Task1Titanic-survival-prediction-Codsoft

August 4, 2024

1 CodSoft DataScience Internship

1.1 Task 1: TITANIC SURVIVAL PREDICTION

[43]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[4]:
```
df = pd.read_csv("Titanic-Dataset.csv")
df.head()
```

[4]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         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

   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
```

Droping unnecessary Columns in the dataset

[5]:
```
new_df=df.drop(['PassengerId','Name','Cabin','Ticket'],axis=1)
new_df.head()
```

[5]:
```
   Survived  Pclass     Sex   Age  SibSp  Parch     Fare Embarked
0         0       3    male  22.0      1      0   7.2500        S
1         1       1  female  38.0      1      0  71.2833        C
2         1       3  female  26.0      0      0   7.9250        S
3         1       1  female  35.0      1      0  53.1000        S
4         0       3    male  35.0      0      0   8.0500        S
```

[6]:
```python
new_df.describe().round(3)
```

[6]:
```
       Survived   Pclass      Age    SibSp    Parch     Fare
count   891.000  891.000  714.000  891.000  891.000  891.000
mean      0.384    2.309   29.699    0.523    0.382   32.204
std       0.487    0.836   14.526    1.103    0.806   49.693
min       0.000    1.000    0.420    0.000    0.000    0.000
25%       0.000    2.000   20.125    0.000    0.000    7.910
50%       0.000    3.000   28.000    0.000    0.000   14.454
75%       1.000    3.000   38.000    1.000    0.000   31.000
max       1.000    3.000   80.000    8.000    6.000  512.329
```

[7]:
```python
new_df.isnull().sum()
```

[7]:
```
Survived      0
Pclass        0
Sex           0
Age         177
SibSp         0
Parch         0
Fare          0
Embarked      2
dtype: int64
```

Handling Null Values and Pre Processing the dataset.

[8]:
```python
new_df['Age'] = new_df['Age'].fillna(new_df['Age'].mean())
```

[9]:
```python
new_df['Embarked']=new_df['Embarked'].fillna(new_df['Embarked'].value_counts().
 ↪idxmax())
```

[10]:
```python
new_df.isnull().sum()
```

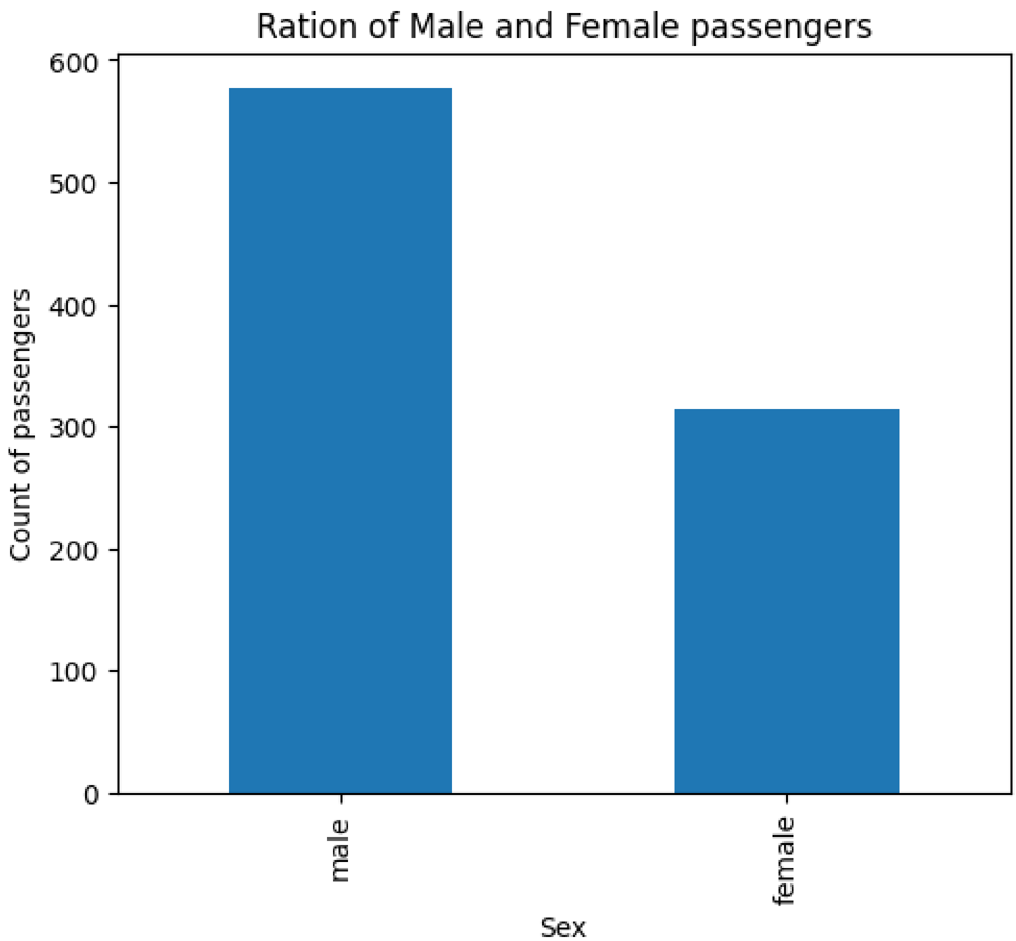
[10]:
```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
```

```
Embarked    0
dtype: int64
```

every columns are free from missing value

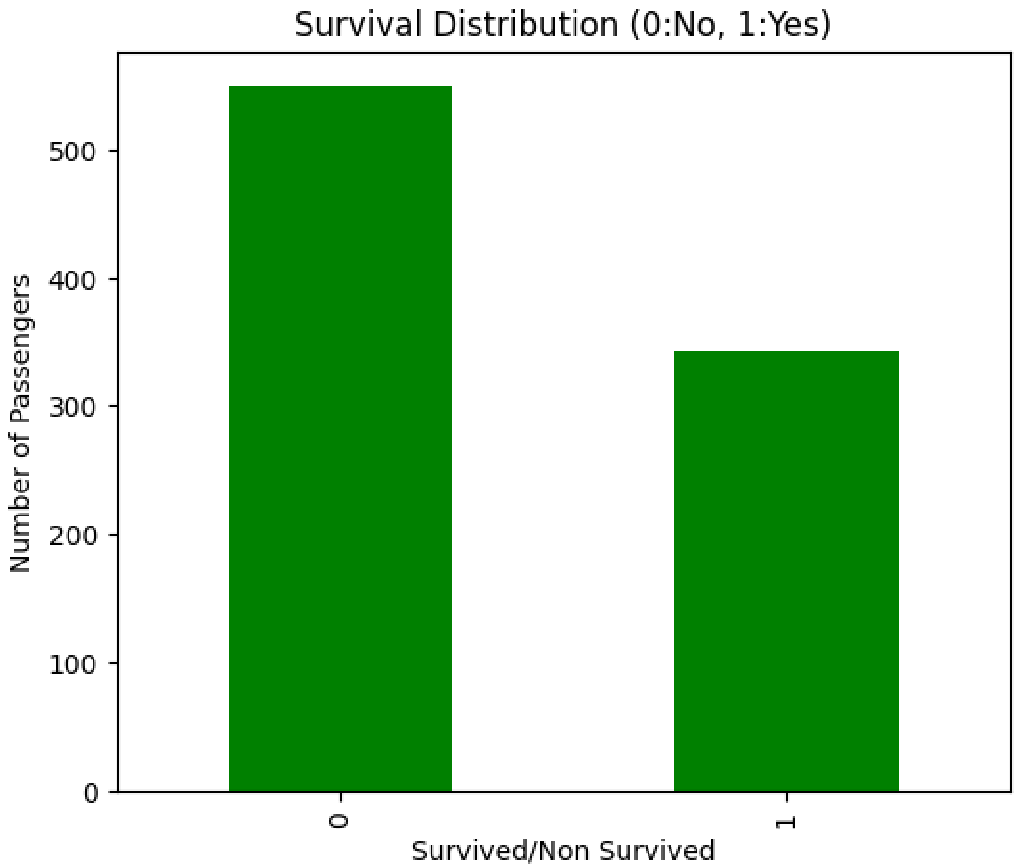
2 Exploratory Data Analysis

```
[11]: # Data Visualization
ax1 = new_df['Sex'].value_counts().plot(kind='bar',x='Survived',
                                        figsize=(6,5))
plt.title("Ration of Male and Female passengers")
plt.ylabel("Count of passengers")
plt.xlabel("Sex")
plt.show()
```



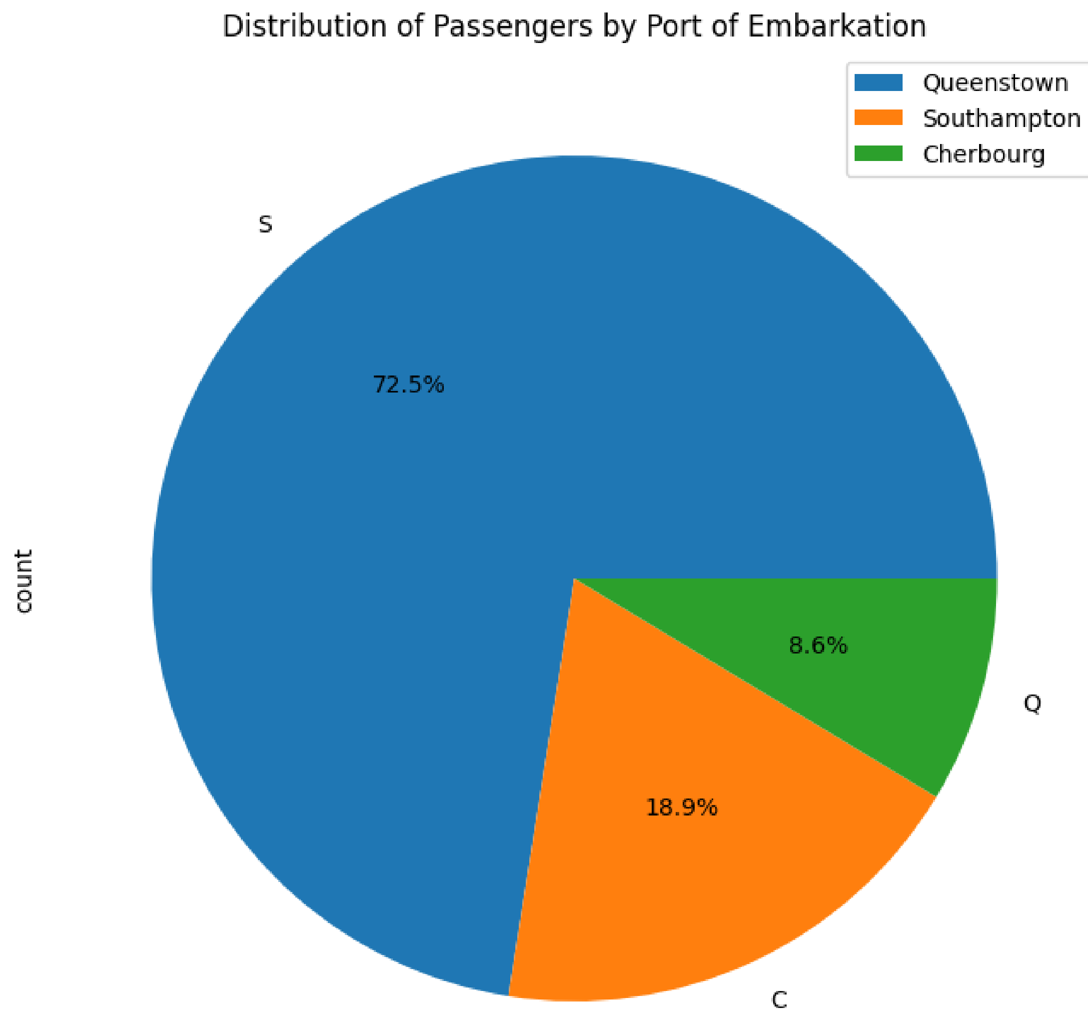
Here we cann see there is more male passengers than female passenger

[12]:
```
new_df['Survived'].value_counts().plot(kind='bar',
                                        figsize=(6,5),color="g")
plt.title("Survival Distribution (0:No, 1:Yes)")
plt.ylabel("Number of Passengers")
plt.xlabel("Survived/Non Survived")
plt.show()
```



From the above graph we can conclude there is more number of deaths than Survived passengers. Rest in peace.

[13]:
```
new_df['Embarked'].value_counts().plot(kind='pie',figsize=(8,20), autopct = '%1.
↪1f%%')
plt.title("Distribution of Passengers by Port of Embarkation")
plt.legend(['Queenstown','Southampton','Cherbourg'])
plt.show()
```



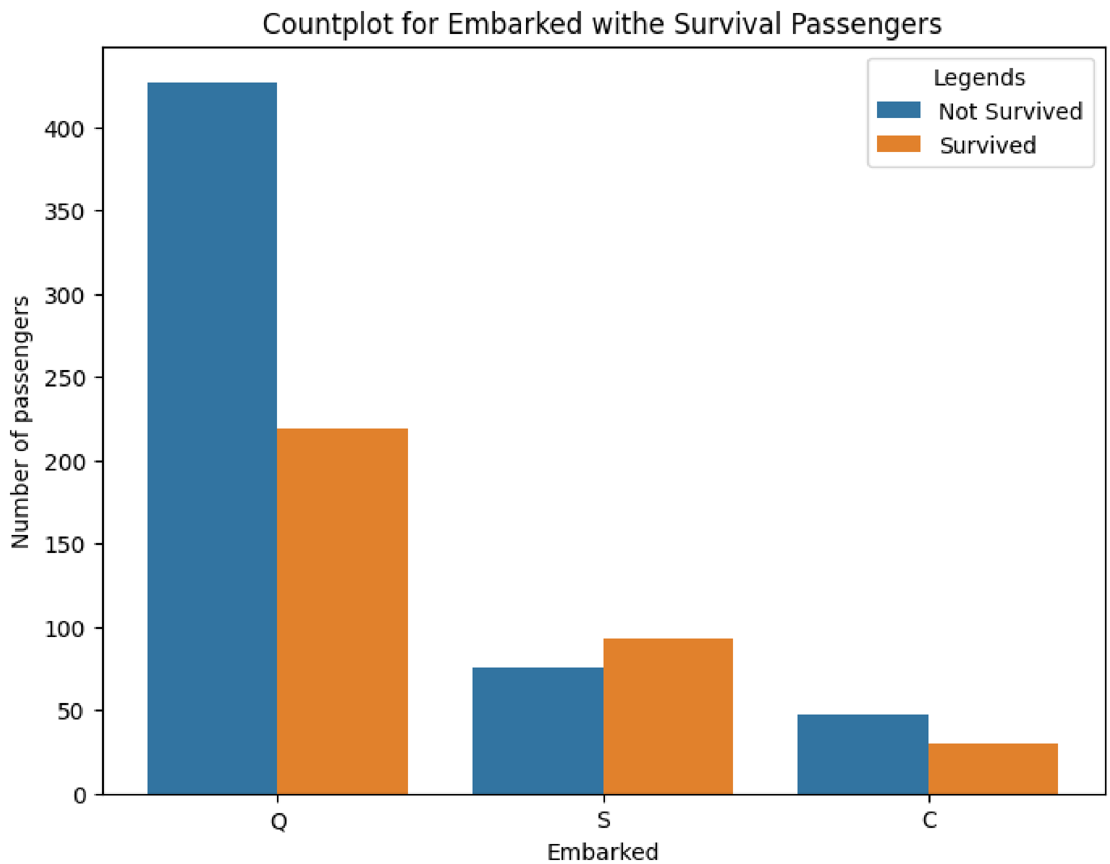
From the above pie chart the most passengers are from Southampton

[20]:
```
_, ax = plt.subplots(figsize=(8,6))
sns.countplot(data = new_df, x = "Embarked", hue = "Survived", ax = ax)
ax.set_title("Countplot for Embarked withe Survival Passengers")
ax.set_xlabel("Embarked")
ax.set_xticklabels(['Q','S','C'])
ax.set_ylabel("Number of passengers")
ax.legend(title = 'Legends', labels = ['Not Survived','Survived'])
plt.plot()
```

```
/tmp/ipykernel_3956/561260779.py:5: UserWarning: set_ticklabels() should only be
used with a fixed number of ticks, i.e. after set_ticks() or using a
```

```
FixedLocator.
  ax.set_xticklabels(['Q','S','C'])
```

[20]: []



[ ]:

3 Developing Machine learning model to predict survival

Changing the categorical data into numerical data by using Label Encoder

[21]:
```
new_df['Sex'] = new_df['Sex'].apply({'male':1, 'female':0}.get)
```

[22]:
```
new_df['Embarked'] = new_df['Embarked'].apply({'S':1, 'Q':2,'C':3}.get)
```

[23]:
```
new_df.head()
```

[23]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	1	22.0	1	0	7.2500	1

```
1         1        1    0   38.0       1       0   71.2833          3
2         1        3    0   26.0       0       0    7.9250          1
3         1        1    0   35.0       1       0   53.1000          1
4         0        3    1   35.0       0       0    8.0500          1
```

3.0.1 Dividing data into Dependent and independent variable for model development

[24]:
```
x = new_df.drop(['Survived'],axis=1)
y = new_df['Survived']
```

Diving data into training and testing sets

[25]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y, test_size=0.
 ↪2,random_state=3)
```

[26]:
```
print("size of x_train dataset ",x_train.shape)
```

```
size of x_train dataset  (712, 7)
```

[27]:
```
print("size of x_test dataset",x_test.shape)
```

```
size of x_test dataset (179, 7)
```

[28]:
```
print("Size of y_train dataset ",y_train.shape)
```

```
Size of y_train dataset  (712,)
```

[29]:
```
print("Size of y_test dataset ",y_test.shape)
```

```
Size of y_test dataset  (179,)
```

4 Machine learning models

4.0.1 1. DecisionTreeClassifier

[30]:
```
from sklearn.tree import DecisionTreeClassifier
import sklearn.tree as tree
```

[31]:
```
DecisionTree = DecisionTreeClassifier()
```

[33]:
```
# Training Data
DecisionTree.fit(x_train,y_train)
```

[33]:
```
DecisionTreeClassifier()
```

[35]:
```
DecisionTree
```

[35]: DecisionTreeClassifier()

[36]:
```
Predictions = DecisionTree.predict(x_test)
print(Predictions)
```

```
[0 1 0 0 0 0 1 0 0 0 0 1 1 0 0 0 1 0 0 1 1 1 0 1 1 0 1 0 1 1 1 1 0 1 0 0 0
 0 1 0 1 1 0 0 1 0 0 1 1 1 1 0 1 0 1 1 0 0 1 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1
 1 0 1 0 0 0 0 1 1 0 0 0 0 0 1 0 0 1 1 0 0 0 1 1 1 1 1 1 1 0 0 0 0 0 1 0 0
 0 0 0 1 1 1 1 0 0 1 1 0 0 1 0 0 1 0 1 1 0 1 1 1 1 1 0 0 0 0 1 1 0 1 0 1 0
 1 0 1 0 1 1 1 0 0 0 0 1 0 0 0 0 0 0 1 0 1 0 0 1 1 0 0 0 0 0 1]
```

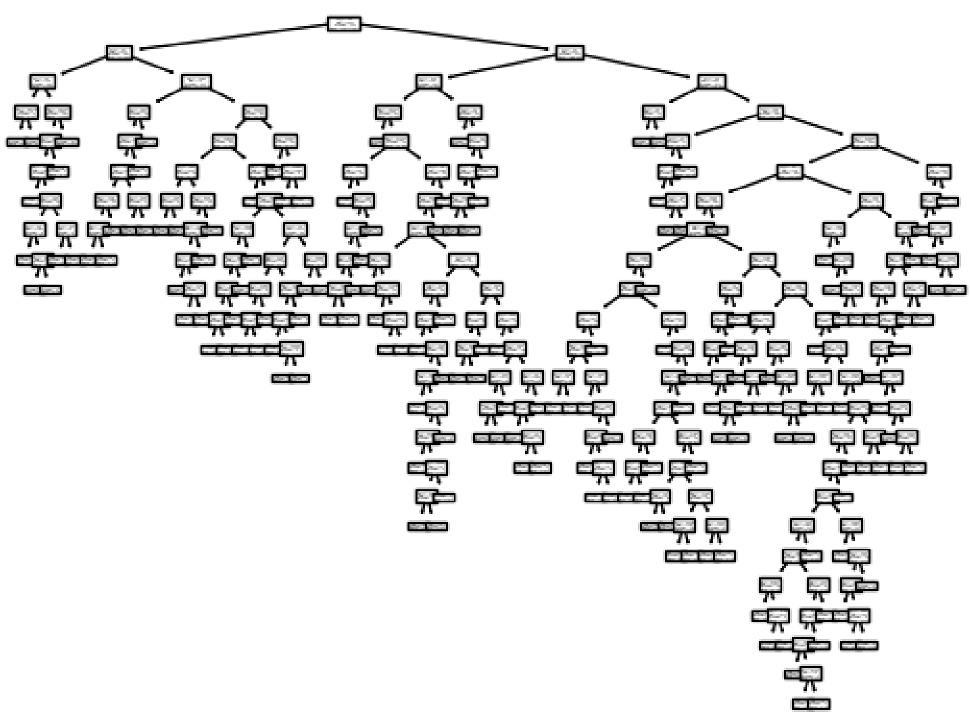
DecisionTree Model Evaluation

[48]:
```
from sklearn import metrics
accuracyScore = metrics.accuracy_score(y_test,Predictions)
accuracyScore2 = metrics.confusion_matrix(y_test,Predictions)
print("Accuracy of the DecisionTree model is ",accuracyScore)
print("Accuracy score using confusion_matrix is ",accuracyScore2)
```

```
Accuracy of the DecisionTree model is  0.7877094972067039
Accuracy score using confusion_matrix is  [[87 22]
 [16 54]]
```

We can see Our Decision Tree model is 78% accurate

[47]:
```
tree.plot_tree(DecisionTree)
plt.figsize=(20,20)
plt.show()
```



The model is 78% accurate in prediction of the survival of the passengers

4.0.2 2. Support Vector Machine (SVM) Machine learning Model

[51]:
```
from sklearn import svm
Classification1 = svm.SVC(kernel = 'rbf')
```

[52]:
```
#Trainin data
Classification1.fit(x_train,y_train)
```

[52]:
```
SVC()
```

[54]:
```
# Prediction
Prediction2 = Classification1.predict(x_test)
print(Prediction2)
```

```
[0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 1 1 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0
 0 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 1
 1 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 1 0 1 0 0 0 1 0 1 0 0 0 0 0 1 0 0 0 0 0 0
 0 0 1 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0]
```

[57]:
```
# Model Evaluation
from sklearn import metrics
accuracyScore1 = metrics.accuracy_score(y_test,Prediction2)
conMatrix1 = metrics.confusion_matrix(y_test,Prediction2)
```

[58]:
```
print("Accuracy of model is ",accuracyScore1)
```

```
Accuracy of model is  0.6089385474860335
```

[60]:
```
print("Confusion matrix of model is \n",conMatrix1)
```

```
Confusion matrix of model is
 [[94 15]
 [55 15]]
```

The model is 60% accurate in prediction of the survival of the passengers

4.0.3 3. K-Neighbour-Nearest Machine learning Model

[64]:
```
from sklearn.neighbors import KNeighborsClassifier
```

[65]:
```
neigh = KNeighborsClassifier(n_neighbors =  4)
neigh
```

[65]: KNeighborsClassifier(n_neighbors=4)

[66]:
```
neigh.fit(x_train,y_train)
```

[66]: KNeighborsClassifier(n_neighbors=4)

[68]:
```
Prediction2 = neigh.predict(x_test)
```

[69]:
```
print(Prediction2)
```

```
[0 0 0 0 0 0 0 0 1 0 0 0 1 1 0 0 0 1 0 1 1 0 0 1 1 0 0 0 0 1 1 0 0 0 0 0 0
 1 0 0 1 1 0 0 0 0 0 0 0 1 0 0 1 0 0 1 1 0 0 0 0 1 0 0 0 0 0 0 0 1 1 1 0 1
 1 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0 1 0 0 0 1
 0 0 0 0 0 0 0 0 1 0 1 1 0 0 0 1 1 0 1 1 0 0 1 1 1 0 0 1 0 0 1 0 0 0 0 0 0
 1 0 1 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0]
```

[71]:
```
# Evaluation of the Model
accuracyScore2 = metrics.accuracy_score(y_test,Prediction2)
print("The Accuracy of the model is",accuracyScore2)
```

```
The Accuracy of the model is 0.6536312849162011
```

[72]:
```
con_Matrix = metrics.confusion_matrix(y_test,Prediction2)
print(con_Matrix)
```

```
[[88 21]
 [41 29]]
```

The KNN model is 65% accurate

5 Conclusions

The best suitable Classification Model for this Titanic Dataset to predict the survival of passenger is DecisionTreeClassifier Model. The model have 75% Accuracy score Which show it can predict the passenger survival chances better than KNN and SVM Classifications

5.0.1 Author

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[ ]:
```

```