusion_matrix, classification_report, ConfusionMa

# Calculate accuracy
accuracy_logreg = accuracy_score(Y_test, y_pred_logreg)
print(f'Logistic Regression Accuracy: {accuracy_logreg:.4f}')

# Calculate recall
recall_logreg = recall_score(Y_test, y_pred_logreg)
print(f'Logistic Regression Recall: {recall_logreg:.4f}')

# Calculate precision
precision_logreg = precision_score(Y_test, y_pred_logreg)
print(f'Logistic Regression Precision: {precision_logreg:.4f}')

# Calculate F1 score
f1_logreg = f1_score(Y_test, y_pred_logreg)
print(f'Logistic Regression F1 Score: {f1_logreg:.4f}')
```

```
# Calculate confusion matrix
conf_matrix = confusion_matrix(Y_test, y_pred_logreg)
print(f'Logistic Regression Confusion Matrix:\n{conf_matrix}')

# For a detailed classification report
report = classification_report(Y_test, y_pred_logreg)
print(f'Logistic Regression Classification Report:\n{report}')
```

```
Logistic Regression Accuracy: 0.8052
Logistic Regression Recall: 0.6731
Logistic Regression Precision: 0.7955
Logistic Regression F1 Score: 0.7292
Logistic Regression Confusion Matrix:
[[145  18]
 [ 34  70]]
Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.89      0.85       163
           1       0.80      0.67      0.73       104

    accuracy                           0.81       267
   macro avg       0.80      0.78      0.79       267
weighted avg       0.80      0.81      0.80       267
```

```
cmd=ConfusionMatrixDisplay(conf_matrix)
cmd.plot()
plt.show()
```



KNN

```
from sklearn.neighbors import KNeighborsClassifier

# Instantiate the KNN model with a chosen number of neighbors (e.g., 5)
knn = KNeighborsClassifier(n_neighbors=5)

# Train the model
knn.fit(X_train, Y_train)
```

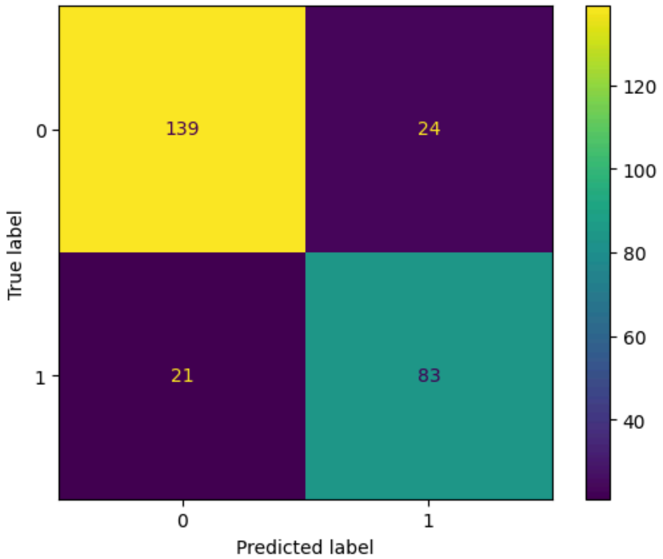
```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

```
# Make predictions on the test set
y_pred_knn = knn.predict(X_test)
```

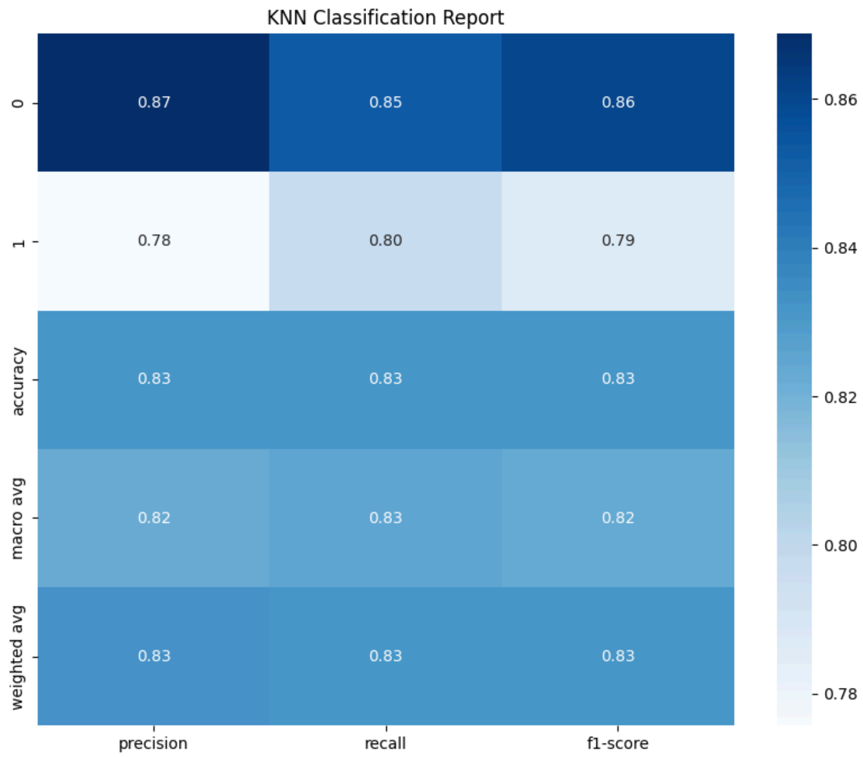
```
# Calculate accuracy
accuracy_knn = accuracy_score(Y_test, y_pred_knn)
print(f'KNN Accuracy: {accuracy_knn:.4f}')

# Calculate recall
recall_knn = recall_score(Y_test, y_pred_knn)
print(f'KNN Recall: {recall_knn:.4f}')

# Calculate precision
precision_knn = precision_score(Y_test, y_pred_knn)
print(f'KNN Precision: {precision_knn:.4f}')

# Calculate F1 score
f1_knn = f1_score(Y_test, y_pred_knn)
print(f'KNN F1 Score: {f1_knn:.4f}')

# Calculate confusion matrix
conf_matrix_knn = confusion_matrix(Y_test, y_pred_knn)
print(f'KNN Confusion Matrix:\n{conf_matrix_knn}')

# For a detailed classification report
report_knn = classification_report(Y_test, y_pred_knn)
print(f'KNN Classification Report:\n{report_knn}')
```

```
KNN Accuracy: 0.8315
KNN Recall: 0.7981
KNN Precision: 0.7757
KNN F1 Score: 0.7867
KNN Confusion Matrix:
[[139  24]
 [ 21  83]]
KNN Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.85      0.86       163
           1       0.78      0.80      0.79       104

    accuracy                           0.83       267
   macro avg       0.82      0.83      0.82       267
weighted avg       0.83      0.83      0.83       267
```

```
cmd=ConfusionMatrixDisplay(conf_matrix_knn)
cmd.plot()
plt.show()
```




```
# Convert the classification report to a DataFrame for plotting
report_knn_df = pd.DataFrame(classification_report(Y_test, y_pred_knn, output_dict=True)).transpose()

# Plot the classification report
plt.figure(figsize=(10, 8))
sns.heatmap(report_knn_df[['precision', 'recall', 'f1-score']], annot=True, cmap='Blues', fmt='.2f', cbar=True)
plt.title('KNN Classification Report')
plt.show()
```



Naive Bayes

```
from sklearn.naive_bayes import GaussianNB

# Instantiate the Naive Bayes model
nb = GaussianNB()

# Train the model
nb.fit(X_train, Y_train)
```

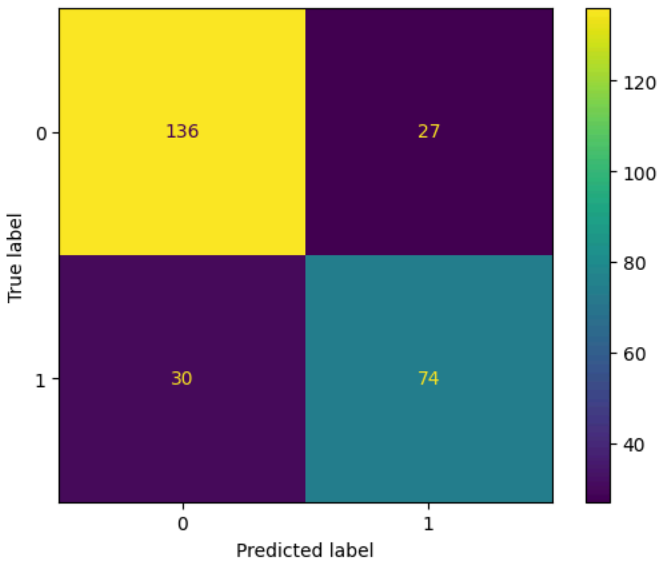
```
▾ GaussianNB
GaussianNB()
```

```
# Make predictions on the test set
y_pred_nb = nb.predict(X_test)
```

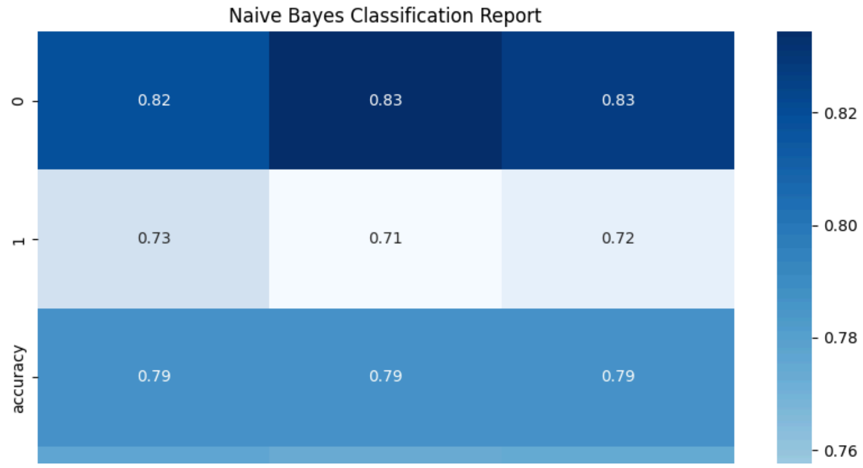
```
# Calculate accuracy
accuracy_nb = accuracy_score(Y_test, y_pred_nb)
print(f'Naive Bayes Accuracy: {accuracy_nb:.4f}')

# Calculate recall
recall_nb = recall_score(Y_test, y_pred_nb)
print(f'Naive Bayes Recall: {recall_nb:.4f}')

# Calculate precision
precision_nb = precision_score(Y_test, y_pred_nb)
print(f'Naive Bayes Precision: {precision_nb:.4f}')

# Calculate F1 score
f1_nb = f1_score(Y_test, y_pred_nb)
print(f'Naive Bayes F1 Score: {f1_nb:.4f}')

# Calculate confusion matrix
conf_matrix_nb = confusion_matrix(Y_test, y_pred_nb)
print(f'Naive Bayes Confusion Matrix:\n{conf_matrix_nb}')

# For a detailed classification report
report_nb = classification_report(Y_test, y_pred_nb)
print(f'Naive Bayes Classification Report:\n{report_nb}')
```

```
Naive Bayes Accuracy: 0.7865
Naive Bayes Recall: 0.7115
Naive Bayes Precision: 0.7327
Naive Bayes F1 Score: 0.7220
Naive Bayes Confusion Matrix:
[[136  27]
 [ 30  74]]
Naive Bayes Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.83      0.83       163
           1       0.73      0.71      0.72       104

    accuracy                           0.79       267
   macro avg       0.78      0.77      0.77       267
weighted avg       0.79      0.79      0.79       267
```

```
cmd=ConfusionMatrixDisplay(conf_matrix_nb)
cmd.plot()
plt.show()
```




```
# Convert the classification report to a DataFrame for plotting
report_nb_df = pd.DataFrame(classification_report(Y_test, y_pred_nb, output_dict=True)).transpose()

# Plot the classification report
plt.figure(figsize=(10, 8))
sns.heatmap(report_nb_df[['precision', 'recall', 'f1-score']], annot=True, cmap='Blues', fmt='.2f', cbar=True)
plt.title('Naive Bayes Classification Report')
plt.show()
```


Naive Bayes Classification Report
0.82
0.83
0.83
0.73
0.71
0.72
0.79
0.79
0.79
0
1
accuracy
0.82
0.80
0.78
0.76