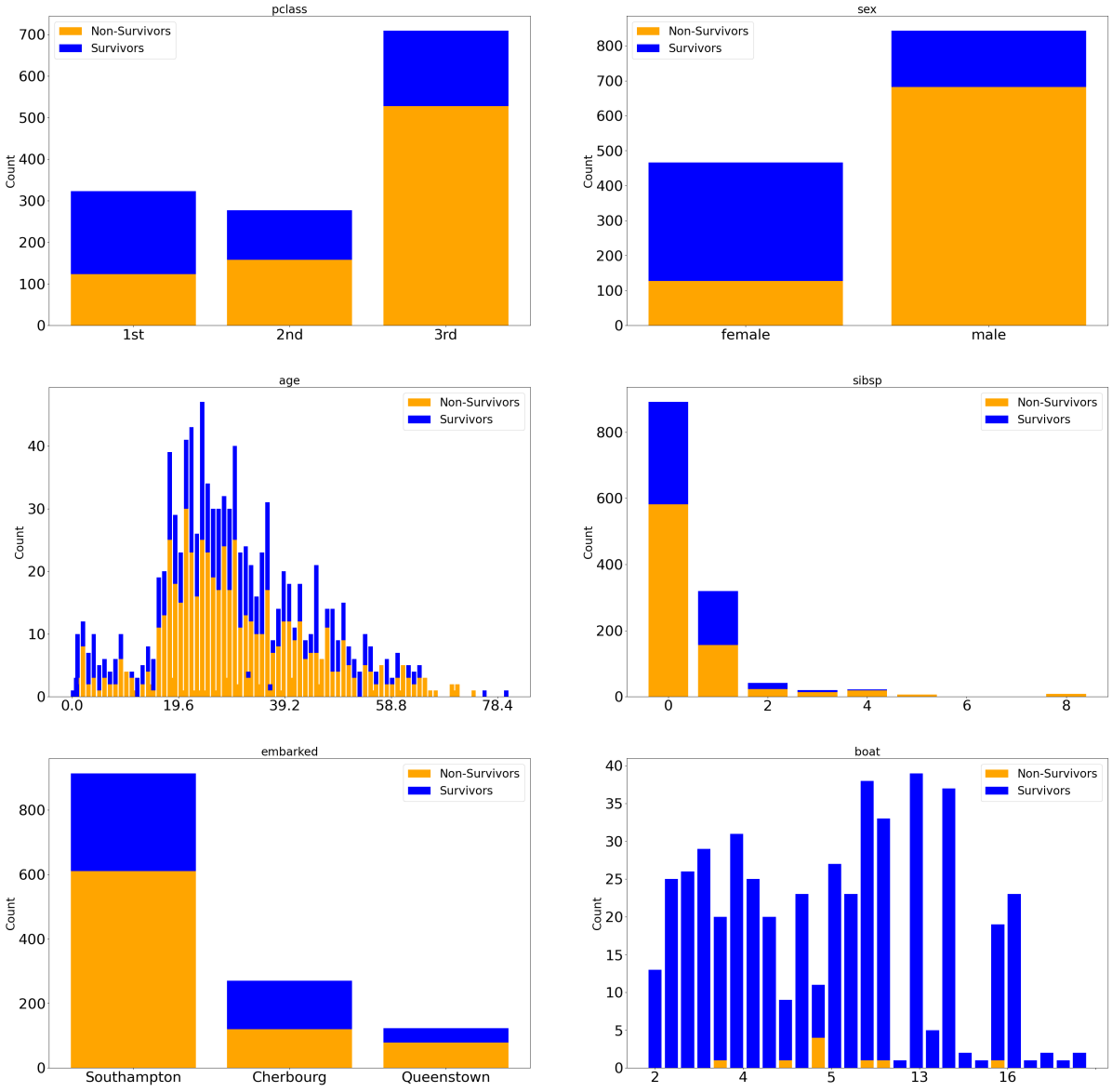
In [512…
```
#All imports which are used below
import pandas as pd
import numpy as np
from sklearn import tree
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_validate as cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import KFold
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
```

In [513…
```
#Read the file
df = pd.read_csv("./Titanic.csv")
df = df.replace(np.nan, '')
df = df[["pclass","survived","sex","age","sibsp","parch","ticket","fare","cabin","e
```

In [514…
```
#Create dictionary to plot the data
def createDict(listName,survivedList):
    dictTemp = {}
    for i in range(0,len(survivedList)):
        if listName[i] == "":
            continue
        if(listName[i] in dictTemp):
            if(survivedList[i] == 1):
                dictTemp[listName[i]][0] = dictTemp[listName[i]][0] + 1
            else:
                dictTemp[listName[i]][1] = dictTemp[listName[i]][1] + 1
        else:
            if(survivedList[i] == 1):
                dictTemp[listName[i]] = [1,0]
            else:
                dictTemp[listName[i]] = [0,1]
    return dictTemp
```

In [515…
```
#Create list so that we can plot the data in for loop
def createList(dictName):
    survivorList = []
    NonSurvivorList = []
    for i in dictName.keys():
        survivorList.append(dictName[i][0])
        NonSurvivorList.append(dictName[i][1])
    return [survivorList,NonSurvivorList]
```

In [516…
```
#Plotting the data using matplotlib
col = ["pclass","sex","age","sibsp","embarked","boat"]
plt.rcParams.update({'font.size': 30})
figure, axis = plt.subplots(3,2,figsize=(40, 40))
for i,ax in zip(col,axis.flatten()):
    d = createDict(df[i].tolist(),df["survived"].tolist())
    survivorList = createList(d)
    if(len(d.keys()) > 20):
        ax.set_xticks(np.arange(0,100, len(d.keys())/5))
    ax.bar(d.keys(), survivorList[1], color="Orange")
    ax.bar(d.keys(),survivorList[0],bottom=survivorList[1], color="Blue")
    ax.set_ylabel("Count",fontsize=24)
    ax.legend(["Non-Survivors", "Survivors"],fontsize=24)
    ax.set_title(i,fontsize=24)
```



We can observe from the data that, the one who managed to board on the rescue boat survived

In [517…
```
# Considering the columns for splitting the data.
df_train = df[["pclass","sex","age","sibsp"]]   #These are the independent variable
df_test = df[["survived"]]                      #This is the dependent variable
df_train = df_train.replace('',float('NaN'))
tempDf = pd.get_dummies(df_train[['pclass','sex']])  # Create the dummies for pclas
df_train = pd.concat([df_train, tempDf], axis=1)     #Add the dummy dataframe into
df_train = df_train.drop(["pclass","sex","pclass_1st","sex_male"], axis=1) #Drop th
                                                                           #the dum
```

In [518…
```
#Splitting the data
X_train,X_test,y_train,y_test = train_test_split(df_train,df_test,test_size=0.3, ra
```

In [519…
```
#Creating the instance of classifier and fitting the training data
dtree = DecisionTreeClassifier(max_depth = 5, random_state = 0)
dtree = dtree.fit(X_train, y_train)
```

In [520…
```
# text_representation = tree.export_text(dtree)
```

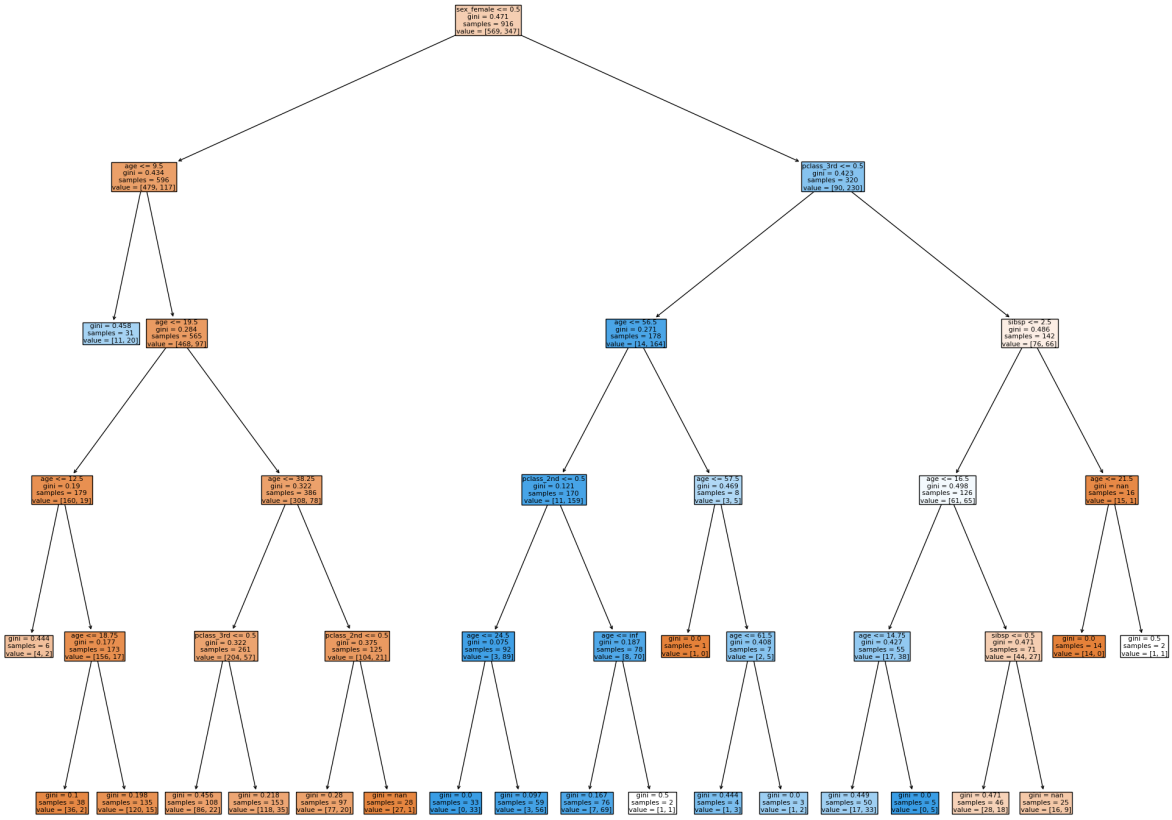
```
# print(text_representation)
```

In [521…

```
#Plotting the tree
fig = plt.figure(figsize=(25,20))
tree.plot_tree(dtree,
                   feature_names=["age","sibsp","pclass_2nd","pclass_3rd","sex_fema
                   filled=True)
```

Out[521]:
```
[Text(0.4166666666666667, 0.9166666666666666, 'sex_female <= 0.5\ngini = 0.471\nsamples = 916\nvalue = [569, 347]'),
 Text(0.125, 0.75, 'age <= 9.5\ngini = 0.434\nsamples = 596\nvalue = [479, 117]'),
 Text(0.09722222222222222, 0.5833333333333334, 'gini = 0.458\nsamples = 31\nvalue = [11, 20]'),
 Text(0.1527777777777778, 0.5833333333333334, 'age <= 19.5\ngini = 0.284\nsamples = 565\nvalue = [468, 97]'),
 Text(0.05555555555555555, 0.4166666666666667, 'age <= 12.5\ngini = 0.19\nsamples = 179\nvalue = [160, 19]'),
 Text(0.027777777777777776, 0.25, 'gini = 0.444\nsamples = 6\nvalue = [4, 2]'),
 Text(0.08333333333333333, 0.25, 'age <= 18.75\ngini = 0.177\nsamples = 173\nvalue = [156, 17]'),
 Text(0.05555555555555555, 0.08333333333333333, 'gini = 0.1\nsamples = 38\nvalue = [36, 2]'),
 Text(0.1111111111111111, 0.08333333333333333, 'gini = 0.198\nsamples = 135\nvalue = [120, 15]'),
 Text(0.25, 0.4166666666666667, 'age <= 38.25\ngini = 0.322\nsamples = 386\nvalue = [308, 78]'),
 Text(0.19444444444444445, 0.25, 'pclass_3rd <= 0.5\ngini = 0.322\nsamples = 261\nvalue = [204, 57]'),
 Text(0.16666666666666666, 0.08333333333333333, 'gini = 0.456\nsamples = 108\nvalue = [86, 22]'),
 Text(0.2222222222222222, 0.08333333333333333, 'gini = 0.218\nsamples = 153\nvalue = [118, 35]'),
 Text(0.3055555555555556, 0.25, 'pclass_2nd <= 0.5\ngini = 0.375\nsamples = 125\nvalue = [104, 21]'),
 Text(0.2777777777777778, 0.08333333333333333, 'gini = 0.28\nsamples = 97\nvalue = [77, 20]'),
 Text(0.3333333333333333, 0.08333333333333333, 'gini = nan\nsamples = 28\nvalue = [27, 1]'),
 Text(0.7083333333333334, 0.75, 'pclass_3rd <= 0.5\ngini = 0.423\nsamples = 320\nvalue = [90, 230]'),
 Text(0.5416666666666666, 0.5833333333333334, 'age <= 56.5\ngini = 0.271\nsamples = 178\nvalue = [14, 164]'),
 Text(0.4722222222222222, 0.4166666666666667, 'pclass_2nd <= 0.5\ngini = 0.121\nsamples = 170\nvalue = [11, 159]'),
 Text(0.4166666666666667, 0.25, 'age <= 24.5\ngini = 0.075\nsamples = 92\nvalue = [3, 89]'),
 Text(0.3888888888888889, 0.08333333333333333, 'gini = 0.0\nsamples = 33\nvalue = [0, 33]'),
 Text(0.4444444444444444, 0.08333333333333333, 'gini = 0.097\nsamples = 59\nvalue = [3, 56]'),
 Text(0.5277777777777778, 0.25, 'age <= inf\ngini = 0.187\nsamples = 78\nvalue = [8, 70]'),
 Text(0.5, 0.08333333333333333, 'gini = 0.167\nsamples = 76\nvalue = [7, 69]'),
 Text(0.5555555555555556, 0.08333333333333333, 'gini = 0.5\nsamples = 2\nvalue = [1, 1]'),
 Text(0.6111111111111112, 0.4166666666666667, 'age <= 57.5\ngini = 0.469\nsamples = 8\nvalue = [3, 5]'),
 Text(0.5833333333333334, 0.25, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(0.6388888888888888, 0.25, 'age <= 61.5\ngini = 0.408\nsamples = 7\nvalue = [2, 5]'),
 Text(0.6111111111111112, 0.08333333333333333, 'gini = 0.444\nsamples = 4\nvalue = [1, 3]'),
 Text(0.6666666666666666, 0.08333333333333333, 'gini = 0.0\nsamples = 3\nvalue = [1, 2]'),
 Text(0.875, 0.5833333333333334, 'sibsp <= 2.5\ngini = 0.486\nsamples = 142\nvalue = [76, 66]'),
 Text(0.8055555555555556, 0.4166666666666667, 'age <= 16.5\ngini = 0.498\nsamples = 126\nvalue = [61, 65]'),
 Text(0.75, 0.25, 'age <= 14.75\ngini = 0.427\nsamples = 55\nvalue = [17, 38]'),
 Text(0.7222222222222222, 0.08333333333333333, 'gini = 0.449\nsamples = 50\nvalue = [17, 33]'),
 Text(0.7777777777777778, 0.08333333333333333, 'gini = 0.0\nsamples = 5\nvalue =
```

```
[0, 5]'),
 Text(0.8611111111111112, 0.25, 'sibsp <= 0.5\ngini = 0.471\nsamples = 71\nvalue =
[44, 27]'),
 Text(0.8333333333333334, 0.08333333333333333, 'gini = 0.471\nsamples = 46\nvalue
= [28, 18]'),
 Text(0.8888888888888888, 0.08333333333333333, 'gini = nan\nsamples = 25\nvalue =
[16, 9]'),
 Text(0.9444444444444444, 0.4166666666666667, 'age <= 21.5\ngini = nan\nsamples =
16\nvalue = [15, 1]'),
 Text(0.9166666666666666, 0.25, 'gini = 0.0\nsamples = 14\nvalue = [14, 0]'),
 Text(0.9722222222222222, 0.25, 'gini = 0.5\nsamples = 2\nvalue = [1, 1]')]
```



In [522…
```
#Calculating the accuracy
y_pred = dtree.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
```

```
Accuracy: 0.78
```

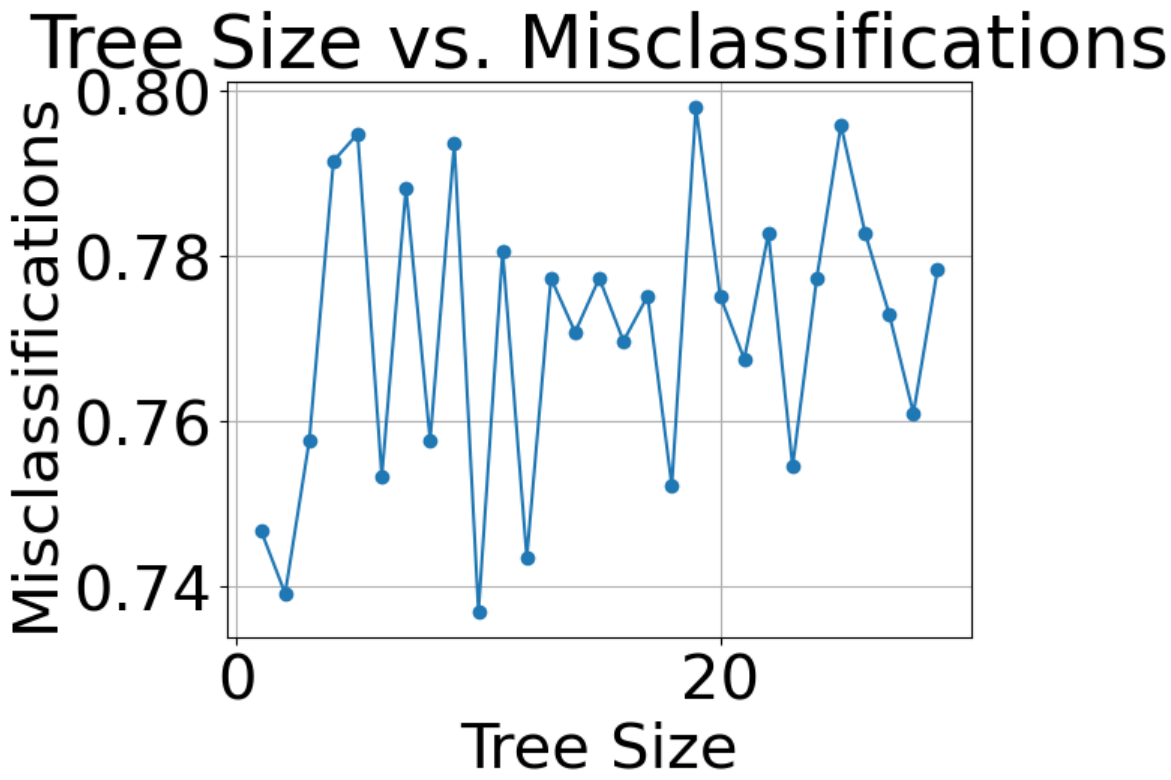
In [538…
```
#Calulating the misclassification using Kfold classification by varrying the tree s
tree_sizes = range(1, 30)
misclassifications = []
for size in tree_sizes:
    model = DecisionTreeClassifier(max_depth=size)
    kfold = KFold(n_splits=5, shuffle=True, random_state=42)
    misclassification = cross_val_score(model, X_train, y_train, cv=kfold, scoring=
    misclassifications.append(misclassification)
```

In [539…
```
print(misclassifications)
```

```
[0.7467628890472795, 0.7391126158232358, 0.7576740318365408, 0.7915538132573058,
0.7948503207412687, 0.7533024471370873, 0.7882810643858399, 0.7576918507959135, 0.
7937099073414113, 0.7369149441672607, 0.780624851508672, 0.7434723212164409, 0.777
3402233309574, 0.7707887859349014, 0.7773580422903302, 0.7697137087194108, 0.77519
00688999762, 0.7522036113090995, 0.7980993110002377, 0.7751781895937275, 0.7675338
560228082, 0.7827928248990259, 0.7545022570681873, 0.7773699215965788, 0.795931337
6098837, 0.7828225231646472, 0.7729508196721311, 0.760976478973628, 0.778456878118
3179]
```

In [540…

```
#Plotting the misclassification vs tree size for analysis of the best tree size/dep
plt.plot(tree_sizes, misclassifications, marker='o')
plt.title('Tree Size vs. Misclassifications')
plt.xlabel('Tree Size')
plt.ylabel('Misclassifications')
plt.grid(True)
plt.show()
```

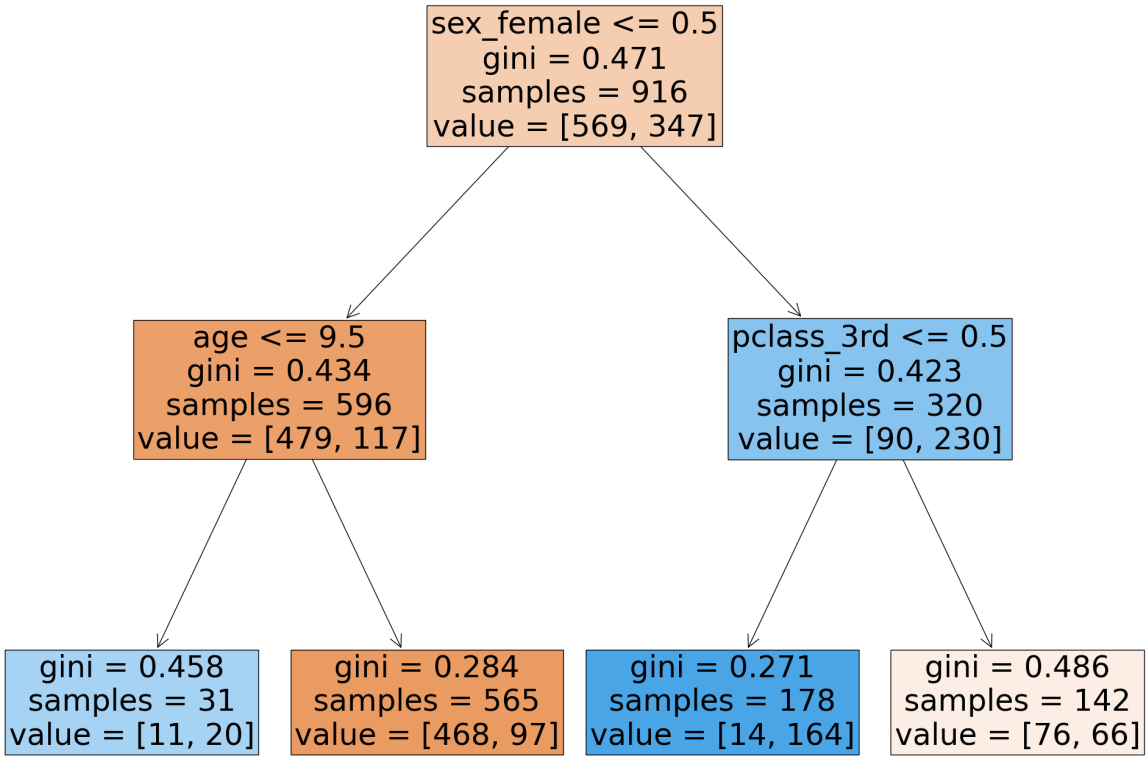


As seen above the best depth is 2

In [444…

```
#Fitting the classifier using the best depth found in the above step and plotting t
dtree = DecisionTreeClassifier(max_depth = 2, random_state = 0)
dtree = dtree.fit(X_train, y_train)
fig = plt.figure(figsize=(25,20))
tree.plot_tree(dtree,
                   feature_names=["age","sibsp","pclass_2nd","pclass_3rd","sex_fema
                   filled=True)
```

Out[444]:
```
[Text(0.5, 0.8333333333333334, 'sex_female <= 0.5\ngini = 0.471\nsamples = 916\nva
lue = [569, 347]'),
 Text(0.25, 0.5, 'age <= 9.5\ngini = 0.434\nsamples = 596\nvalue = [479, 117]'),
 Text(0.125, 0.16666666666666666, 'gini = 0.458\nsamples = 31\nvalue = [11, 20]'),
 Text(0.375, 0.16666666666666666, 'gini = 0.284\nsamples = 565\nvalue = [468, 9
7]'),
 Text(0.75, 0.5, 'pclass_3rd <= 0.5\ngini = 0.423\nsamples = 320\nvalue = [90, 23
0]'),
 Text(0.625, 0.16666666666666666, 'gini = 0.271\nsamples = 178\nvalue = [14, 16
4]'),
 Text(0.875, 0.16666666666666666, 'gini = 0.486\nsamples = 142\nvalue = [76, 6
6]')]
```



In [445…
```
y_pred = dtree.predict(X_test) #Predicting the values
```

In [446…
```
#Calculating the accuracy

accuracy = accuracy_score(y_test, y_pred)

print(f"Total Accuracy: {accuracy:.2f}")
```

```
Total Accuracy: 0.77
```

In [447…
```
#Calculating the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
```

In [448…
```
TP = conf_matrix[1, 1]  # True Positives
TN = conf_matrix[0, 0]  # True Negative
```

In [449…
```
print("percent survivors correctly predicted",((TP/(TP+conf_matrix[0, 1]))*100))
print("percent fatalities correctly predicted",((TN/(TN+conf_matrix[1, 0]))*100))
```

```
percent survivors correctly predicted 88.09523809523809
percent fatalities correctly predicted 74.4336569579288
```

Random Forest

In [450…
```
df_train = pd.concat([df_train, df_test], axis=1)
df_train.dropna(inplace = True)
df_test = df_train["survived"]
df_train.drop(["survived"], axis=1)
```

Out[450]:

	age	sibsp	pclass_2nd	pclass_3rd	sex_female
0	29.0000	0	0	0	1
1	0.9167	1	0	0	0
2	2.0000	1	0	0	1
3	30.0000	1	0	0	0
4	25.0000	1	0	0	1
...	...	...	...	...	...
1301	45.5000	0	0	1	0
1304	14.5000	1	0	1	1
1306	26.5000	0	0	1	0
1307	27.0000	0	0	1	0
1308	29.0000	0	0	1	0

1046 rows × 5 columns

In [451…
```
X_train,X_test,y_train,y_test = train_test_split(df_train,df_test,test_size=0.3, ra
```

In [452…
```
#Fitting the data in random forest classifier
clf = RandomForestClassifier(n_estimators=50,max_depth=3,random_state=42)  # You co
clf.fit(X_train, y_train)
```

Out[452]:

▾ RandomForestClassifier

```
RandomForestClassifier(max_depth=3, n_estimators=50, random_state=42)
```

In [453…
```
##Predicting the values
y_pred = clf.predict(X_test)
```

In [454…
```
#Calculating the accuracy

accuracy = accuracy_score(y_test, y_pred)

print(f"Total Accuracy: {accuracy:.2f}")
```

```
Total Accuracy: 1.00
```

In [455…
```
#Calculating the confusion matrix

conf_matrix = confusion_matrix(y_test, y_pred)
TP = conf_matrix[1, 1]  # True Positives
TN = conf_matrix[0, 0]  # True Negative
print("percent survivors correctly predicted",((TP/(TP+conf_matrix[0, 1]))*100))
print("percent fatalities correctly predicted",((TN/(TN+conf_matrix[1, 0]))*100))
```

```
percent survivors correctly predicted 100.0
percent fatalities correctly predicted 100.0
```

As we can see there is 100 % accuracy in predictions. So we can conclude that random forest is better compared to descision tree in this case

In [ ]: