# Titanic Survival Prediction

## 🚢 Objective

Build a machine learning model to predict whether a passenger survived the Titanic disaster using a dataset from Kaggle.

## 📁 Dataset

[Kaggle Titanic Dataset]

## 🧪 Features Used

- Age
- Sex
- Pclass
- Fare
- SibSp
- Parch
- Embarked

## ⚙️ How to Run

1. Upload dataset (`train.csv` and `test.csv`) in Colab.
2. Run the `src/titanic_model.ipynb` notebook.
3. Model output and performance will be printed.

## 📊 Evaluation Metrics

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

## ✅ Model Used

Random Forest Classifier (scikit-learn)

Start coding or generate with AI.

```
# Titanic Survival Prediction ML Model

# Step 1: Import Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score



# Step 2: Load Dataset (Upload manually in Colab)
from google.colab import files
uploaded = files.upload()

import os
import zipfile

# Move kaggle.json to the right folder
!mkdir -p ~/.kaggle
!mv kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json

# Download the dataset using Kaggle API
!kaggle datasets download -d brendan45774/test-file

# Unzip the dataset
with zipfile.ZipFile("test-file.zip", 'r') as zip_ref:
    zip_ref.extractall("titanic_data")

# List extracted files
os.listdir("titanic_data")

import pandas as pd

train_data = pd.read_csv("titanic_data/tested.csv")
test_data = pd.read_csv("titanic_data/tested.csv")

train_data.head()
```

Choose Files kaggle.json

- **kaggle.json**(application/json) - 66 bytes, last modified: 13/4/2025 - 100% done

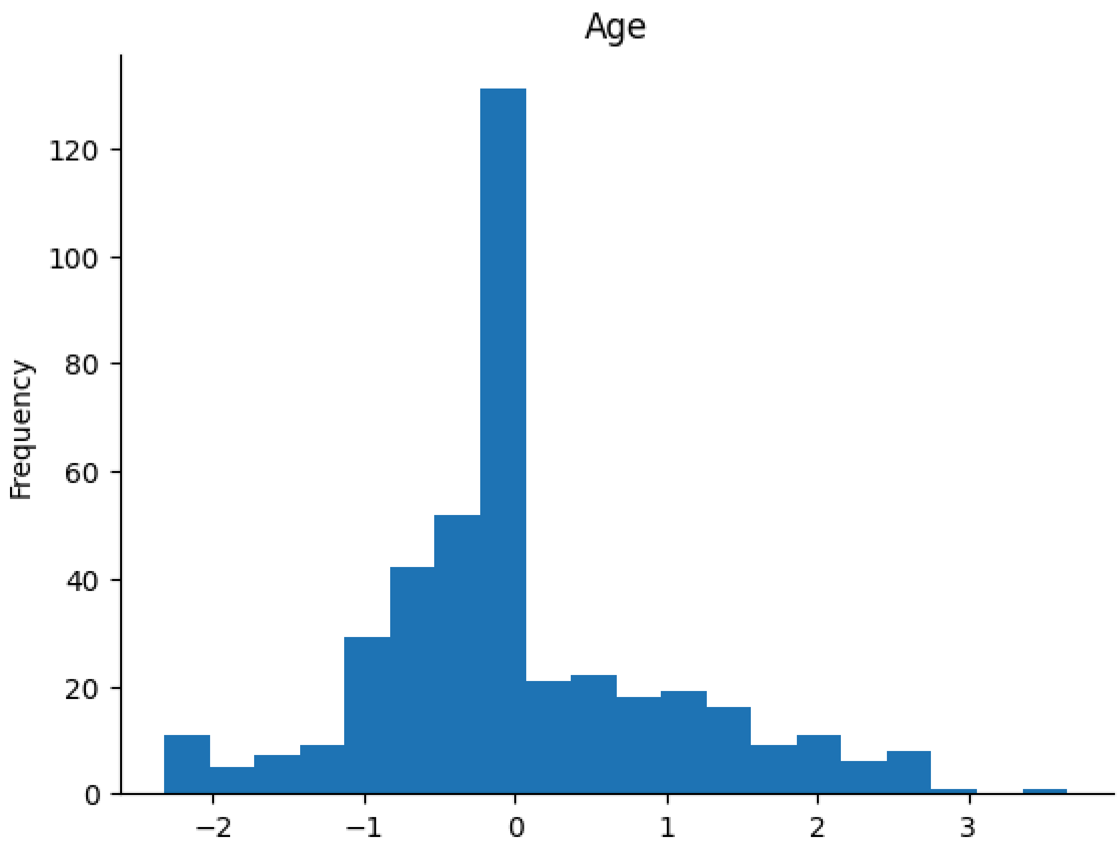
```
Saving kaggle.json to kaggle.json
Dataset URL: https://www.kaggle.com/datasets/brendan45774/test-file
License(s): CC0-1.0
test-file.zip: Skipping, found more recently modified local copy (use --force t
```

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Far |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 892 | 0 | 3 | Kelly, Mr. James | male | 34.5 | 0 | 0 | 330911 | 7.829 |
| **1** | 893 | 1 | 3 | Wilkes, Mrs. James (Ellen Needs) | female | 47.0 | 1 | 0 | 363272 | 7.000 |

Next steps: Generate code with `train_data` View recommended plots New interactive sheet

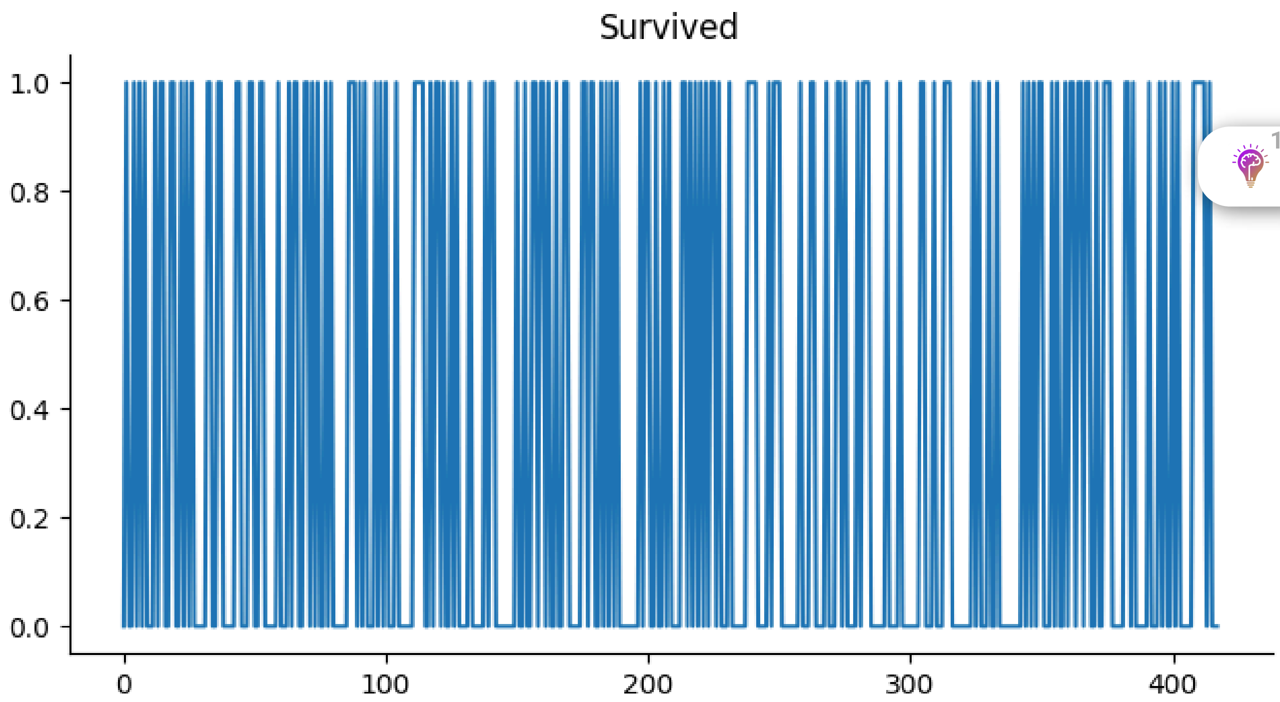
## Age

Show code




## Survived

Show code




```
# Step 3: Explore and Clean Data
print("Missing values in train data:\n", train_data.isnull().sum())

# Fill missing Age with median, Embarked with mode
train_data["Age"].fillna(train_data["Age"].median(), inplace=True)
train_data["Embarked"].fillna(train_data["Embarked"].mode()[0], inplace=True)

# Drop Cabin (too many missing values)
train_data.drop("Cabin", axis=1, inplace=True)

# Drop irrelevant columns
train_data.drop(["Name", "Ticket", "PassengerId"], axis=1, inplace=True)
```

```
Missing values in train data:
 PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
<ipython-input-6-310263fd1c03>:5: FutureWarning: A value is trying to be set on a cop
The behavior will change in pandas 3.0. This inplace method will never work because t

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({


  train_data["Age"].fillna(train_data["Age"].median(), inplace=True)
<ipython-input-6-310263fd1c03>:6: FutureWarning: A value is trying to be set on a cop
```

```
The behavior will change in pandas 3.0. This inplace method will never work because t

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({

  train_data["Embarked"].fillna(train_data["Embarked"].mode()[0], inplace=True)
```

```
# Step 4: Encode Categorical Variables
label_encoders = {}
for column in ["Sex", "Embarked"]:
    le = LabelEncoder()
    train_data[column] = le.fit_transform(train_data[column])
    label_encoders[column] = le


# Step 5: Feature Scaling
scaler = StandardScaler()
numeric_cols = ["Age", "Fare", "SibSp", "Parch"]
train_data[numeric_cols] = scaler.fit_transform(train_data[numeric_cols])


# Step 6: Model Training
X = train_data.drop("Survived", axis=1)
y = train_data["Survived"]
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)

model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

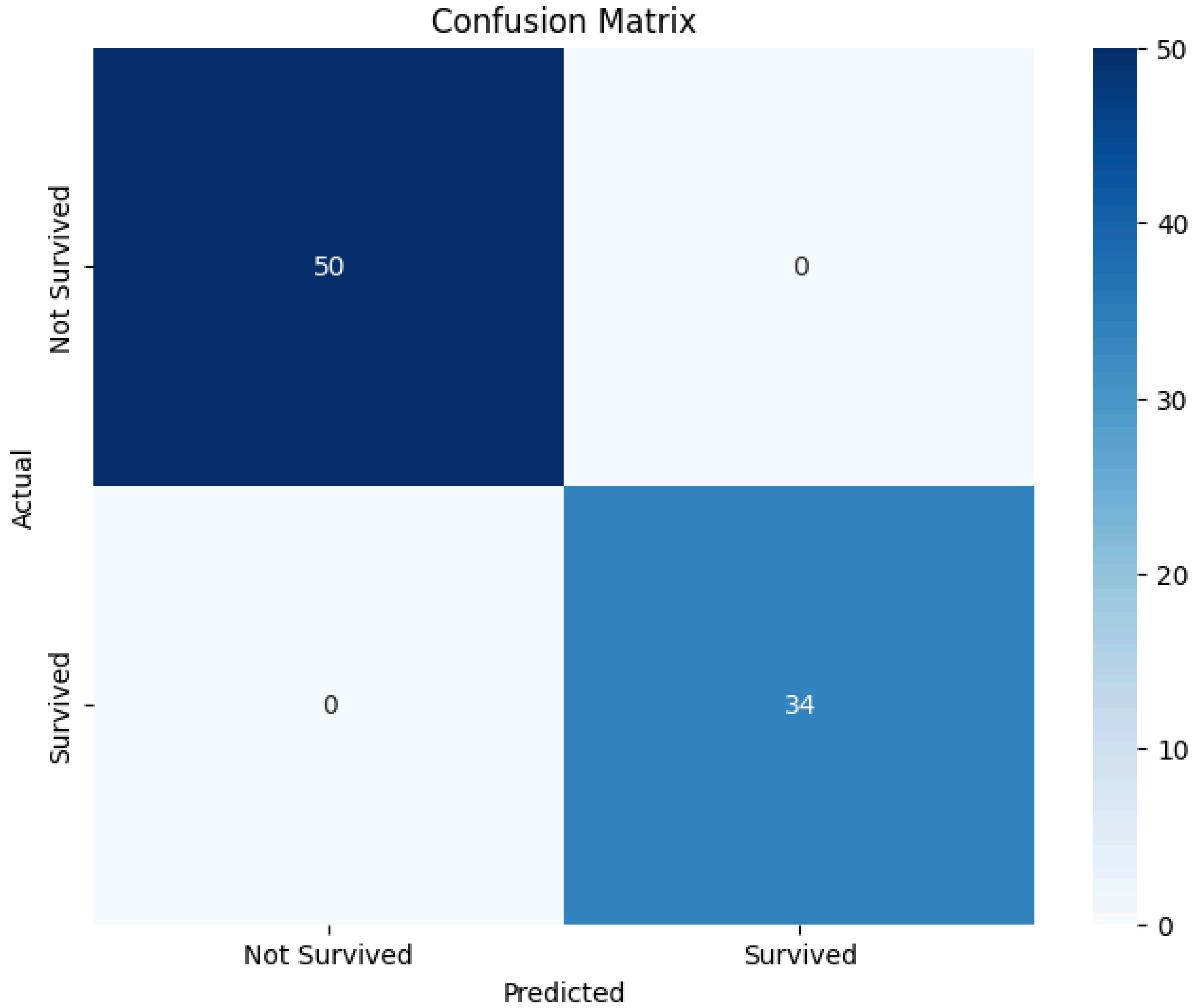
```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

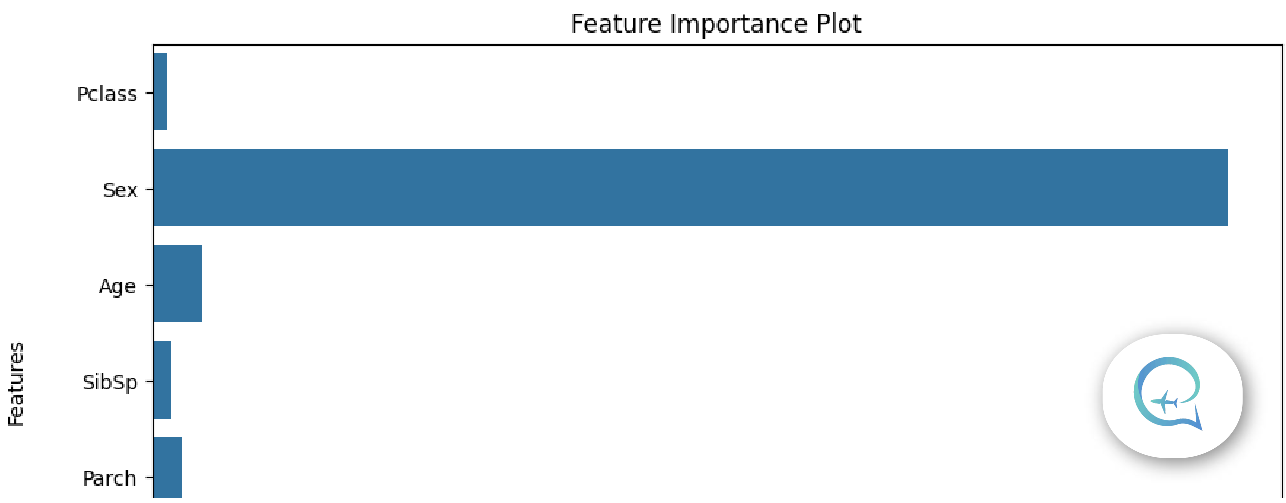
```
# Step 7: Evaluation
y_pred = model.predict(X_val)

print("Accuracy:", accuracy_score(y_val, y_pred))
print("Classification Report:\n", classification_report(y_val, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_val, y_pred))
```

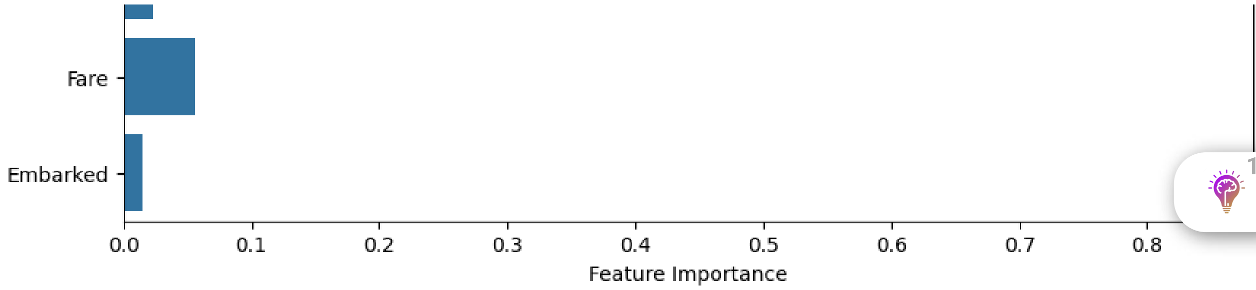
```
Accuracy: 1.0
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        50
           1       1.00      1.00      1.00        34

    accuracy                           1.00        84
   macro avg       1.00      1.00      1.00        84
weighted avg       1.00      1.00      1.00        84

Confusion Matrix:
 [[50  0]
 [ 0 34]]
```

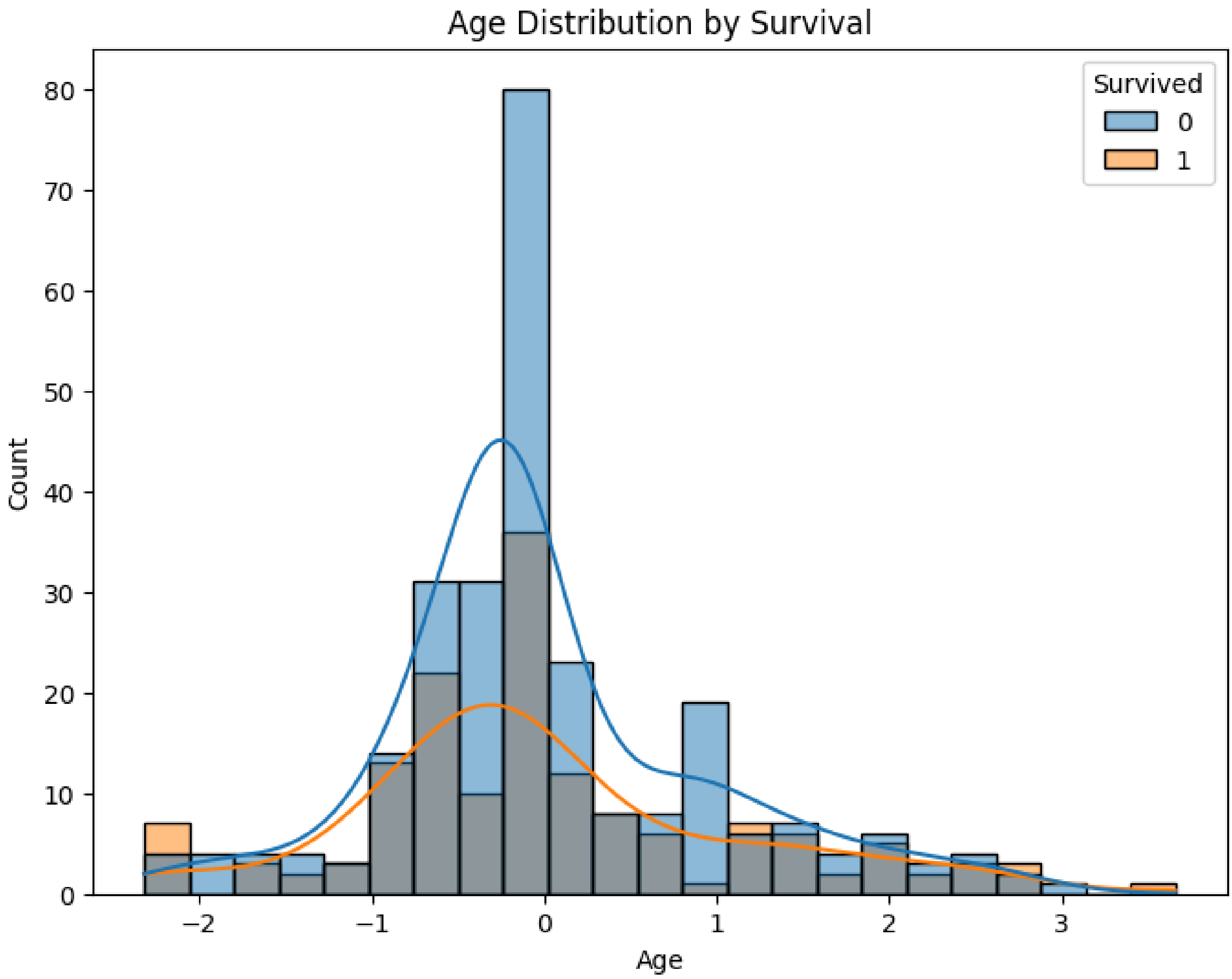
```
# prompt: Generate some of the important results should be represented using a visualisat

import matplotlib.pyplot as plt
import seaborn as sns

# ... (your existing code) ...

# Step 7: Evaluation and Visualization
y_pred = model.predict(X_val)

print("Accuracy:", accuracy_score(y_val, y_pred))
print("Classification Report:\n", classification_report(y_val, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_val, y_pred))

# Visualize the Confusion Matrix
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix(y_val, y_pred), annot=True, fmt="d", cmap="Blues",
            xticklabels=["Not Survived", "Survived"], yticklabels=["Not Survived", "Survi
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()


# Feature Importance Visualization
feature_importances = model.feature_importances_
feature_names = X_train.columns

plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importances, y=feature_names)
plt.xlabel("Feature Importance")
plt.ylabel("Features")
plt.title("Feature Importance Plot")
plt.show()

# Visualize the distribution of a key feature (e.g., Age) for survived vs. not survived
plt.figure(figsize=(8, 6))
sns.histplot(x='Age', hue='Survived', data=train_data, kde=True)
plt.title("Age Distribution by Survival")
plt.xlabel("Age")
plt.ylabel("Count")
plt.show()

# Visualize the survival rate based on passenger class (Pclass)
plt.figure(figsize=(8, 6))
sns.countplot(x='Pclass', hue='Survived', data=train_data)
plt.title("Survival Rate by Passenger Class")
plt.xlabel("Passenger Class")
plt.ylabel("Count")
plt.show()
```

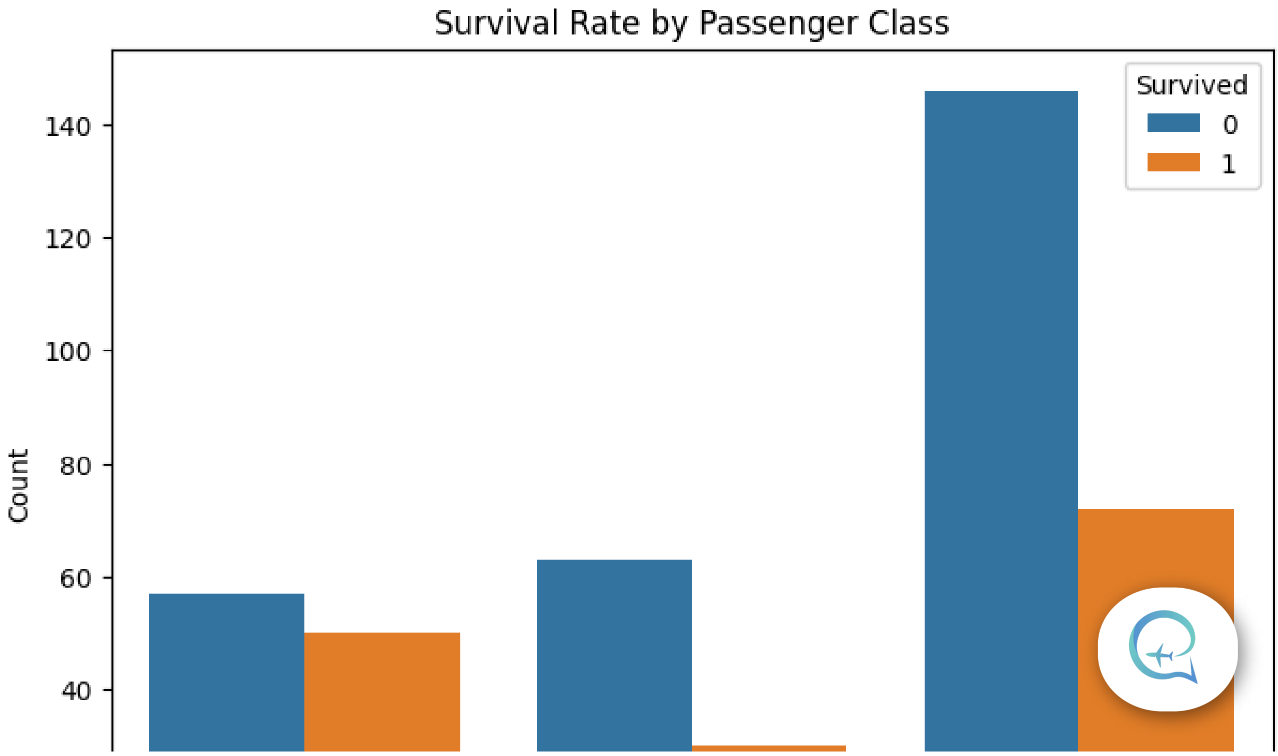
```
Accuracy: 1.0
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        50
           1       1.00      1.00      1.00        34

    accuracy                           1.00        84
   macro avg       1.00      1.00      1.00        84
weighted avg       1.00      1.00      1.00        84

Confusion Matrix:
 [[50  0]
 [ 0 34]]
```




Fare
Embarked
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Feature Importance


Age Distribution by Survival
Survived
0
1
Count
80
70
60
50
40
30
20
10
0
−2
−1
0
1
2
3
Age


Survival Rate by Passenger Class
Survived
0
1
Count
140
120
100
80
60
40