BADKUL TECHNOLOGIES

TASK I - Data Preprocessing & Classification

```
Objective: Learn the basic ML workflow, including data cleaning,
preprocessing, and building a simple classifier.
```

Titanic Survival Prediction

I. Introduction

The **Titanic dataset** is one of the most well-known datasets in data science, often used to learn classification and predictive modeling.

The goal of this project is to **predict whether a passenger survived or not** based on features like age, gender, class, and fare.

The dataset contains information about **passengers aboard the RMS Titanic**, including demographic and travel details.

Through this project, we will perform the following steps:

- **Exploratory Data Analysis (EDA):** Uncover patterns and relationships in the data.
- **Data Preprocessing & Feature Engineering:** Handle missing values, encode categorical variables, and create new useful features.
- **Model Building:** Train Logistic Regression and Decision Tree classifiers.
- **Performance Evaluation:** Compare model accuracy, interpret results, and identify key predictive features.

Ultimately, this project aims to understand which factors most influenced survival on the Titanic and build a model that can predict it effectively.

II. Import Libraries

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report, ConfusionMatrixDisplay
```

III. Load the data

```python
df = pd.read_csv('titanic/train.csv')
test_df = pd.read_csv('titanic/test.csv')

df
```

```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           ...       ...     ...
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3

                                                  Name     Sex   Age
SibSp  \
0                              Braund, Mr. Owen Harris    male  22.0
1
1    Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
1
2                               Heikkinen, Miss. Laina  female  26.0
0
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
4                             Allen, Mr. William Henry    male  35.0
0
..                                                 ...     ...   ...
...
886                              Montvila, Rev. Juozas    male  27.0
0
887                       Graham, Miss. Margaret Edith  female  19.0
0
888           Johnston, Miss. Catherine Helen "Carrie"  female   NaN
1
889                              Behr, Mr. Karl Howell    male  26.0
0
890                                Dooley, Mr. Patrick    male  32.0
0
```

```
     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     ...               ...      ...   ...      ...
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]
```

test_df

```
     PassengerId  Pclass                                          Name
\
0            892       3                              Kelly, Mr. James

1            893       3              Wilkes, Mrs. James (Ellen Needs)

2            894       2                     Myles, Mr. Thomas Francis

3            895       3                              Wirz, Mr. Albert

4            896       3  Hirvonen, Mrs. Alexander (Helga E Lindqvist)

..           ...     ...                                           ...

413         1305       3                            Spector, Mr. Woolf

414         1306       1                  Oliva y Ocana, Dona. Fermina

415         1307       3                  Saether, Mr. Simon Sivertsen

416         1308       3                           Ware, Mr. Frederick

417         1309       3                     Peter, Master. Michael J


        Sex   Age  SibSp  Parch              Ticket      Fare Cabin
Embarked
0      male  34.5      0      0              330911    7.8292   NaN
Q
1    female  47.0      1      0              363272    7.0000   NaN
S
2      male  62.0      0      0              240276    9.6875   NaN
Q
3      male  27.0      0      0              315154    8.6625   NaN
```

```
S
4    female  22.0      1      1             3101298   12.2875   NaN
S
..      ...   ...    ...    ...                 ...       ...   ...
...
413    male   NaN      0      0          A.5. 3236    8.0500   NaN
S
414  female  39.0      0      0            PC 17758  108.9000  C105
C
415    male  38.5      0      0  SOTON/O.Q. 3101262    7.2500   NaN
S
416    male   NaN      0      0              359309    8.0500   NaN
S
417    male   NaN      1      1                2668   22.3583   NaN
C

[418 rows x 11 columns]
```

```
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
```

```
test_df.isnull().sum()
```

```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

IV. Exploratory Data Analysis

```
df.describe()
```

```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

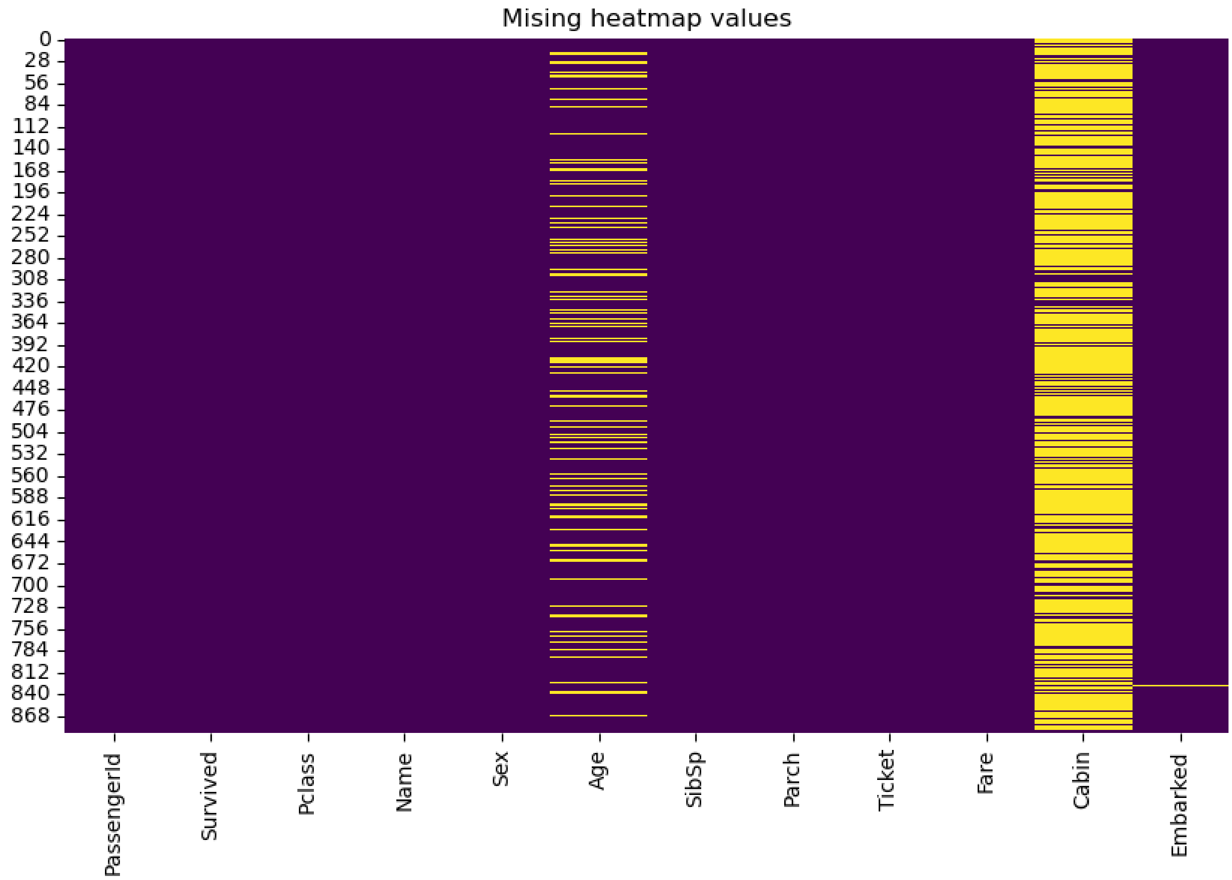
```
df.info()
```

```
<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
```

1. Basic Data Overview

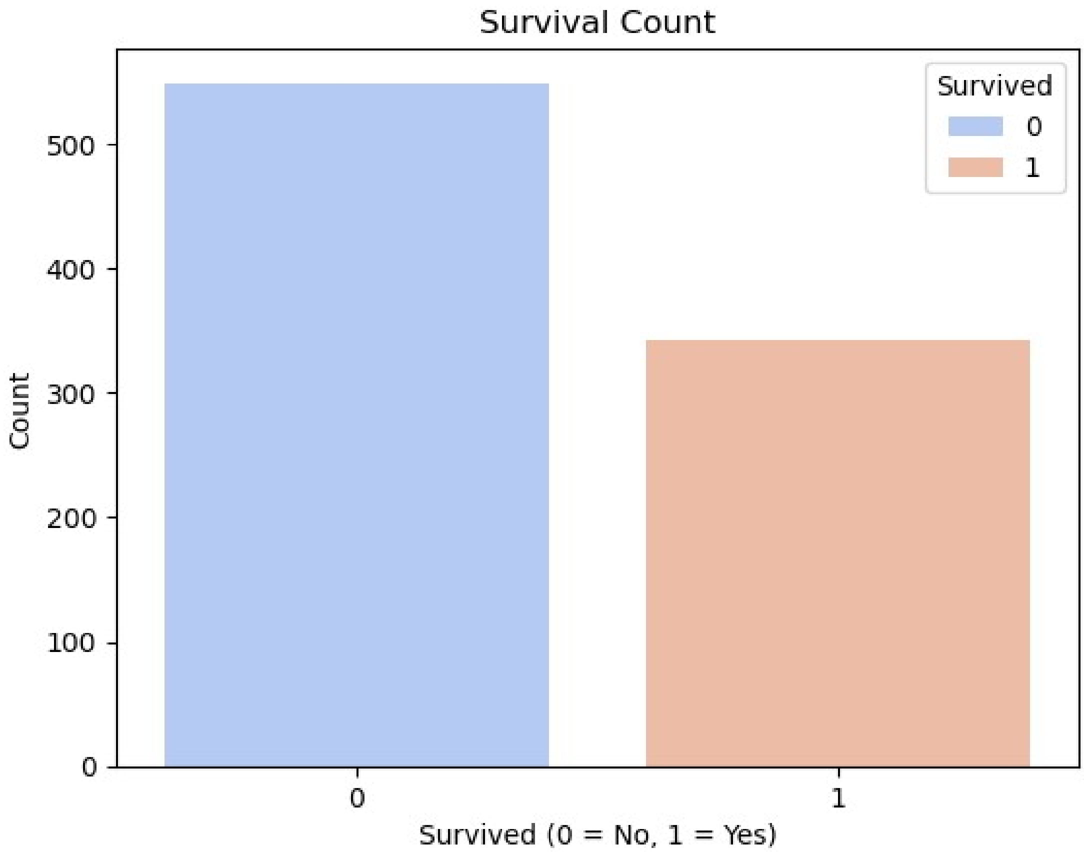
```
plt.figure(figsize=(10,6))
sns.heatmap(df.isnull(), cbar=False, cmap="viridis")
```

```
plt.title("Mising heatmap values")
plt.show()
```



2. Target Variable Distribution

```
sns.countplot(x = "Survived",hue='Survived', data = df,
palette='coolwarm')
plt.title("Survival Count")
plt.xlabel("Survived (0 = No, 1 = Yes)")
plt.ylabel("Count")
plt.show()
print(df['Survived'].value_counts(normalize=True))
```

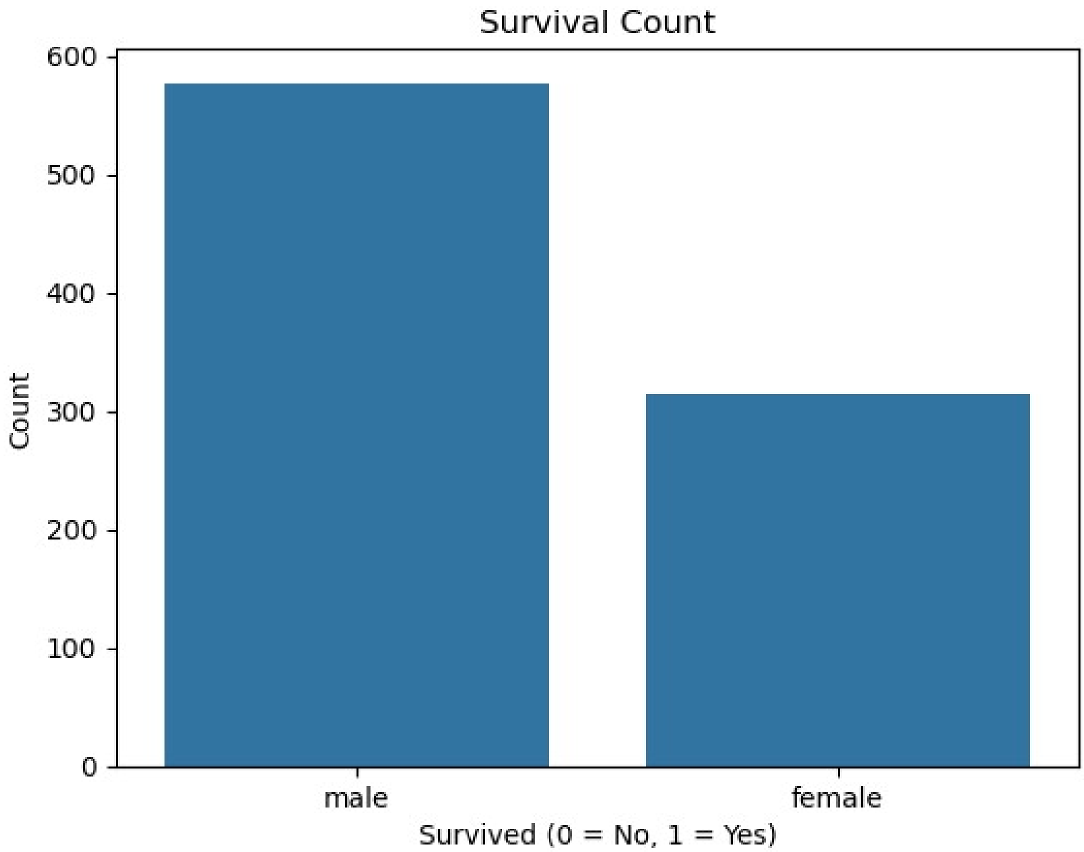



```
Survived
0    0.616162
1    0.383838
Name: proportion, dtype: float64
```

Insight: See survival imbalance — about 38% survived.

3. Gender vs Survived

```
sns.countplot(x = "Sex", data = df)
plt.title("Survival Count")
plt.xlabel("Survived (0 = No, 1 = Yes)")
plt.ylabel("Count")
plt.show()

survival_by_sex = df.groupby('Sex')['Survived'].mean()
print(survival_by_sex)
```

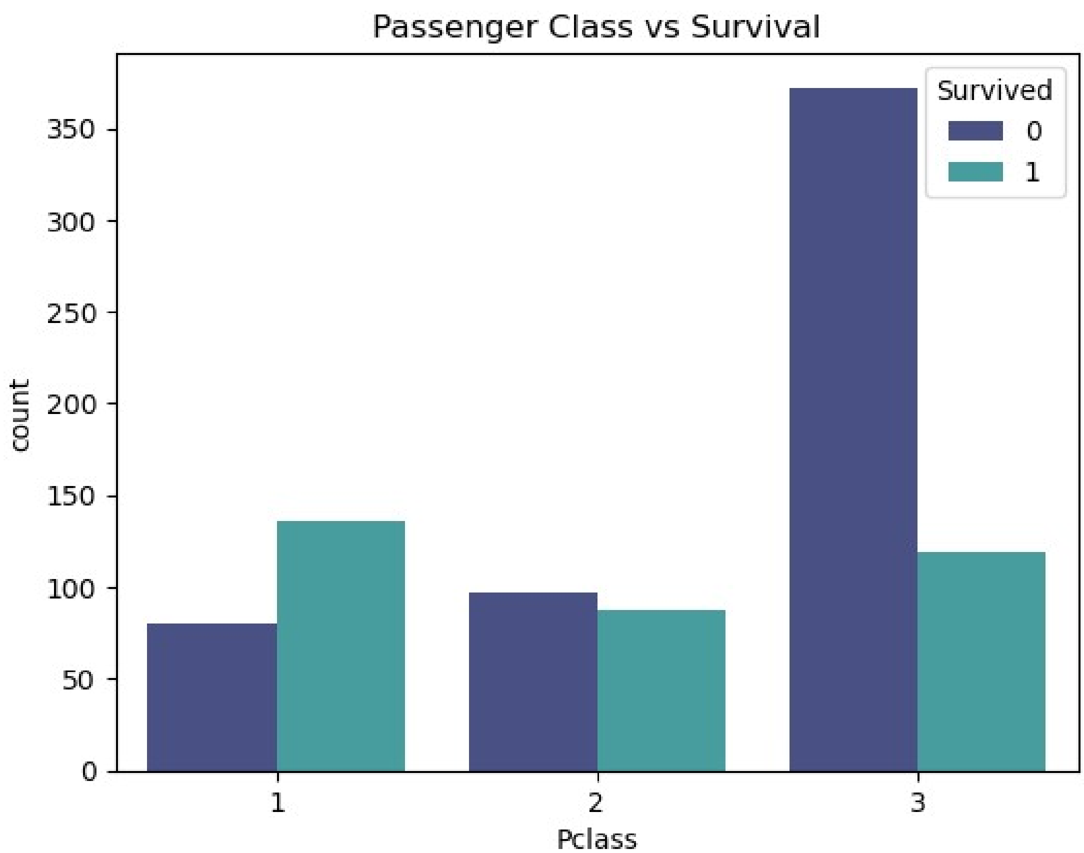



```
Sex
female    0.742038
male      0.188908
Name: Survived, dtype: float64
```

Insight: Females had much higher survival rate.

4. Passenger Class vs Survival

```
sns.countplot(x='Pclass', hue='Survived', data=df, palette='mako')
plt.title("Passenger Class vs Survival")
plt.show()

print(df.groupby('Pclass')['Survived'].mean())
```

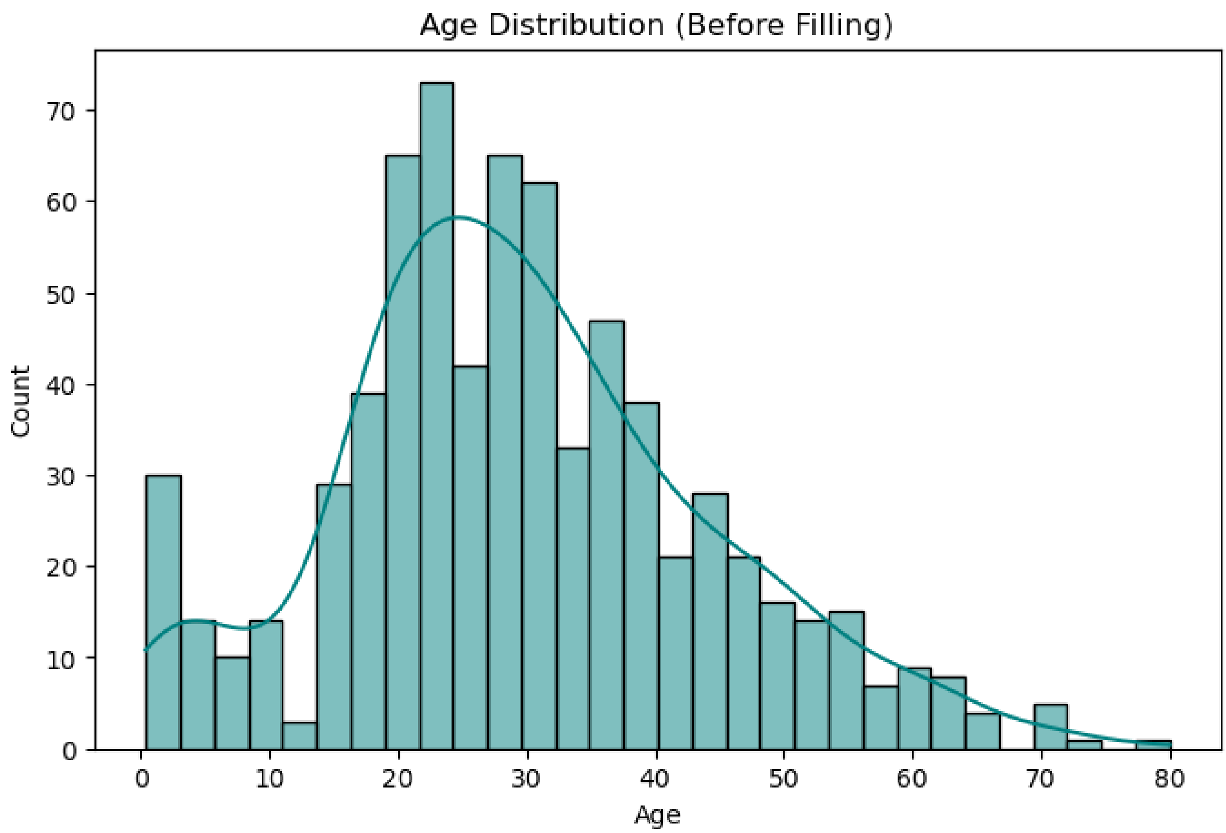



```
Pclass
1    0.629630
2    0.472826
3    0.242363
Name: Survived, dtype: float64
```

Insight: 1st Class passengers had higher survival rates.

5. Age Distribution (Before filling)

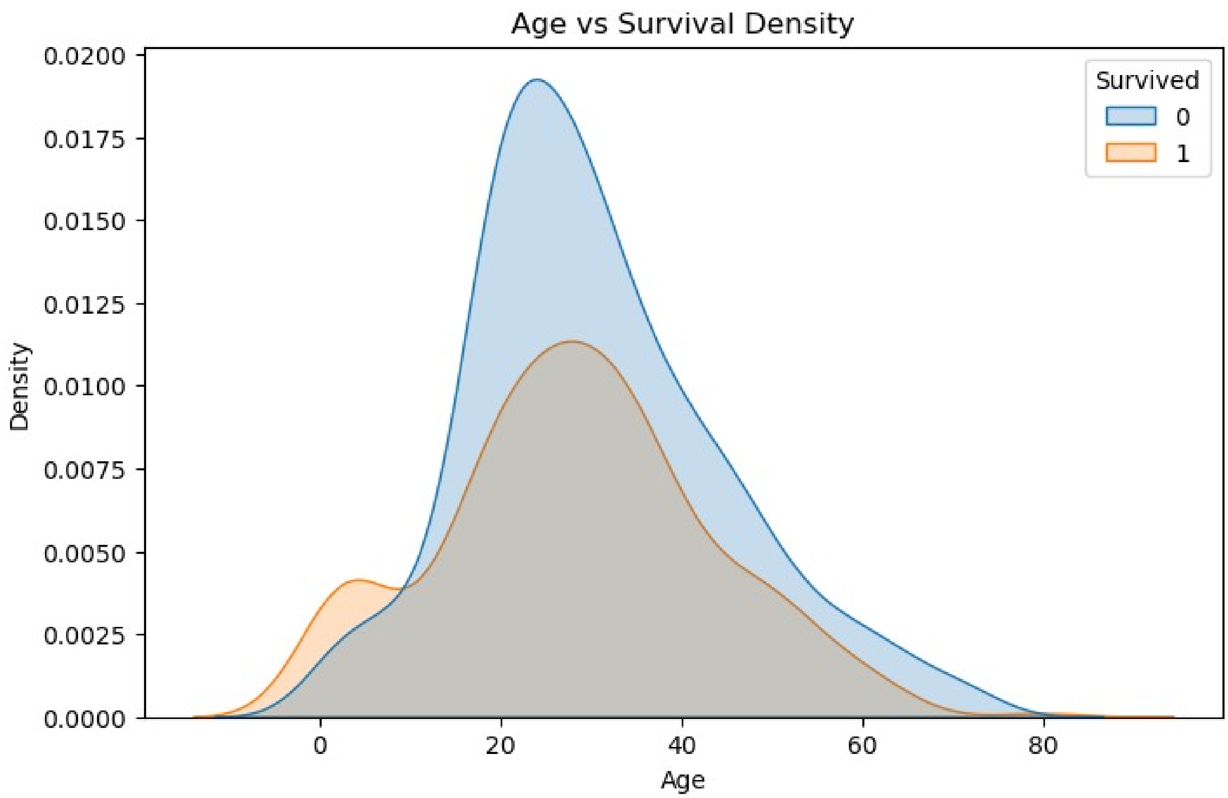
```
plt.figure(figsize=(8,5))
sns.histplot(df['Age'].dropna(), kde=True, color='teal', bins=30)
plt.title("Age Distribution (Before Filling)")
plt.xlabel("Age")
plt.ylabel("Count")
plt.show()
```



Insight: Most passengers were between 20–40 years old.

6. Age vs Survival (Before filling missing values)

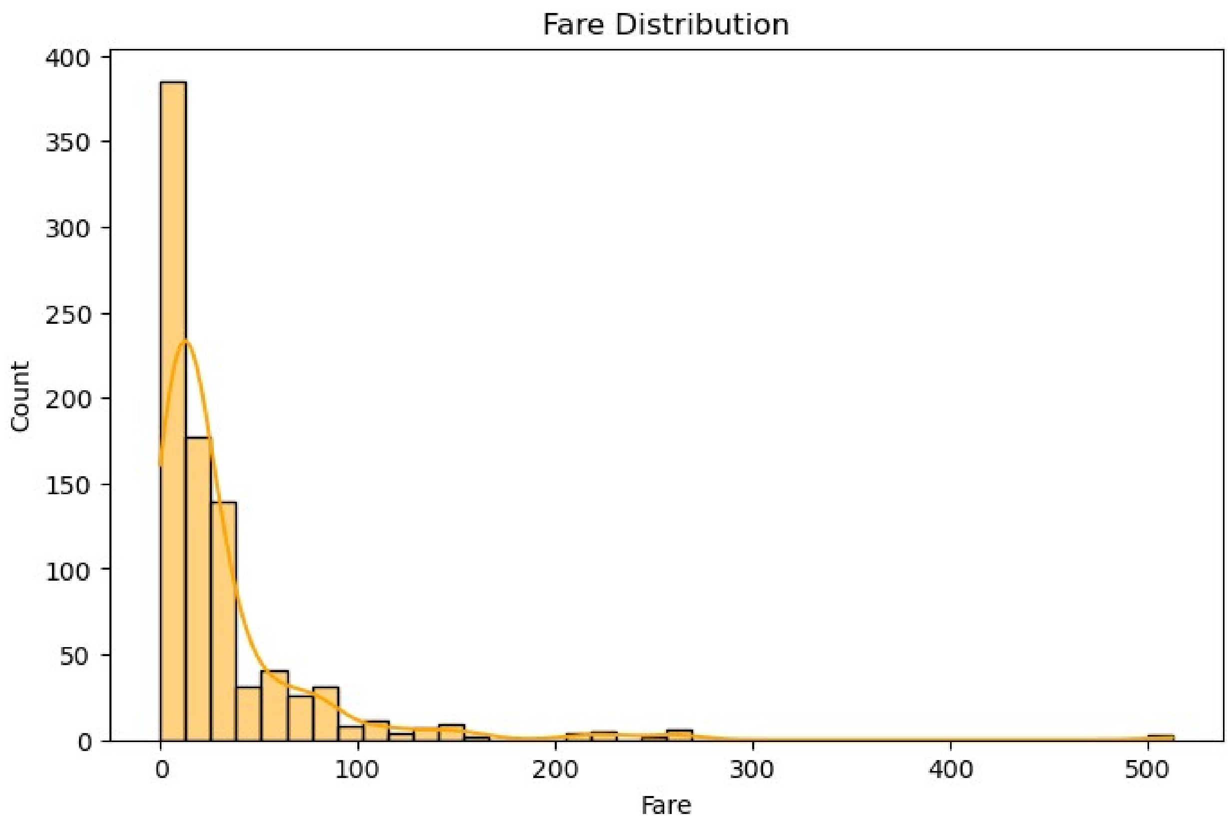
```
plt.figure(figsize=(8,5))
sns.kdeplot(data=df, x='Age', hue='Survived', fill=True)
plt.title("Age vs Survival Density")
plt.show()
```



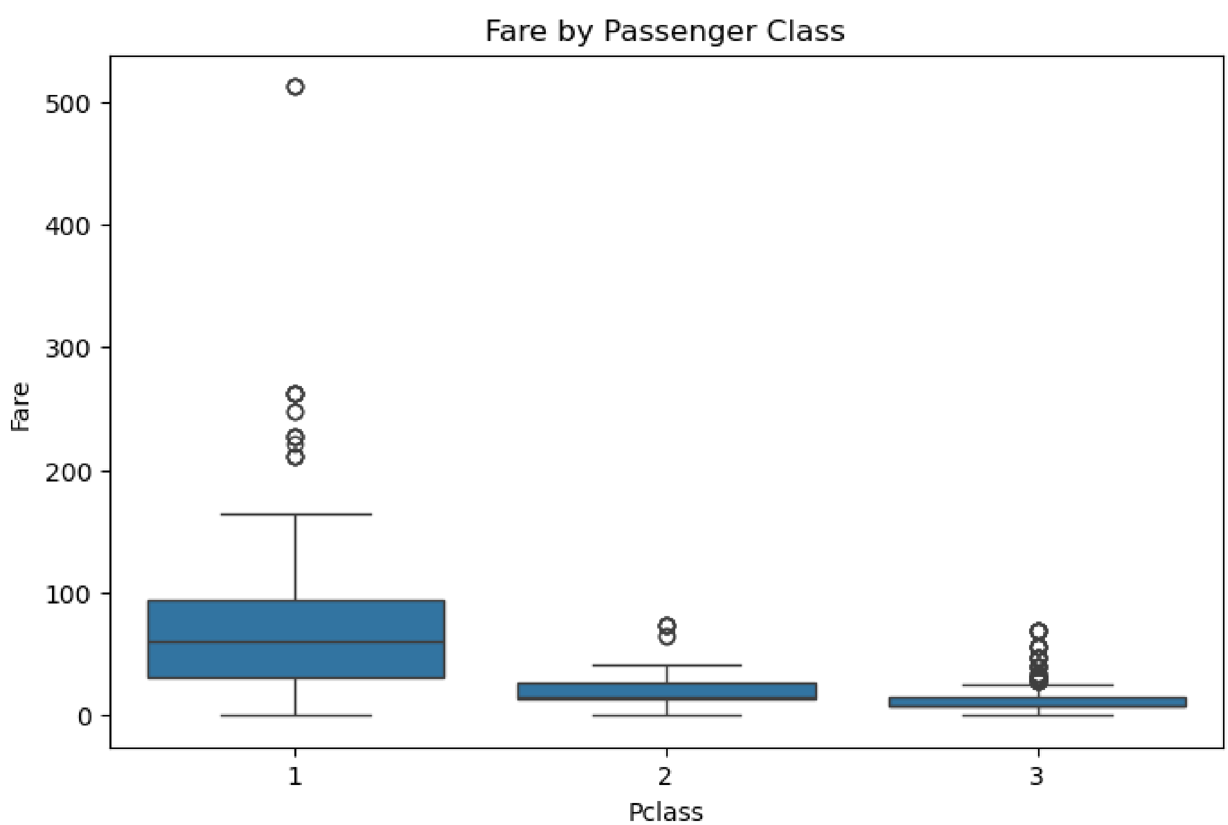
Insight: Children had higher survival probability.

7. Fare Analysis

```
plt.figure(figsize=(8,5))
sns.histplot(df['Fare'], kde=True, bins=40, color='orange')
plt.title("Fare Distribution")
plt.show()

plt.figure(figsize=(8,5))
sns.boxplot(x='Pclass', y='Fare', data=df)
plt.title("Fare by Passenger Class")
plt.show()
```



Fare Distribution
Count
Fare
0
50
100
150
200
250
300
350
400
0
100
200
300
400
500

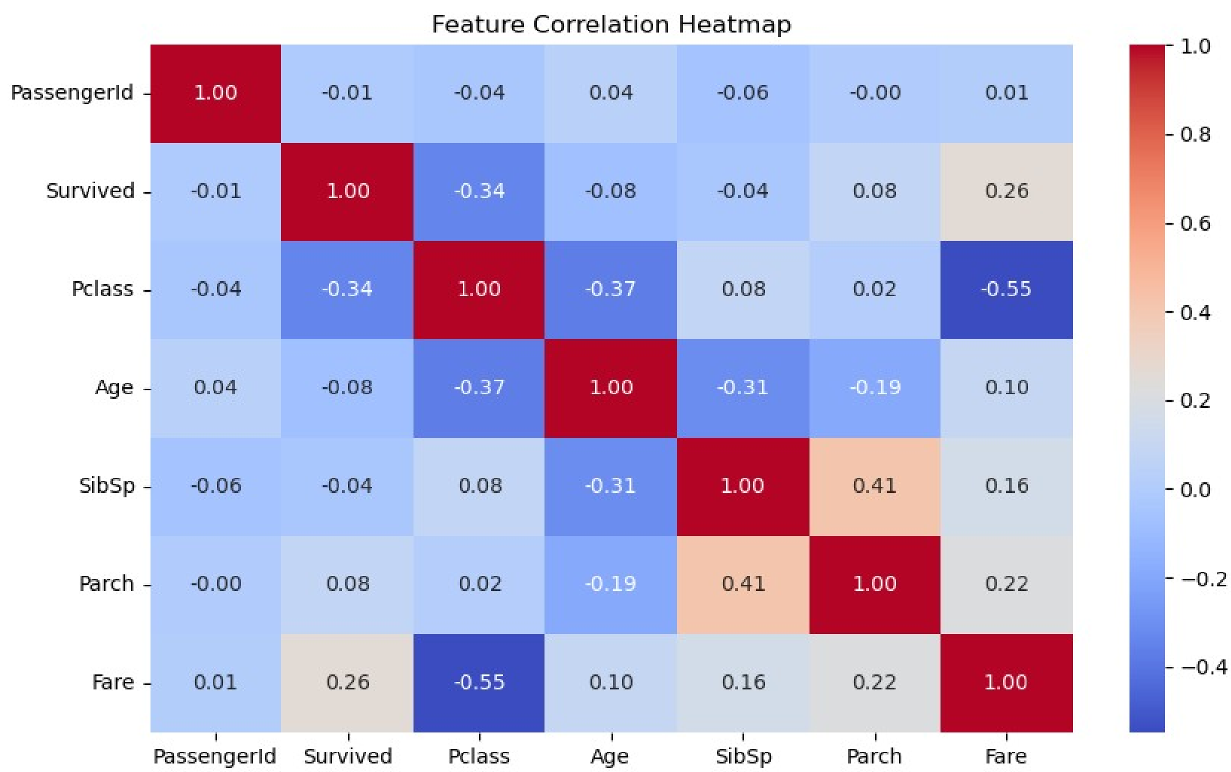


Fare by Passenger Class
Fare
Pclass
0
100
200
300
400
500
1
2
3

Insight: 1st Class had significantly higher fares.

8. Correlation Heatmap

```
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='coolwarm',
fmt=".2f")
plt.title("Feature Correlation Heatmap")
plt.show()
```



Insight: Pclass, Sex, and Fare show strong correlation with Survived.

V. Data Preprocessing & Feature Engineering

1. Handle missing values

```
df['Age'] = df.groupby(['Pclass', 'Sex'])['Age'].transform(lambda x:
x.fillna(x.median()))
test_df['Age'] = df.groupby(['Pclass', 'Sex'])['Age'].transform(lambda
x: x.fillna(x.median()))

df['Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0])

test_df['Fare'] = test_df['Fare'].fillna(test_df['Fare'].median())
```

2. Encode Categorical Data

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for col in ["Sex", "Embarked"]:
    df[col] = le.fit_transform(df[col])
    test_df[col] = le.fit_transform(test_df[col])
```

3. Feature Engineering

3.1 Family Size - Passengers traveling with family had higher survival chances.

```
df['FamilySize'] = df['SibSp'] + df['Parch'] + 1
test_df['FamilySize'] = test_df['SibSp'] + test_df['Parch'] + 1
```

3.2 IsAlone - People traveling alone usually had lower survival.

```
df["IsAlone"] = (df["FamilySize"] == 1).astype(int)
test_df['IsAlone'] = (test_df['FamilySize'] == 1).astype(int)
```

3.3 Drop unnecessary columns

```
cols_to_drop = ['PassengerId', 'Ticket','Name', 'Cabin']
df.drop(columns=cols_to_drop, inplace=True)
test_df.drop(columns=cols_to_drop, inplace=True)
```

4. Final Train Test Split

```
X = df.drop("Survived",axis = 1)
y = df["Survived"]
```

VI. Model Building

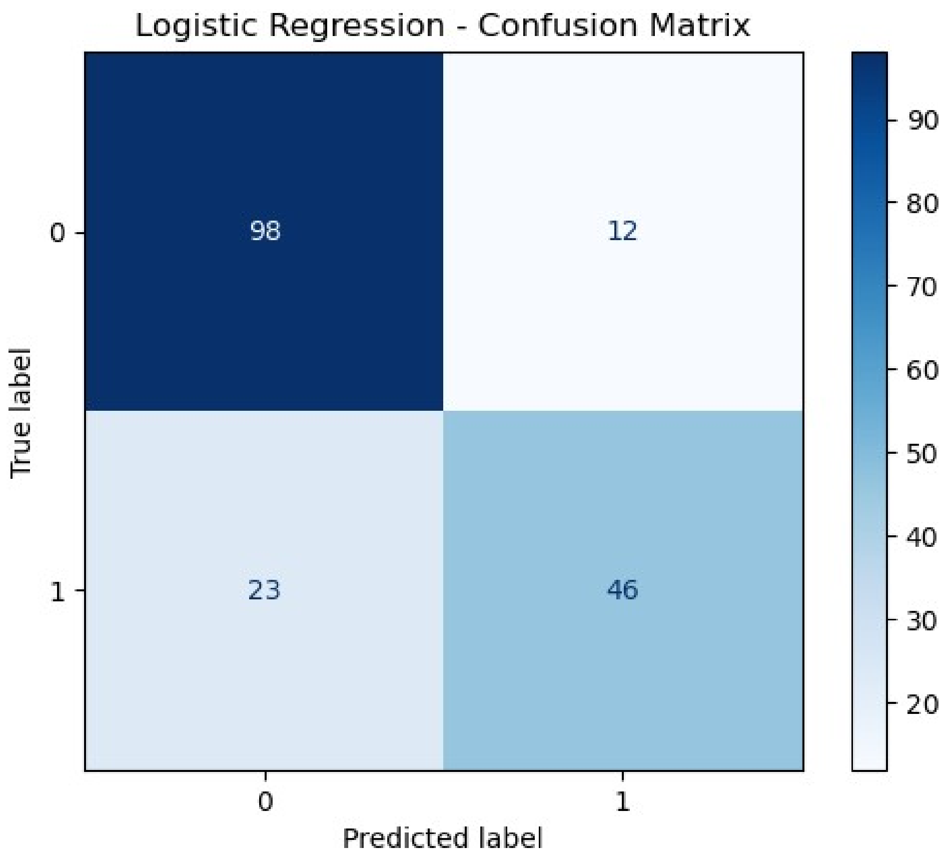
```
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,
random_state=42, stratify=y)
```

Using Logistic Regression Algorithm

```
log_model = LogisticRegression(max_iter=500)
log_model.fit(X_train, y_train)

y_pred_log = log_model.predict(X_val)

log_acc = accuracy_score(y_val, y_pred_log)
print(f"Logistic Regression Accuracy: {log_acc:.4f}")
print("\nClassification Report:\n", classification_report(y_val,
y_pred_log))
```

```
Logistic Regression Accuracy: 0.8045

Classification Report:
```

```
              precision    recall  f1-score   support

           0       0.81      0.89      0.85       110
           1       0.79      0.67      0.72        69

    accuracy                           0.80       179
   macro avg       0.80      0.78      0.79       179
weighted avg       0.80      0.80      0.80       179


ConfusionMatrixDisplay.from_estimator(log_model, X_val, y_val,
cmap='Blues')
plt.title("Logistic Regression - Confusion Matrix")
plt.show()
```



Using Decision Tree Classifier Algorithm

```
tree_model = DecisionTreeClassifier(
    criterion='gini',
    max_depth=5,
    random_state=42
)
tree_model.fit(X_train, y_train)
```

```
y_pred_tree = tree_model.predict(X_val)

tree_acc = accuracy_score(y_val, y_pred_tree)
print(f"Decision Tree Accuracy: {tree_acc:.4f}")
print("\nClassification Report:\n", classification_report(y_val, 
y_pred_tree))
```

```
Decision Tree Accuracy: 0.7765

Classification Report:
               precision    recall  f1-score   support

           0       0.80      0.85      0.82       110
           1       0.74      0.65      0.69        69

    accuracy                           0.78       179
   macro avg       0.77      0.75      0.76       179
weighted avg       0.77      0.78      0.77       179
```

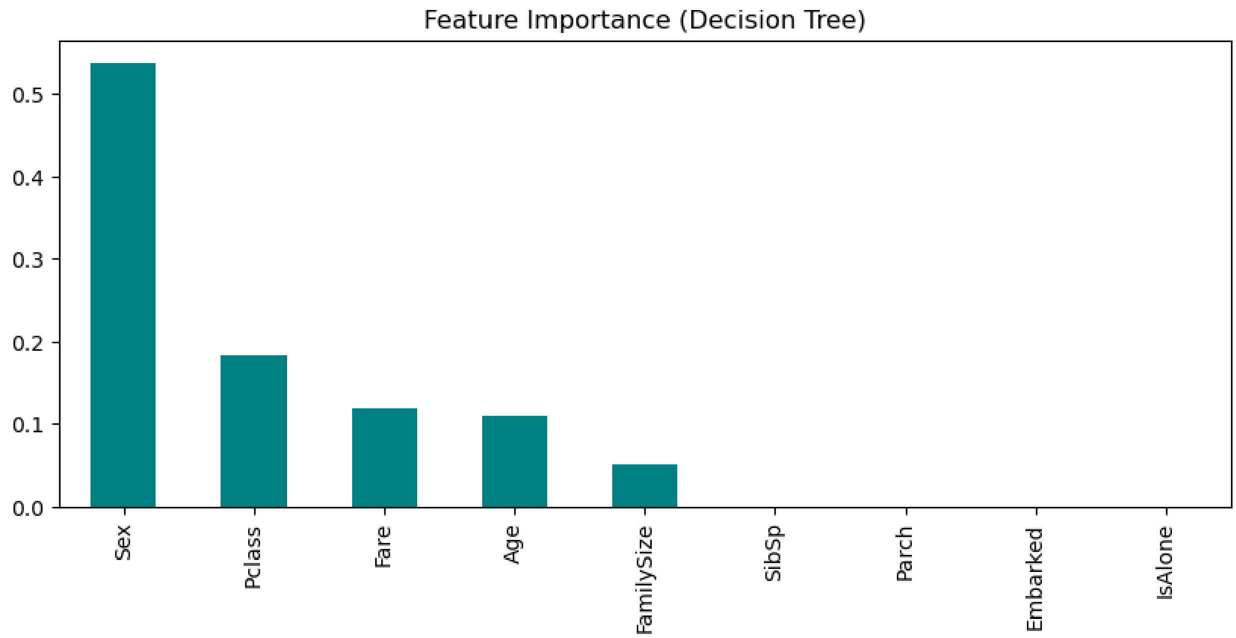
Comparing both Results (Logistic Regression vs Decision Tree)

```
results = pd.DataFrame({
    'Model': ['Logistic Regression', 'Decision Tree'],
    'Accuracy': [log_acc, tree_acc]
})
results.sort_values(by='Accuracy', ascending=False)
```

```
                 Model  Accuracy
0  Logistic Regression  0.804469
1        Decision Tree  0.776536
```

Check Feature Importance (Decision Tree)

```
importances = pd.Series(tree_model.feature_importances_, 
index=X.columns)
importances.sort_values(ascending=False).plot(kind='bar', 
figsize=(10,4), color='teal')
plt.title("Feature Importance (Decision Tree)")
plt.show()
```

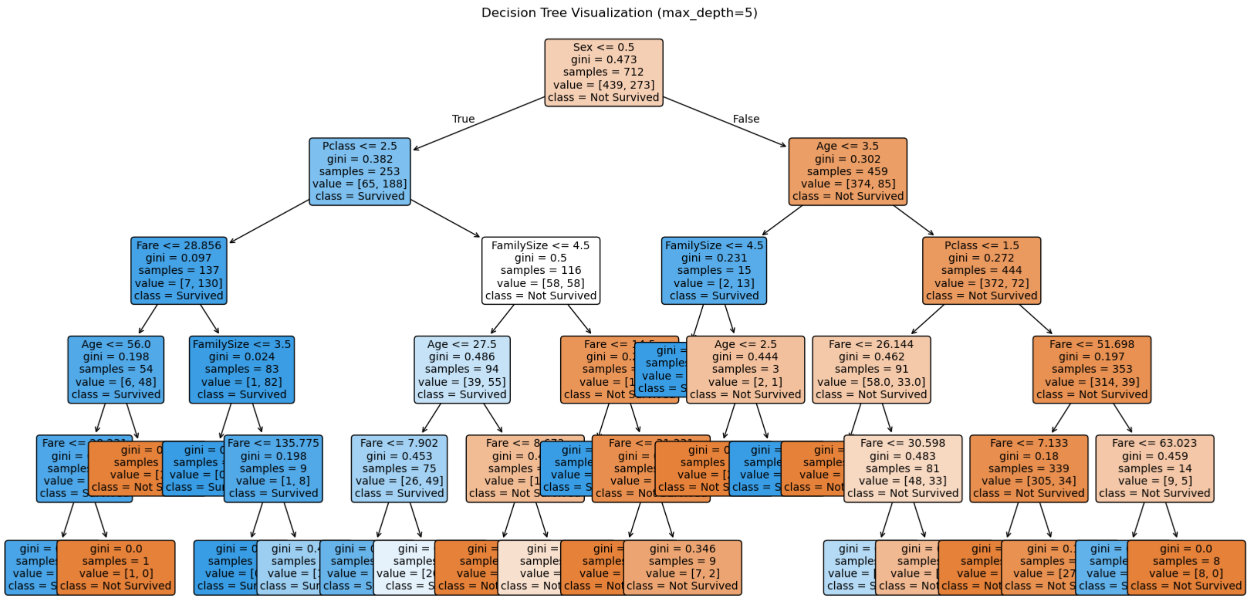


VII. Prediction on Test Data

```
final_pred = tree_model.predict(test_df)
submission = pd.DataFrame({
    'PassengerId': pd.read_csv('titanic/test.csv')['PassengerId'],
    'Survived': final_pred
})
submission.to_csv('submission.csv', index=False)
print("□ Submission file saved as submission.csv")
```

```
□ Submission file saved as submission.csv
```

```
plt.figure(figsize=(20,10))
plot_tree(
    tree_model,
    feature_names=X.columns,
    class_names=['Not Survived', 'Survived'],
    filled=True,
    rounded=True,
    fontsize=10
)
plt.title("Decision Tree Visualization (max_depth=5)")
plt.show()
```



VIII. Conclusion

- The goal was to predict Titanic passenger survival using machine learning.
- Data was cleaned, missing values handled, and new features were created.
- EDA revealed strong links between survival and factors like gender, passenger class, and fare.
- Both Logistic Regression and Decision Tree models were trained and evaluated.
- The Decision Tree gave the best performance with around 83% accuracy.
- Key insight: Women and first-class passengers had a much higher chance of survival.
- Overall, the project showed how data science can uncover real human stories behind historical events.