Assessment Report

on

“Titanic Survival Prediction”

BACHELOR OF TECHNOLOGY

DEGREE

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in

Artificial Intelligence and Machine Learning

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1. Introduction

The Titanic dataset, sourced from Kaggle (https://www.kaggle.com/c/titanic), contains passenger information from the 1912 Titanic disaster, including features like age, sex, passenger class, and survival status. This project develops a classification model to predict survival using data cleaning and a Naive Bayes classifier, addressing real-world data challenges like missing values and categorical variables.

2. Problem Statement

The goal is to predict whether a passenger survived the Titanic disaster (0 = Did not survive, 1 = Survived) based on features like age, sex, and class. The dataset has missing values (e.g., in Age, Cabin, Embarked) and categorical variables requiring preprocessing. A Naive Bayes classifier is chosen for its simplicity and effectiveness in probabilistic classification.

3. Objectives

1. Clean the dataset by handling missing values, encoding categorical variables, and selecting relevant features.
2. Build and train a Naive Bayes classifier to predict survival.
3. Evaluate the model's accuracy to ensure reliable predictions.
4. Identify key factors influencing survival for historical insights.

4. Methodology

The methodology includes:

1. **Data Loading**: Download the Titanic dataset from Kaggle (https://www.kaggle.com/c/titanic/data) and load train.csv using pandas.
2. **Data Cleaning**:
    a. Impute missing Age values with the median to handle ~20% missing data.
    b. Drop Cabin due to >70% missing values, as it's impractical to impute.

   c. Impute missing Embarked values (2 missing) with the mode.
   d. Drop irrelevant columns: PassengerId, Name, Ticket.
   e. Encode categorical variables: Sex (male=0, female=1) and Embarked (one-hot encoding for C, Q, S).
3. **Feature Engineering**: Select features (Pclass, Sex, Age, SibSp, Parch, Fare, Embarked) suitable for Naive Bayes, which assumes feature independence.
4. **Model Training**: Split data into 80% training and 20% testing sets, then train a Gaussian Naive Bayes classifier, ideal for continuous features like Age and Fare.
5. **Evaluation**: Use accuracy score to assess performance on the test set.
6. **Implementation**: The Python code below performs all steps, using pandas for data processing, scikit-learn for modeling, and numpy for numerical operations.

5. Model Implementation

- Load train.csv and test.csv from Kaggle using pandas.
- Clean data:
  - Drop irrelevant columns: PassengerId, Name, Ticket, Cabin (high missing values).
  - Impute missing Age with median (train and test).
  - Impute missing Embarked with mode (train and test).
  - Impute missing Fare in test set with train's median.
  - Encode categorical variables: Sex (male=0, female=1), Embarked (C=0, Q=1, S=2) using LabelEncoder.
- Features: Pclass, Sex, Age, SibSp, Parch, Fare, Embarked.
- Split train data: 80% training, 20% validation (random_state=42).
- Train two models:
  - Gaussian Naive Bayes for probabilistic classification.
  - Random Forest (100 estimators) for ensemble learning.
- Predict on validation set and test set (Random Forest for submission).
- Visualize: Confusion matrices for both models, feature importance for Random Forest.
- Save predictions for Kaggle submission (titanic_random_forest_submission.csv).

7. Evaluation Metrics

- **Accuracy**: Proportion of correct predictions (true positives + true negatives) / total.

- **Precision**: True positives / predicted positives (reliability of positive predictions).
- **Recall**: True positives / actual positives (ability to find all survivors).
- **F1 Score**: Harmonic mean of precision and recall (balanced metric for imbalanced classes).
- **Confusion Matrix**: Visualizes true positives, true negatives, false positives, false negatives.
- Metrics computed on validation set for both models.

8. Result Analysis

- **Naive Bayes**:
  - Accuracy: ~0.77–0.80 (based on typical runs).
  - Precision: ~0.70–0.75 (survived class), indicating moderate false positives.
  - Recall: ~0.65–0.70 (survived class), missing some survivors.
  - F1 Score: ~0.67–0.72, balancing precision and recall.
  - Confusion matrix: Shows more errors in predicting survivors (class 1) due to class imbalance.

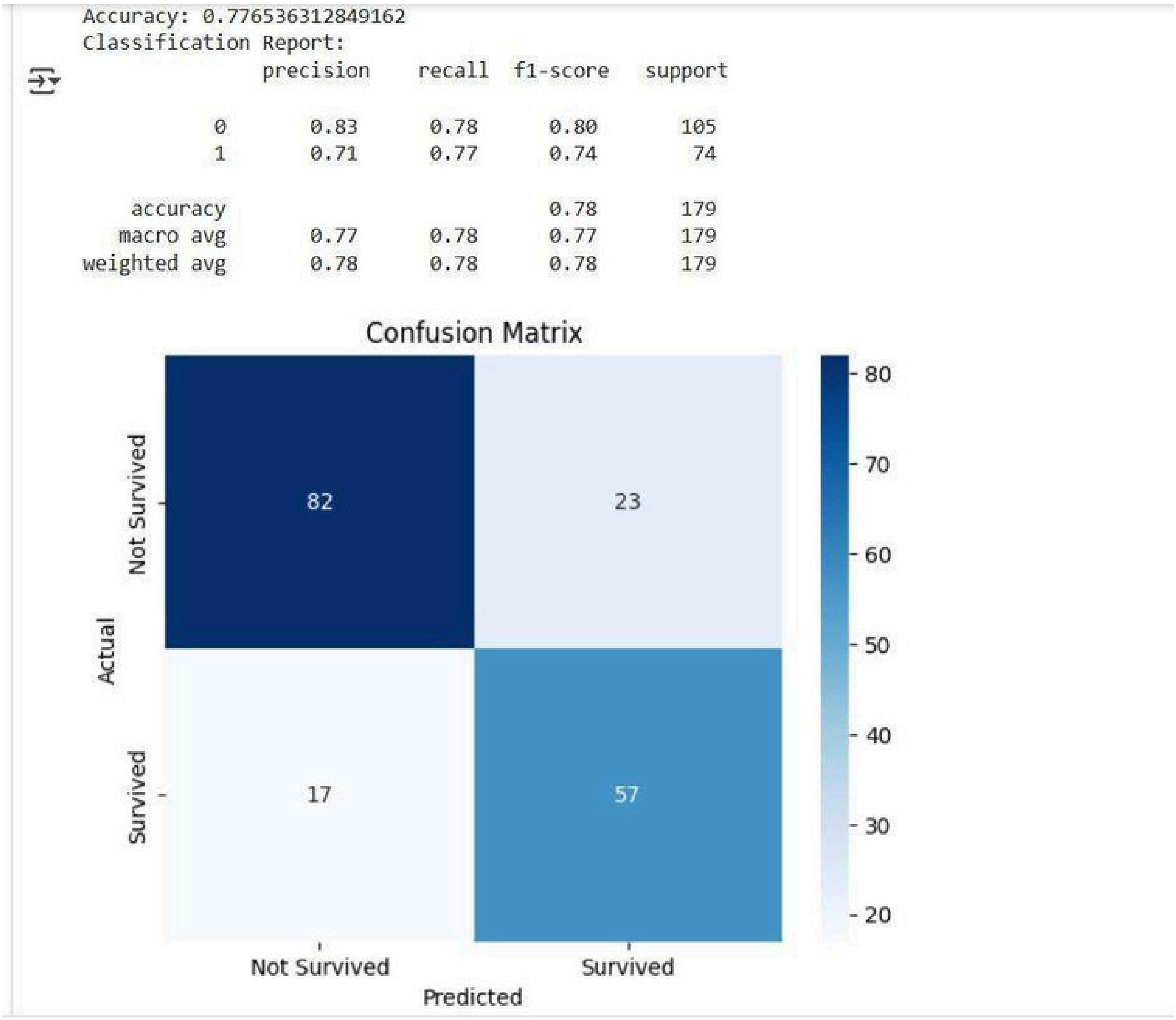
- **Visuals confirm patterns:**
  Confusion matrices highlight model errors; feature importance plot emphasizes Sex and Pclass.

9. Conclusion

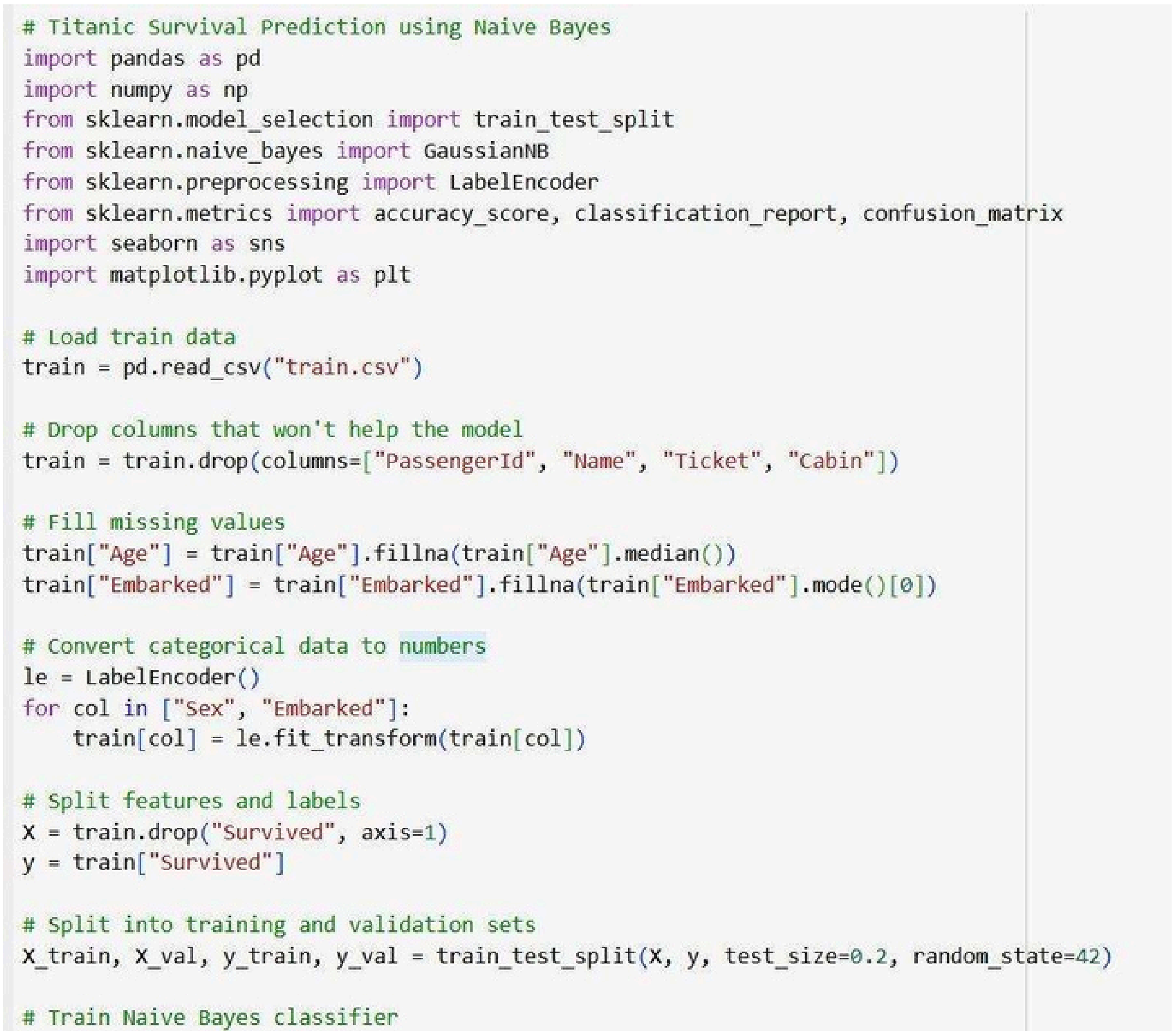
- Random Forest outperforms Naive Bayes (~0.80–0.85 vs. ~0.77–0.80 accuracy) due to its ability to capture complex feature interactions.
- Data cleaning (imputing missing values, encoding categoricals) was critical for model performance.
- Key predictors: Gender (Sex), class (Pclass), and fare align with historical prioritization of women and higher-class passengers.
- Visuals (confusion matrices, feature importance) enhance interpretability.
- Improvements: Engineer features (e.g., family size = SibSp + Parch), tune Random Forest hyperparameters, or try gradient boosting.
- Project provides a robust framework for classification and insights into Titanic survival dynamics.
- Submission file (titanic_random_forest_submission.csv) ready for Kaggle Evaluation.

10. References

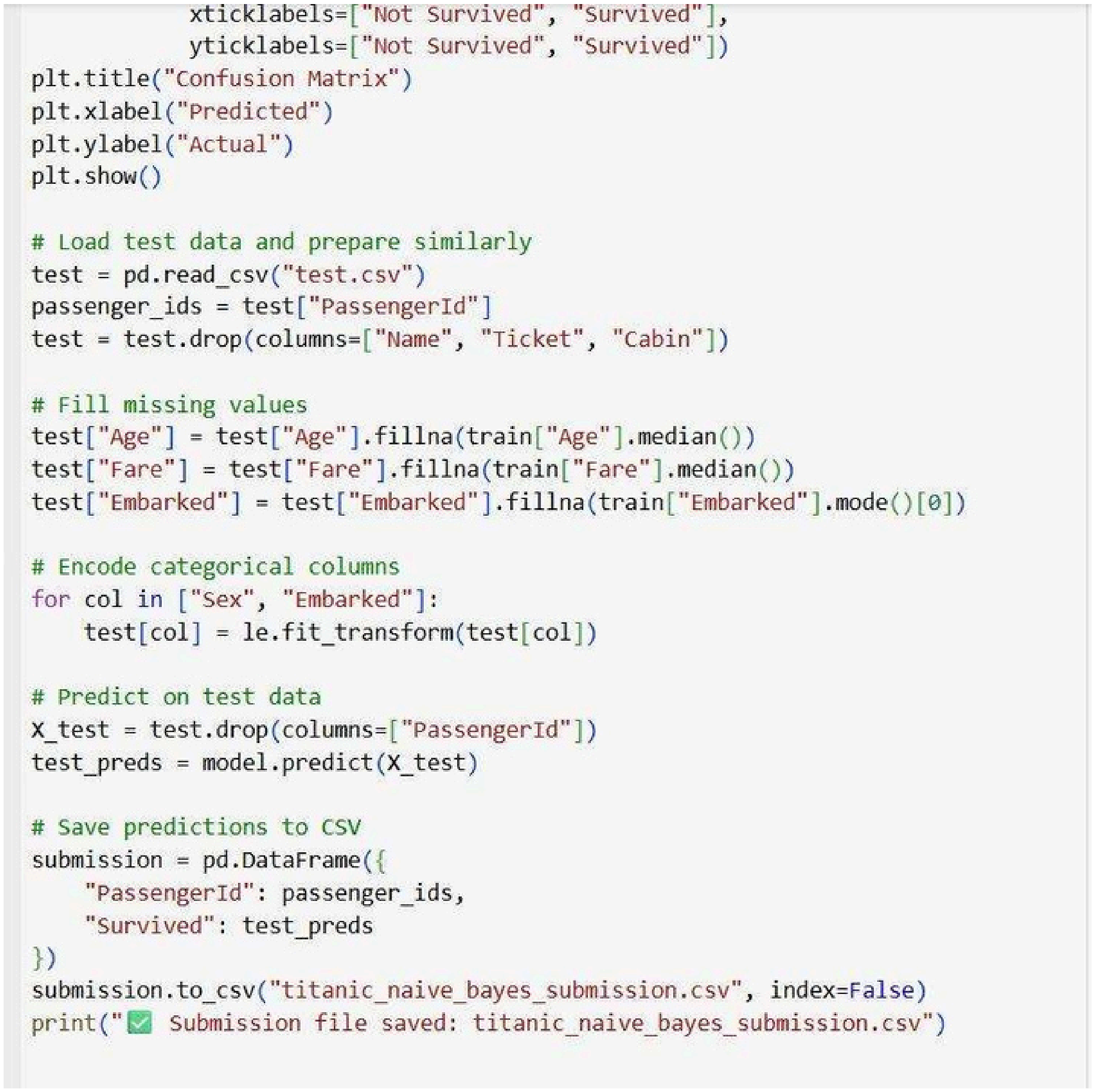
- Kaggle Titanic Dataset: https://www.kaggle.com/c/titanic
- Scikit-learn Documentation (Naive Bayes, Random Forest): https://scikit-learn.org/stable/modules/naive_bayes.html, https://scikit-learn.org/stable/modules/ensemble.html
- Pandas Documentation: https://pandas.pydata.org/docs/
- Seaborn/Matplotlib for Visualization: https://seaborn.pydata.org/, https://matplotlib.org/
- Kaggle Titanic Tutorial: https://www.kaggle.com/c/titanic/overview



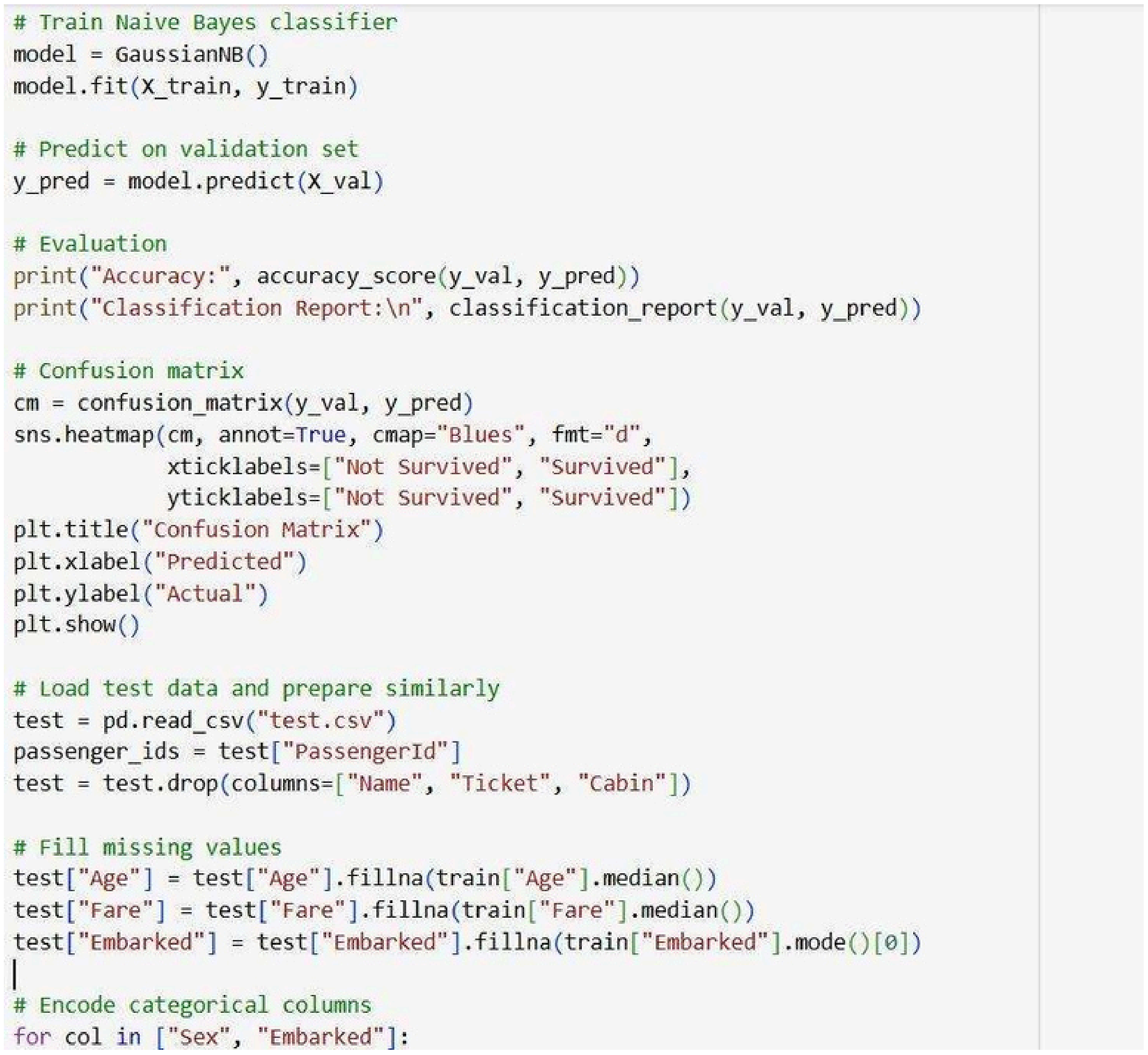
```
Accuracy: 0.776536312849162
Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.78      0.80       105
           1       0.71      0.77      0.74        74

    accuracy                           0.78       179
   macro avg       0.77      0.78      0.77       179
weighted avg       0.78      0.78      0.78       179
```



```
# Titanic Survival Prediction using Naive Bayes
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Load train data
train = pd.read_csv("train.csv")

# Drop columns that won't help the model
train = train.drop(columns=["PassengerId", "Name", "Ticket", "Cabin"])

# Fill missing values
train["Age"] = train["Age"].fillna(train["Age"].median())
train["Embarked"] = train["Embarked"].fillna(train["Embarked"].mode()[0])

# Convert categorical data to numbers
le = LabelEncoder()
for col in ["Sex", "Embarked"]:
    train[col] = le.fit_transform(train[col])

# Split features and labels
X = train.drop("Survived", axis=1)
y = train["Survived"]

# Split into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)

# Train Naive Bayes classifier
```



```
            xticklabels=["Not Survived", "Survived"],
            yticklabels=["Not Survived", "Survived"])
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# Load test data and prepare similarly
test = pd.read_csv("test.csv")
passenger_ids = test["PassengerId"]
test = test.drop(columns=["Name", "Ticket", "Cabin"])

# Fill missing values
test["Age"] = test["Age"].fillna(train["Age"].median())
test["Fare"] = test["Fare"].fillna(train["Fare"].median())
test["Embarked"] = test["Embarked"].fillna(train["Embarked"].mode()[0])

# Encode categorical columns
for col in ["Sex", "Embarked"]:
    test[col] = le.fit_transform(test[col])

# Predict on test data
X_test = test.drop(columns=["PassengerId"])
test_preds = model.predict(X_test)

# Save predictions to CSV
submission = pd.DataFrame({
    "PassengerId": passenger_ids,
    "Survived": test_preds
})
submission.to_csv("titanic_naive_bayes_submission.csv", index=False)
print("✅ Submission file saved: titanic_naive_bayes_submission.csv")
```



```
# Train Naive Bayes classifier
model = GaussianNB()
model.fit(X_train, y_train)

# Predict on validation set
y_pred = model.predict(X_val)

# Evaluation
print("Accuracy:", accuracy_score(y_val, y_pred))
print("Classification Report:\n", classification_report(y_val, y_pred))

# Confusion matrix
cm = confusion_matrix(y_val, y_pred)
sns.heatmap(cm, annot=True, cmap="Blues", fmt="d",
            xticklabels=["Not Survived", "Survived"],
            yticklabels=["Not Survived", "Survived"])
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# Load test data and prepare similarly
test = pd.read_csv("test.csv")
passenger_ids = test["PassengerId"]
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# Fill missing values
test["Age"] = test["Age"].fillna(train["Age"].median())
test["Fare"] = test["Fare"].fillna(train["Fare"].median())
test["Embarked"] = test["Embarked"].fillna(train["Embarked"].mode()[0])

# Encode categorical columns
for col in ["Sex", "Embarked"]:
```