Titanic Classification

About Project

The sinking of the Titanic in 1912 is one of the most infamous shipwrecks in history. Despite limited lifeboat capacity,some passengers were more likely to survive than others. This project aims to predict the likelyhood of survival for passengers aboard the titanic using machine learning techniques. Project Goals:

Prediction Objective: Utilize various machine learning models to predict whether a passenger survived or not. Dataset Exploration: Analyze a dataset containing information about Titanic passengers, such as age, gender, class, and more. Model Comparison: Evaluate the performance of different classification models to determine the most effective predictor. Dataset Description:

The dataset consists of 891 rows and 8 columns. The target variable, 'Survived,' denotes whether a passenger survived (1) or not (0).

Steps

Importing Libraries

Data Collection

Data Analysis

Data Cleaning

Data Modeling

Testing

Importing Libraries

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression

import warnings
warnings.filterwarnings("ignore")
```

Loading Dataset

In [2]:
```python
data_titanic = pd.read_csv("titanic_train.csv")
```

In [3]:
```python
# To see length of dataset
len(data_titanic)
```

Out[3]:
```
891
```

In [4]:
```python
#This is default function which will give the first 5 rows of the dataset
data_titanic.head()
```

Out[4]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

In [5]:
```
#To know about the index of the data
data_titanic.index
```

Out[5]:
```
RangeIndex(start=0, stop=891, step=1)
```

In [6]:
```
#We can see the columns of this dataset using .columns attribute
data_titanic.columns
```

Out[6]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

In [7]:
```
#The info() method will give the information about dataset
data_titanic.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
```

In [8]:
```
data_titanic.shape
```

Out[8]:
```
(891, 12)
```

In [9]:
```
#We can see the data types of each column using attribute dtypes
data_titanic.dtypes
```

Out[9]:
```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

In [10]:
```
#describe() method will give the summary of stats of the dataset
data_titanic.describe()
```

Out[10]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

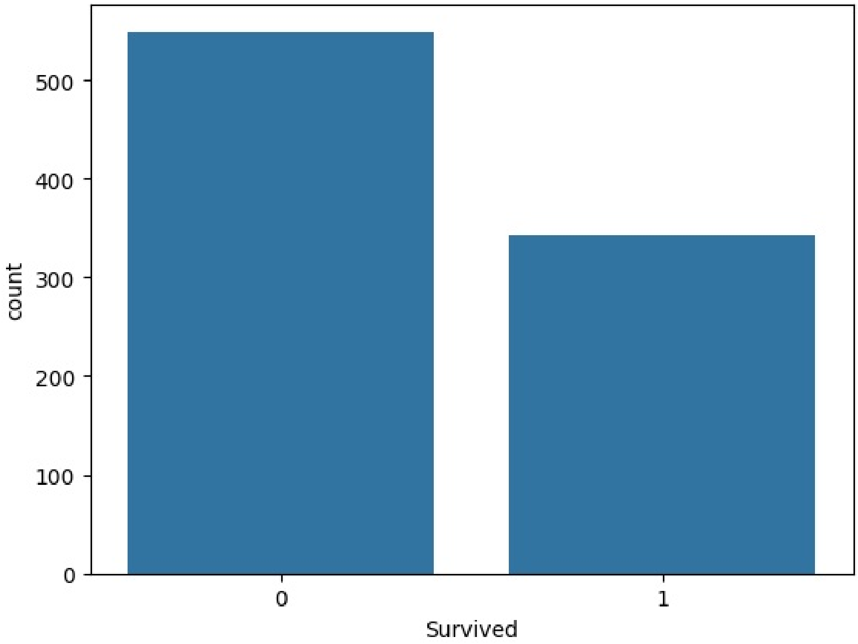
Data Analysis

we'll import seaborn for visually analyzing the data and to find out how many survived vs died using countplot method of seaborn

In [11]:
```
#countplot of survived vs not survived
```

In [12]:
```
sns.countplot(x='Survived',data=data_titanic)
```

Out[12]: <Axes: xlabel='Survived', ylabel='count'>



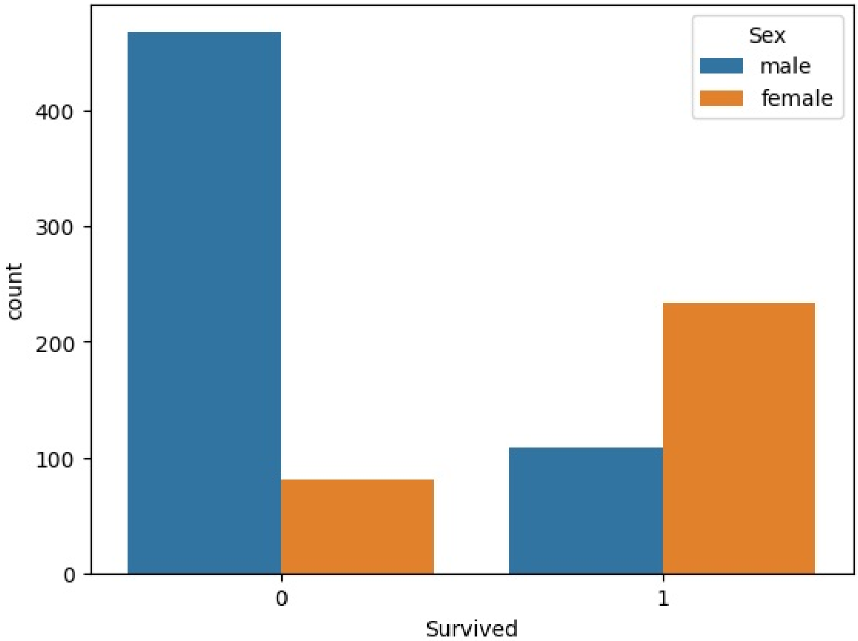
Here, from above countplot we can see that the number of survived passengers is less than the no of not survived passengers but from this countplot I'm not able to see how many male passengers survived and how many female passengers survived. So now I'm going to plot another countplot which will tell me the no of male and female passengers that are survived and not survived.

Male vs Female Survival

In [13]:
```
#Male vs Female survived
```

In [14]:
```
sns.countplot(x='Survived',data=data_titanic,hue='Sex')
```

Out[14]: <Axes: xlabel='Survived', ylabel='count'>



In [15]:
```
#check for null
```

In [16]:
```
data_titanic.isna()
```

Out[16]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	False	False	False	False	False	False	False	False	False	False	True	False
1	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	True	False
3	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	True	False
...	...	...	...	...	...	...	...	...	...	...	...	...
886	False	False	False	False	False	False	False	False	False	False	True	False
887	False	False	False	False	False	False	False	False	False	False	False	False
888	False	False	False	False	False	True	False	False	False	False	True	False
889	False	False	False	False	False	False	False	False	False	False	False	False
890	False	False	False	False	False	False	False	False	False	False	True	False

891 rows × 12 columns

In [17]:
```
#check how many values are null
```

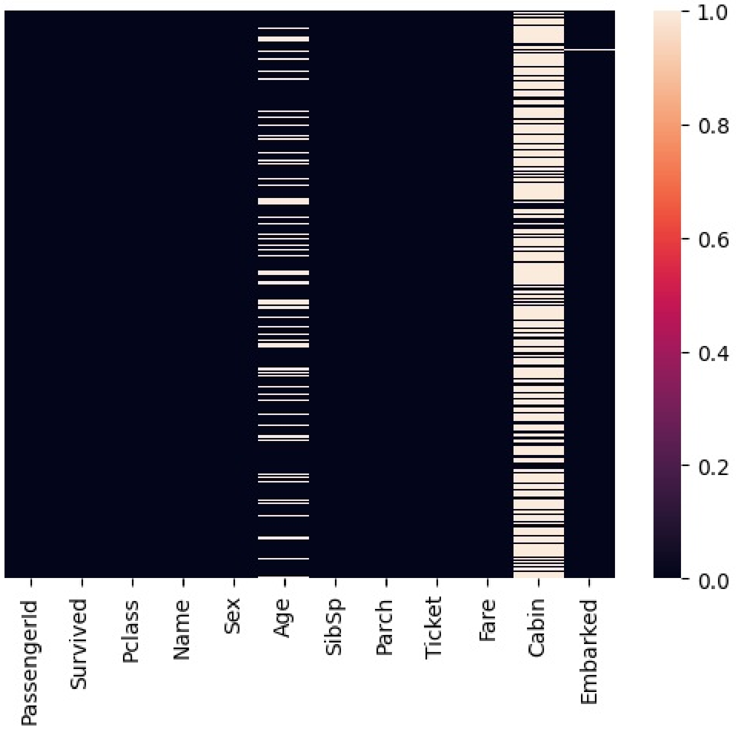
In [18]:
```
data_titanic.isna().sum()
```

Out[18]:
```
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
```

In [19]:
```
#Visualize null values
```

In [20]:
```
sns.heatmap(data_titanic.isna(),yticklabels=False)
```

Out[20]: <Axes: >



From above heatmap we can see that the null values are strongly appeared in cabin column and in age column also but not as strong as cabin column so thats how we visualize the null values in our dataset. so now in order to make a conclusion about null values whether or not we're going to delete this null values or discard this null values or we're going to impute this columns is depends on the the percentage of null values which are appearing in our dataset.

In [21]:
```
#find the % of null values in age column
```

In [22]:
```
(data_titanic['Age'].isna().sum()/len(data_titanic['Age']))*100
```

Out[22]: 19.865319865319865

In [23]:
```
#find the % of null values in cabin column
```

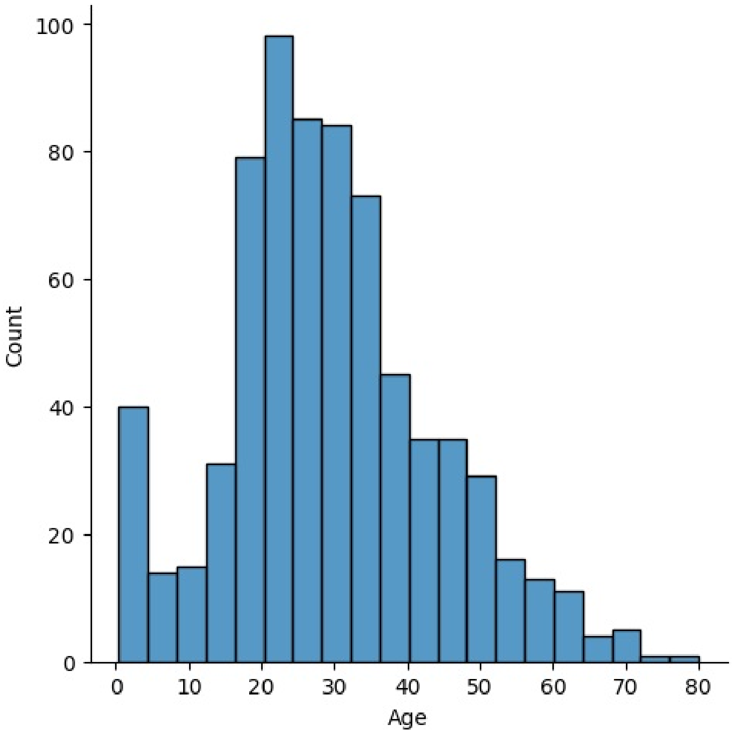
In [24]:
```
(data_titanic['Cabin'].isna().sum()/len(data_titanic['Cabin']))*100
```

Out[24]: 77.10437710437711

In [25]:
```
#find the distribution for the age column
```

In [26]:
```
sns.displot(x='Age',data=data_titanic)
```

Out[26]: <seaborn.axisgrid.FacetGrid at 0x220a1336000>



Data Cleaning

Now we'll fill the missing values for age. in order to feel missing values we'll use fillna method. for now we'll fill the missing age by taking average of all age

In [27]:
```
#fill age column
```

In [28]:
```
data_titanic['Age'].mean()
```

Out[28]: 29.69911764705882

In [29]:
```
data_titanic['Age'].fillna(data_titanic['Age'].mean(),inplace=True)
```

We'll verify null values exist or not Now we'll verify if there are any null values present in the dataset or not

In [30]:
```
#verify null values
```

In [31]:
```
data_titanic['Age'].isna().sum()
```

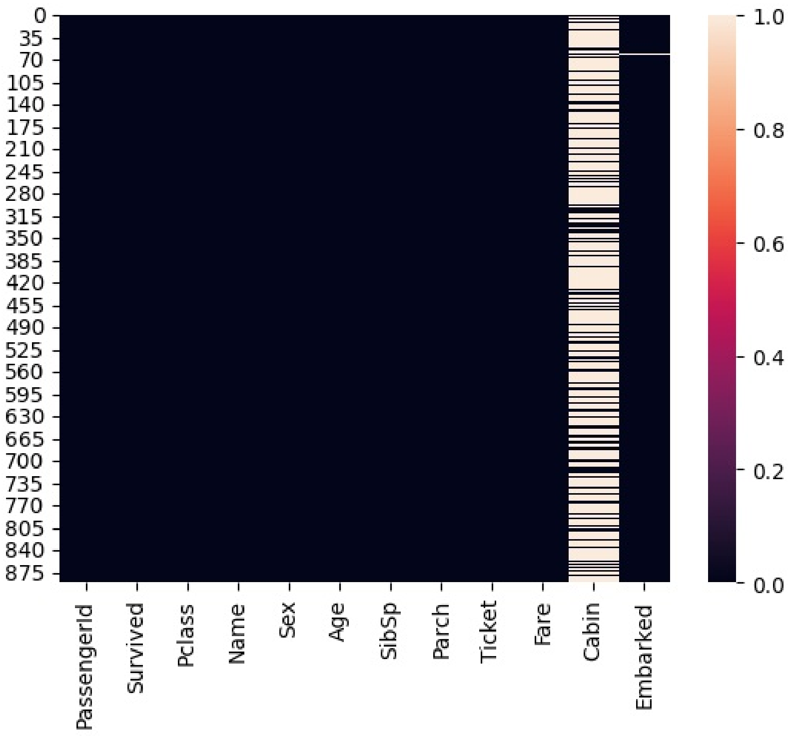
Out[31]: 0

We will visualise the null value using heatmap

we will use heatmap method by passing only records which are null

In [32]:
```
sns.heatmap(data_titanic.isna())
```

Out[32]: <Axes: >



We can see that cabin column has a lot of null values and as such we cannot use it for prediction so we'll drop that column

In [33]:
```
#drop cabin column
```

In [34]:
```
data_titanic.drop('Cabin',axis=1,inplace=True)
```

In [35]:
```
#inorder to see if cabin column is drop or not we'll see the contents of the data
```

In [36]:
```
data_titanic.head()
```

Out[36]:

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

Preparing Data For Model

Now we'll need to convert all Categorical columns to numerical.

In [37]:
```
#Check for the non numeric columns
```

In [38]:
```
data_titanic.dtypes
```

Out[38]:
```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Embarked        object
dtype: object
```

Now we can see Name,Sex,Ticket and Embarked are categorical columns and they're not that useful for machine learning prediction hence we'll eventully drop it. For now we would convert Sex Column to dummies numerical values

In [39]:
```
#Convert Sex column to numerical values
```

In [40]:
```
gender=pd.get_dummies(data_titanic['Sex'],drop_first=True)
```

In [41]:
```
data_titanic.fillna(value=0,inplace=True)
```

In [42]:
```
gender.replace({True:1, False:0}, inplace=True)
```

In [43]:
```
data_titanic['gender']=gender
```

In [44]:
```
data_titanic.head()
```

Out[44]:

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

In [45]:
```
#drop the columns which are not required
```

In [46]:
```
data_titanic.drop(['Name','Sex','Ticket','Embarked'],axis=1,inplace=True)
```

In [47]:
```
data_titanic.head()
```

Out[47]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare	gender
0	1	0	3	22.0	1	0	7.2500	1
1	2	1	1	38.0	1	0	71.2833	0
2	3	1	3	26.0	0	0	7.9250	0
3	4	1	1	35.0	1	0	53.1000	0
4	5	0	3	35.0	0	0	8.0500	1

In [48]:
```
#separate dependent and independent variables
```

In [49]:
```
x=data_titanic[['PassengerId','Pclass','Age','SibSp','Parch','Fare','gender']]
y=data_titanic['Survived']
```

In [50]:
```
x
```

Out[50]:

	PassengerId	Pclass	Age	SibSp	Parch	Fare	gender
0	1	3	22.000000	1	0	7.2500	1
1	2	1	38.000000	1	0	71.2833	0
2	3	3	26.000000	0	0	7.9250	0
3	4	1	35.000000	1	0	53.1000	0
4	5	3	35.000000	0	0	8.0500	1
...	...	...	...	...	...	...	...
886	887	2	27.000000	0	0	13.0000	1
887	888	1	19.000000	0	0	30.0000	0
888	889	3	29.699118	1	2	23.4500	0
889	890	1	26.000000	0	0	30.0000	1
890	891	3	32.000000	0	0	7.7500	1

891 rows × 7 columns

In [51]:
```
y
```

Out[51]:
```
0      0
1      1
2      1
3      1
4      0
      ..
886    0
887    1
888    0
889    1
890    0
Name: Survived, Length: 891, dtype: int64
```

Data Modelling

Building model using Logestic Regression, Support vector machine and Random forest Regressor

Splitting the data into training and test set using train_test_split

In [52]:
```
#train test split
```

In [53]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random_state=42)
```

Logistic Regression

Logistic regression is a statistical method used for binary classification problems, where the target variable has two possible outcomes.Its commonly used in macing learning for tasks predicting yes/no, true/false, or 0/1 outcomes. Unlike linear regression, which predicts continuous values, logistic regression uses the logistic function(also known as sigmoid function)to map input features to a probability score between 0 and 1. This probability represents the likelihood of belonging to a particular class.

In [54]:
```
#import logistic regression
```

In [55]:
```
from sklearn.linear_model import LogisticRegression
```

In [56]:
```
#fit logistic regression
```

In [57]:
```
lr=LogisticRegression()
lr.fit(x_train,y_train)
predict=lr.predict(x_test)
```

Testing

see how our model is performing

In [58]:
```
#print confusion matrix
```

In [59]:
```
from sklearn.metrics import confusion_matrix
```

In [60]:
```
pd.DataFrame(confusion_matrix(y_test,predict),columns=['Predicted No','Predicted Yes'],index=['Actual No','Actua
```

Out[60]:

	Predicted No	Predicted Yes
Actual No	151	24
Actual Yes	37	83

In [61]:
```
#import classification report
```

In [62]:
```
from sklearn.metrics import classification_report
```

In [63]:
```
print(classification_report(y_test,predict))
```

```
              precision    recall  f1-score   support

           0       0.80      0.86      0.83       175
           1       0.78      0.69      0.73       120

    accuracy                           0.79       295
   macro avg       0.79      0.78      0.78       295
weighted avg       0.79      0.79      0.79       295
```

Support Vector Classifier

The Support Vector Classifier (SVC) is a supervised machine learning algorithm used for classification tasks. It's part of the Support Vector Machines (SVM) family. SVC works by finding the optimal hyperplane that best separates different classes in the feature space.

This hyperplane maximizes the margin, which is the distance between the hyperplane and the closest data points from each class (called support vectors). The objective is to achieve a decision boundary that generalizes well to new, unseen data. The algorithm can handle linear and non-linear classification tasks by using different kernel functions like linear, polynomial, radial basis function (RBF), etc. These kernels allow the SVC to map the input space into higher dimensions, making it possible to separate non-linearly separable classes in the transformed space.

In [64]:
```
from sklearn.svm import SVC
SVM =SVC()
SVM.fit(x_train, y_train)
SVM_pred = SVM.predict(x_test)
print("Support Vector Classifier:")
print(classification_report(y_test, SVM_pred))
```

```
Support Vector Classifier:
              precision    recall  f1-score   support

           0       0.61      0.97      0.75       175
           1       0.67      0.10      0.17       120

    accuracy                           0.61       295
   macro avg       0.64      0.53      0.46       295
weighted avg       0.63      0.61      0.51       295
```

Random Forest Classifier

Random Forest is an ensemble learning method that operates by constructing multiple decision trees during training and outputs the mean prediction of the individual trees for regression tasks or the mode for classification tasks. Random forest is a popular choice in machine learning due to its simplicity, robustness, and effectiveness in various types of data and tasks, including regression and classification problems.

In [65]:
```
#Random forest classifier
rf=RandomForestClassifier()
rf.fit(x_train,y_train)
rf_pred = rf.predict(x_test)
print("Random Forest Classifier:")
print(classification_report(y_test,rf_pred))
```

```
Random Forest Classifier:
              precision    recall  f1-score   support

           0       0.81      0.91      0.85       175
           1       0.84      0.68      0.75       120

    accuracy                           0.82       295
   macro avg       0.82      0.80      0.80       295
weighted avg       0.82      0.82      0.81       295
```

Conclusion

So, In this dataset we've apply Logistic regression, support vector classifier and Random forest classifier one by one on our data, we can conclude that we got better accuracy in random forest model which is 0.81 as compare to other two models so it is best to use Random Forest Classifier instead of Support vector Classifier and Lgistic Regression model. Thus the machine learning model to predict the Titanic survival rate based on given dataset is executed successfully using Random Forest Classifier,Logistic Regression and Support Vector Classifier.