Titanic Survival Prediction Project

Project Overview: This Jupyter Notebook documents the Titanic Survival Prediction project, which aims to predict passenger survival during the tragic sinking of the Titanic. We analyze various factors such as socio-economic status, age, gender, and more to develop an accurate survival prediction model.

Project Highlights:

- Data Loading and Exploration
- Data Preprocessing
- Model Training and Evaluation
- Experimenting with Multiple Algorithms
- Selecting and Fine-Tuning the Best Model

Project Objectives:

- Analyze and visualize Titanic dataset
- Build predictive models to determine survival
- Evaluate and compare model performance
- Provide insights for passenger survival factors

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Task: The task is to create a system that predicts whether a person would survive the Titanic sinking based on factors such as socio-economic status, age, gender, and more.

Data Loading and Exploration

In [1]:
```
import pandas as pd
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_m
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
train_data = pd.read_csv('train.csv')
test_data = pd.read_csv('test.csv')
```

In [3]:
```
import seaborn as sns
import matplotlib.pyplot as plt

train_data.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
```

In [3]:
```
import seaborn as sns
import matplotlib.pyplot as plt

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```

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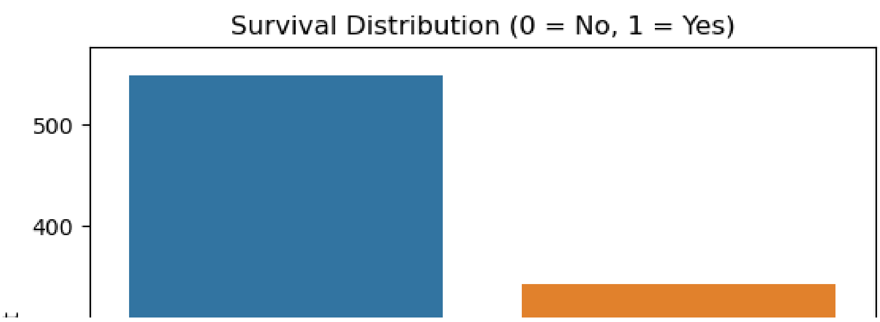
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         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
```

In [4]:
```
train_data.head()
```

Out[4]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	I
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	I
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	I

In [5]:
```
sns.countplot(x='Survived', data=train_data)
plt.title('Survival Distribution (0 = No, 1 = Yes)')
plt.show()
```



In [5]:
```
sns.countplot(x='Survived', data=train_data)
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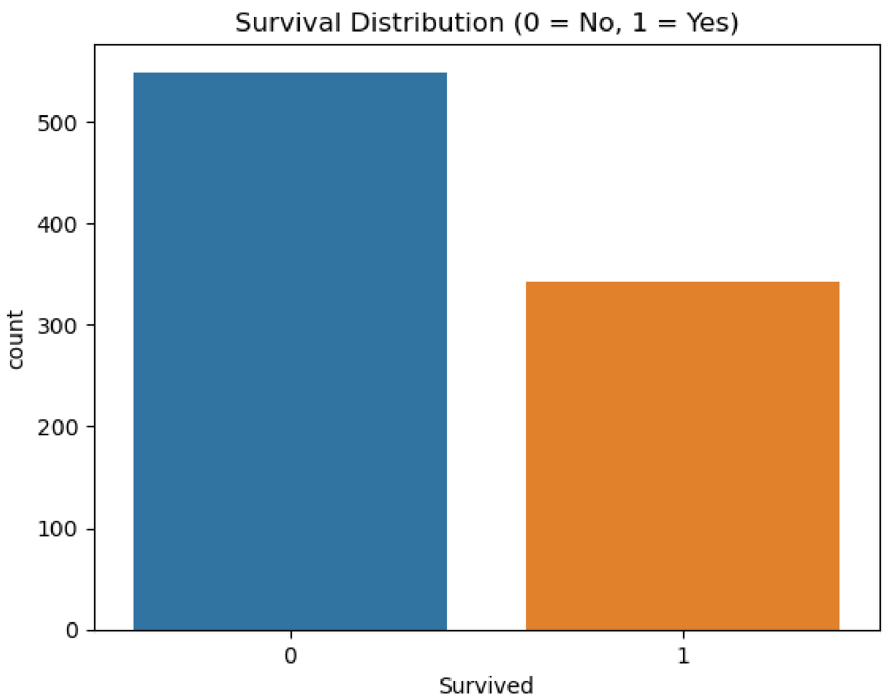
```



In [6]:
```
import pandas as pd
from sklearn.impute import SimpleImputer

train_data = pd.read_csv('train.csv')
test_data = pd.read_csv('test.csv')
```

In [7]:
```
train_data.drop(['Name', 'Ticket', 'Cabin'], axis=1, inplace=True)
test_data.drop(['Name', 'Ticket', 'Cabin'], axis=1, inplace=True)
```

In [8]:
```
num_imputer = SimpleImputer(strategy='mean')
train_data[['Age', 'Fare']] = num_imputer.fit_transform(train_data[['Age', 'Fa
test_data[['Age', 'Fare']] = num_imputer.transform(test_data[['Age', 'Fare']])
```

In [9]:
```
train_data = pd.get_dummies(train_data, columns=['Sex', 'Embarked'], drop_firs
test_data = pd.get_dummies(test_data, columns=['Sex', 'Embarked'], drop_first=
```

In [10]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_m

# Split the data into features (X_train) and the target variable (y_train)
y_train = train_data['Survived']
X_train = train_data.drop('Survived', axis=1)
```

In [11]:
```
# Split the training data into training and validation sets (80% training, 20%
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_s
```

In [12]:
```
# Initialize the Logistic Regression model
model = LogisticRegression()
```

In [15]:
```
# Calculate the accuracy on the validation data
accuracy = accuracy_score(y_valid, y_valid_pred)
print(f"Accuracy on Validation Data: {accuracy:.2f}")
```

```
Accuracy on Validation Data: 0.78
```

In [13]:
```
# Train the model on the training data
model.fit(X_train, y_train)
```

Out[13]:
```
▸ LogisticRegression
```

In [16]:
```
# Print a classification report for more detailed evaluation
print("\nClassification Report:")
print(classification_report(y_valid, y_valid_pred))
```

In [14]:
```
# Make predictions on the validation data
y_valid_pred = model.predict(X_valid)
```

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

           0       0.79      0.84      0.81       105
           1       0.75      0.69      0.72        74
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Out[13]:
```
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```
Classification Report:
              precision    recall  f1-score   support

           0       0.79      0.84      0.81       105
           1       0.75      0.69      0.72        74

    accuracy                           0.78       179
   macro avg       0.77      0.76      0.77       179
weighted avg       0.78      0.78      0.77       179
```

In [17]:
```python
# Display a confusion matrix to visualize true positives, true negatives, fals
print("\nConfusion Matrix:")
print(confusion_matrix(y_valid, y_valid_pred))
```

```
Confusion Matrix:
[[88 17]
 [23 51]]
```

In [18]:
```python
# Initialize different classification models
models = [
    ('Logistic Regression', LogisticRegression()),
    ('Random Forest', RandomForestClassifier(random_state=42)),
    ('Support Vector Machine', SVC()),
    ('K-Nearest Neighbors', KNeighborsClassifier()),
    ('Decision Tree', DecisionTreeClassifier(random_state=42))
]
```

In [19]:
```python
# Evaluate each model using cross-validation
for name, model in models:
    scores = cross_val_score(model, X_train, y_train, cv=5, scoring='accuracy'
    mean_accuracy = scores.mean()
    std_accuracy = scores.std()

    print(f"{name}:")
    print(f"Mean Accuracy: {mean_accuracy:.2f}")
    print(f"Standard Deviation: {std_accuracy:.2f}")
    print()
```

```
Logistic Regression:
Mean Accuracy: 0.77
Standard Deviation: 0.04

Random Forest:
Mean Accuracy: 0.81
Standard Deviation: 0.01

Support Vector Machine:
Mean Accuracy: 0.65
Standard Deviation: 0.01

K-Nearest Neighbors:
Mean Accuracy: 0.62
Standard Deviation: 0.03

Decision Tree:
Mean Accuracy: 0.73
Standard Deviation: 0.02
```

In [21]:
```python
best_model = RandomForestClassifier(random_state=42)
best_model.fit(X_train, y_train)
y_valid_pred = best_model.predict(X_valid)
```

In [22]:
```python
accuracy = accuracy_score(y_valid, y_valid_pred)
print(f"Accuracy on Validation Data: {accuracy:.2f}")
print("\nClassification Report:")
print(classification_report(y_valid, y_valid_pred))
print("\nConfusion Matrix:")
print(confusion_matrix(y_valid, y_valid_pred))
```

```
Accuracy on Validation Data: 0.83

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

```
..
Mean Accuracy: 0.65
Standard Deviation: 0.01
K-Nearest Neighbors:
Mean Accuracy: 0.62
Standard Deviation: 0.03

Decision Tree:
Mean Accuracy: 0.73
Standard Deviation: 0.02
```

In [21]:

```
best_model = RandomForestClassifier(random_state=42)
best_model.fit(X_train, y_train)
y_valid_pred = best_model.predict(X_valid)
```

In [22]:

```
accuracy = accuracy_score(y_valid, y_valid_pred)
print(f"Accuracy on Validation Data: {accuracy:.2f}")
print("\nClassification Report:")
print(classification_report(y_valid, y_valid_pred))
print("\nConfusion Matrix:")
print(confusion_matrix(y_valid, y_valid_pred))
```

```
Accuracy on Validation Data: 0.83

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.90      0.86       105
           1       0.83      0.74      0.79        74

    accuracy                           0.83       179
   macro avg       0.83      0.82      0.82       179
weighted avg       0.83      0.83      0.83       179


Confusion Matrix:
[[94 11]
 [19 55]]
```