Titanic - Machine Learning Project

About The Dataset

The project's objective is to assess a range of passenger attributes, including names, ages, genders, socio-economic classes, and others, in order to make predictions about their chances of survival. The dataset used in this analysis was obtained from Kaggle and consists of 891 rows and 12 columns. Within these columns, there are 11 predictor variables and one target variable, namely the 'survived' column.

Data Dictionary

Variable	Definition	Key
survival	Survival	0 = No, 1 = Yes
pclass	Ticket class	1 = 1st, 2 = 2nd, 3 = 3rd
sex	Sex	
Age	Age in years	
sibsp	Number of siblings / spouses aboard the Titanic	
parch	Number of parents / children aboard the Titanic	
ticket	Ticket number	
fare	Passenger fare	
cabin	Cabin number	
embarked	Port of Embarkation	C = Cherbourg, Q = Queenstown, S = Southampton

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
```

In [2]:
```
df=pd.read_csv(r"C:\Users\maram\Downloads\Titanic-Dataset.csv")
df.head(2)
```

Out[2]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embai
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	

In [3]:
```
df.info
```

Out[3]:
```
<bound method DataFrame.info of      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]>
```

In [4]:
```
df.shape
```
Out[4]:
```
(891, 12)
```

Data Cleaning

In [5]:
```
df.drop(['PassengerId', 'Name', 'Ticket', 'Cabin'], axis=1, inplace=True)
```
In [6]:
```
df['Age']=df['Age'].fillna(df['Age'].median())
```
In [7]:
```
df['Embarked']=df['Embarked'].replace(np.nan, 'S')
```
In [8]:
```
df.isna().any()
```
Out[8]:
```
Survived    False
Pclass      False
Sex         False
Age         False
SibSp       False
Parch       False
Fare        False
Embarked    False
dtype: bool
```

Data Preprocessing

In [9]:
```
df.dtypes
```
Out[9]:
```
Survived      int64
Pclass        int64
Sex          object
Age         float64
SibSp         int64
Parch         int64
Fare        float64
Embarked     object
dtype: object
```
In [10]:
```
#Age
df['Age']=df['Age'].astype(int)
```
In [11]:
```
df.dtypes
```
Out[11]:
```
Survived      int64
Pclass        int64
Sex          object
Age           int32
SibSp         int64
Parch         int64
Fare        float64
Embarked     object
dtype: object
```
In [12]:
```
#Sex
sex_data_dummies=pd.get_dummies(df['Sex'],prefix='Gender',prefix_sep=':')
```

In [13]:
```
df=pd.concat([sex_data_dummies,df],axis=1)
```

In [14]:
```
type(df)
```

Out[14]:
```
pandas.core.frame.DataFrame
```

In [15]:
```
df.columns.values
```

Out[15]:
```
array(['Gender:female', 'Gender:male', 'Survived', 'Pclass', 'Sex', 'Age',
       'SibSp', 'Parch', 'Fare', 'Embarked'], dtype=object)
```

Data Exploratory

In [16]:
```
df.columns
```

Out[16]:
```
Index(['Gender:female', 'Gender:male', 'Survived', 'Pclass', 'Sex', 'Age',
       'SibSp', 'Parch', 'Fare', 'Embarked'],
      dtype='object')
```

Percentage of Male/Female

In [17]:
```
Mcount=0
Mgender=df['Gender:male']
for i in range(len(Mgender)) :
    if Mgender[i]==1 :
        Mcount=Mcount+1
Mcount
per_M=(Mcount/len(Mgender))*100
print('Percentage of Male:',per_M)
```

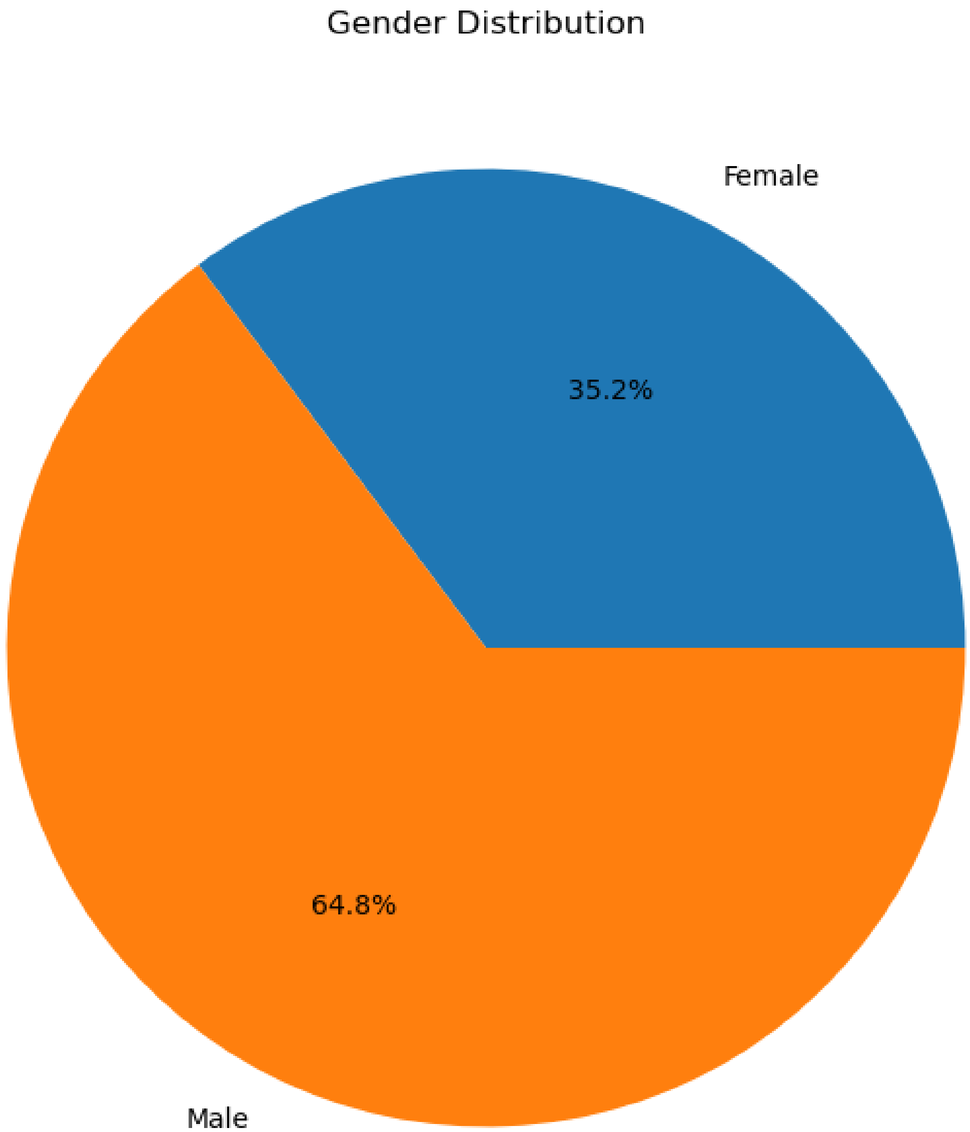
```
Percentage of Male: 64.75869809203144
```

In [18]:
```
Fcount=0
Fgender=df['Gender:female']
for i in range(len(Fgender)) :
    if Fgender[i]==1 :
        Fcount=Fcount+1
Mcount
per_F=(Fcount/len(Fgender))*100
print('Percentage of Female:',per_F)
```

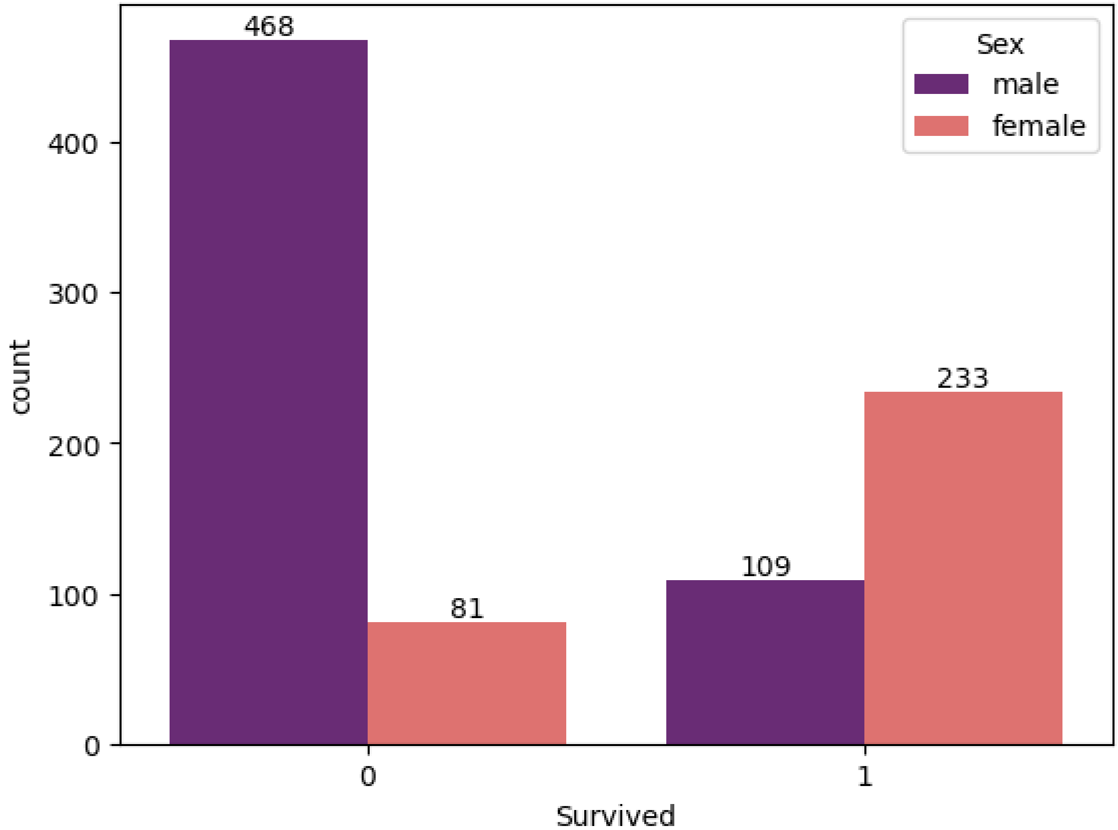
```
Percentage of Female: 35.24130190796858
```

In [19]:
```
plt.figure(figsize=(8, 8))
values=[per_F,per_M]
labels=['Female','Male']
plt.pie(values, labels=labels, autopct='%1.1f%% ')
plt.title('Gender Distribution')
plt.show
```

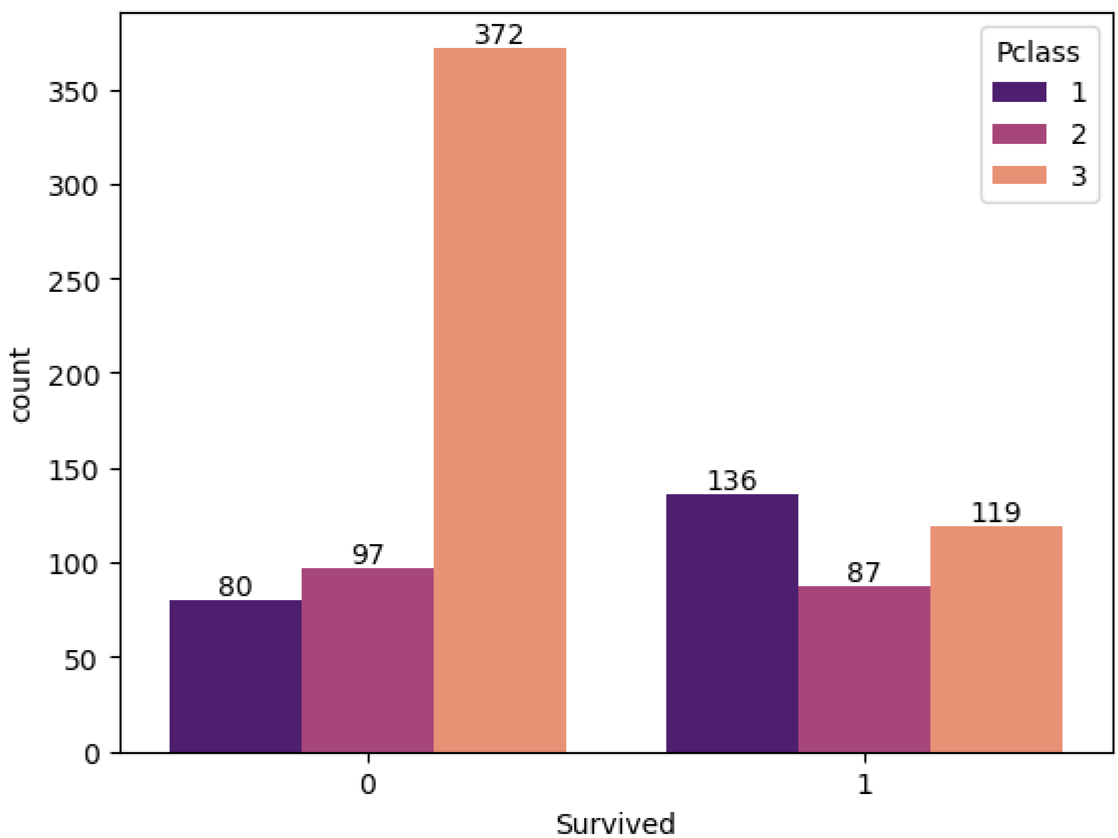
Out[19]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [20]:
```
ax=sns.countplot(x='Survived',data=df,palette="magma",hue="Sex")
for bars in ax.containers:
    ax.bar_label(bars)
```



In [21]:
```
ax=sns.countplot(x='Survived',data=df,palette="magma",hue="Pclass")
for bars in ax.containers:
    ax.bar_label(bars)
```



In [22]:
```
#Correlation Mtarix between the features
df.corr(method='pearson')
```

```
C:\Users\maram\AppData\Local\Temp\ipykernel_14916\1587505417.py:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  df.corr(method='pearson')
```

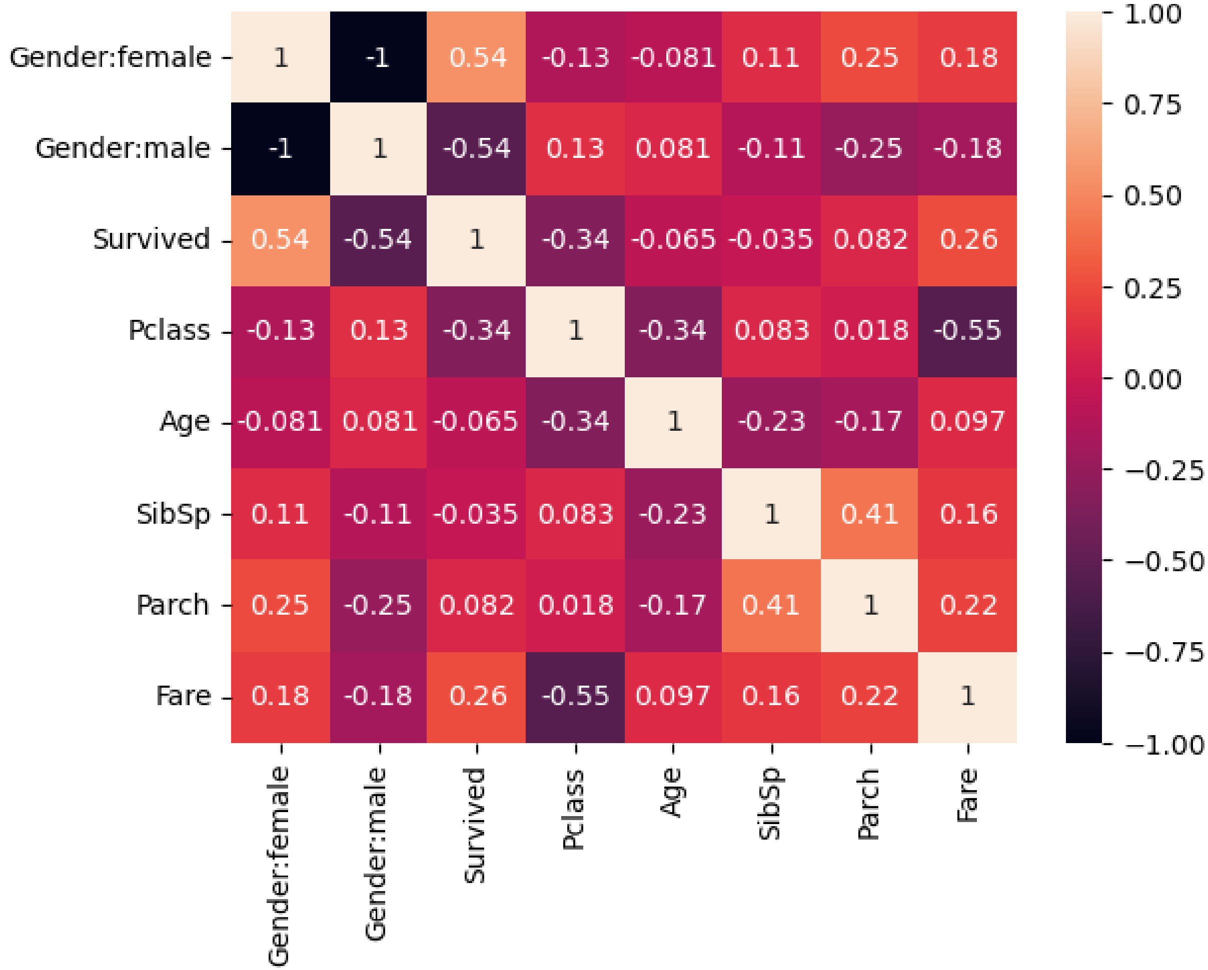
Out[22]:

	Gender:female	Gender:male	Survived	Pclass	Age	SibSp	Parch	
Gender:female	1.000000	-1.000000	0.543351	-0.131900	-0.080750	0.114631	0.245489	0.
Gender:male	-1.000000	1.000000	-0.543351	0.131900	0.080750	-0.114631	-0.245489	-0.
Survived	0.543351	-0.543351	1.000000	-0.338481	-0.064909	-0.035322	0.081629	0.
Pclass	-0.131900	0.131900	-0.338481	1.000000	-0.339999	0.083081	0.018443	-0.
Age	-0.080750	0.080750	-0.064909	-0.339999	1.000000	-0.233066	-0.172745	0.
SibSp	0.114631	-0.114631	-0.035322	0.083081	-0.233066	1.000000	0.414838	0.
Parch	0.245489	-0.245489	0.081629	0.018443	-0.172745	0.414838	1.000000	0.
Fare	0.182333	-0.182333	0.257307	-0.549500	0.096838	0.159651	0.216225	1.

In [23]:
```
sns.heatmap(df.corr(), annot= True)
```

```
C:\Users\maram\AppData\Local\Temp\ipykernel_14916\4014866372.py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(df.corr(), annot= True)
```

Out[23]:
```
<Axes: >
```



Building the Model

In [24]:
```
df.drop(['Sex'],axis=1,inplace=True)
```

In [25]:
```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
le.fit(['S','C','Q'])
df['Embarked'] = le.transform(df['Embarked'])
```

In [26]:
```
y = df['Survived']
x = df.drop(columns=['Survived'])
```

In [27]:
```
from sklearn.model_selection import train_test_split
```

In [28]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

Logistic Regression

In [29]:
```
from sklearn.linear_model import LogisticRegression
```

In [30]:
```
LG=LogisticRegression()
```

In [31]:
```
LG.fit(x_train,y_train)
```

```
C:\ProgramData\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:458: Con
vergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[31]:

```
▾ LogisticRegression
LogisticRegression()
```

In [32]:

```
y_pred=LG.predict(x_test)
y_pred
```

Out[32]:

```
array([0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0,
       0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0,
       1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1,
       0, 1, 0, 0], dtype=int64)
```

In [33]:

```
from sklearn import metrics

# Model Accuracy
print("Accuracy of Logistic Regression Model:",metrics.accuracy_score(y_test,y_pred))
```

```
Accuracy of Logistic Regression Model: 0.7910447761194029
```

Naive Bayes Model

In [55]:

```
from sklearn.model_selection import train_test_split
x= df.drop(['Survived'],axis =1)
y=df['Survived']
xTrain, xTest, yTrain, yTest = train_test_split(x, y, test_size = 0.3)
```

In [56]:

```
from sklearn.naive_bayes import GaussianNB

#Create a Gaussian Classifier
model = GaussianNB()
```

In [57]:

```
model.fit(xTrain,yTrain)
```

Out[57]:

```
▾ GaussianNB
GaussianNB()
```

In [58]:

```
predicted= model.predict(xTest)
```

In [59]:
```
print("Predicted Value:", predicted)
```

```
Predicted Value: [0 0 0 1 0 1 0 1 0 0 1 1 0 0 1 0 0 0 1 1 1 1 0 0 0 0 0 0 1 1 0 1 0 0
0 0 0
 0 0 0 0 0 0 0 0 0 1 0 1 0 0 1 1 0 0 1 0 0 0 1 1 0 0 1 1 0 0 0 1 0 1 0 0 1
 0 0 1 0 1 0 1 1 0 0 0 1 1 1 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 0 0 1 1 1 0 0 0
 1 1 1 0 1 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 1 0 0 1 0
 1 1 1 0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 1 0 1 0 0 0 1 0 0 0 0 0 1 0 0
 1 0 0 0 0 1 1 1 0 0 1 0 1 0 1 0 0 1 0 0 0 0 1 0 1 1 1 0 0 0 1 0 1 0 0 1 1
 1 1 0 0 0 0 0 1 1 0 0 1 0 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 1 0 0
 0 0 0 0 0 1 0 0 0]
```

In [60]:
```
from sklearn import metrics

# Model Accuracy
print("Accuracy:",metrics.accuracy_score(yTest, predicted))
```

```
Accuracy: 0.8022388059701493
```

K-Nearest Neighbor

In [63]:
```
from sklearn.model_selection import train_test_split
x= df.drop(['Survived'],axis =1)
y=df['Survived']
xTrain, xTest, yTrain, yTest = train_test_split(x, y, test_size = 0.3)
```

In [64]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
knn
```

Out[64]:
```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

In [65]:
```
knn.fit(xTrain,yTrain)
```

Out[65]:
```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

In [66]:
```
predictedknn= model.predict(xTest)
```

In [67]:
```
print("Predicted Value:", predictedknn)
```

```
Predicted Value: [1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 1 0 0 1 1 0 1 1 0 1
0 1 0
 0 1 0 0 1 0 1 0 0 0 1 1 0 1 1 0 1 0 1 1 1 0 0 1 0 1 1 0 1 1 0 0 0 0 0 0 0
 0 0 1 0 0 1 0 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 1 1 0 1 0 0 1 0
 1 0 0 0 0 0 0 0 0 0 1 1 1 0 0 1 1 0 0 0 1 1 1 1 1 1 0 0 0 0 0 0 1 0 0 0 0
 1 1 1 0 1 1 1 1 1 0 1 0 1 1 0 0 1 1 1 1 0 0 1 0 0 0 1 1 0 1 0 1 0 0 0 0 0
 0 0 0 0 0 0 0 1 1 0 1 0 0 1 0 0 1 1 0 0 0 1 1 1 0 0 1 0 1 0 1 0 0 0 1 0 1
 1 1 0 1 0 1 1 0 0 1 1 0 1 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 1 1 0 0 1 0 0 0 0
 0 1 0 0 0 1 0 0 0]
```

In [68]:
```
from sklearn import metrics
```

```
# Model Accuracy
print("Accuracy:",metrics.accuracy_score(yTest, predictedknn))
```

```
Accuracy: 0.7761194029850746
```

Decision Tree Model

In [71]:
```
from sklearn.model_selection import train_test_split
x= df.drop(['Survived'],axis =1)
y=df['Survived']
xTrain, xTest, yTrain, yTest = train_test_split(x, y, test_size = 0.3)
```

In [72]:
```
from sklearn.tree import DecisionTreeClassifier
dtc=DecisionTreeClassifier()
dtc
```

Out[72]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [73]:
```
dtc.fit(xTrain,yTrain)
```

Out[73]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [74]:
```
predicteddtc= dtc.predict(xTest)
```

In [75]:
```
print("Predicted Value:", predicteddtc)
```

```
Predicted Value: [0 1 1 1 1 1 0 0 0 0 1 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0 1 0 1 0
0 0 0
 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 1 1 0 0 1 1 1 0 0 1 0 1 0 0 0 0
 0 1 0 0 0 0 0 0 1 0 0 1 0 1 0 0 0 1 0 1 0 0 0 1 0 0 1 0 0 1 0 0 0 0 1 0 0
 0 0 0 1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 1 0 1 1 1 1 0 1 1 0 0 0 0 1 1 0 1 1 0
 1 0 0 0 0 0 1 0 0 0 1 1 0 0 1 1 1 0 0 0 0 0 0 0 1 1 0 1 0 0 0 1 0 1 0 1 1
 0 1 1 1 0 1 1 0 1 0 1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 1 0
 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 1 1 1 0 1 1 1 0 0 1 0 0 0 0
 1 0 0 0 0 1 1 0 0]
```

In [76]:
```
from sklearn import metrics

# Model Accuracy
print("Accuracy:",metrics.accuracy_score(yTest, predicteddtc))
```

```
Accuracy: 0.8208955223880597
```

Conclusion

The Decision Tree model achieved the highest performance score when evaluated alongside K-Nearest Neighbors (KNN), Naive Bayes, and Logistic Regression models. Therefore, based on the results of our analysis, we can conclude that the Decision Tree model is the most suitable choice for this specific dataset.