titanic-survival-prediction

January 20, 2024

1 TITANIC SURVIVAL PREDICTION

AIM: Building a model that predicts whether a passenger on the Titanic survived or not using the given dataset

IMPORTING ESSENTIAL LIBRARIES

[ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
np.random.seed(42)
```

DATA COLLECTION, PROCESSING AND ANALYSIS

[ ]:
```
#takes a path to a CSV file and reads the data into a DataFrame
df=pd.read_csv("/content/tested.xls")
df
```

[ ]:
```
     PassengerId  Survived  Pclass  \
0            892         0       3
1            893         1       3
2            894         0       2
3            895         0       3
4            896         1       3
..           …        …     …
413         1305         0       3
414         1306         1       1
415         1307         0       3
416         1308         0       3
417         1309         0       3

                                 Name     Sex   Age  SibSp  Parch  \
0                    Kelly, Mr. James    male  34.5      0      0
```

```
1               Wilkes, Mrs. James (Ellen Needs)  female  47.0      1      0
2                      Myles, Mr. Thomas Francis    male  62.0      0      0
3                               Wirz, Mr. Albert    male  27.0      0      0
4   Hirvonen, Mrs. Alexander (Helga E Lindqvist)  female  22.0      1      1
..                                           …       …    …      …    …
413                           Spector, Mr. Woolf    male   NaN      0      0
414                 Oliva y Ocana, Dona. Fermina  female  39.0      0      0
415                 Saether, Mr. Simon Sivertsen    male  38.5      0      0
416                          Ware, Mr. Frederick    male   NaN      0      0
417                    Peter, Master. Michael J    male   NaN      1      1

                 Ticket      Fare Cabin Embarked
0                330911    7.8292   NaN        Q
1                363272    7.0000   NaN        S
2                240276    9.6875   NaN        Q
3                315154    8.6625   NaN        S
4               3101298   12.2875   NaN        S
..                  …        …   …        …
413           A.5. 3236    8.0500   NaN        S
414            PC 17758  108.9000  C105        C
415  SOTON/O.Q. 3101262    7.2500   NaN        S
416              359309    8.0500   NaN        S
417                2668   22.3583   NaN        C

[418 rows x 12 columns]
```

[ ]:
```python
df.head()
```

[ ]:
```
   PassengerId  Survived  Pclass  \
0          892         0       3
1          893         1       3
2          894         0       2
3          895         0       3
4          896         1       3

                                           Name     Sex   Age  SibSp  Parch  \
0                              Kelly, Mr. James    male  34.5      0      0
1              Wilkes, Mrs. James (Ellen Needs)  female  47.0      1      0
2                     Myles, Mr. Thomas Francis    male  62.0      0      0
3                              Wirz, Mr. Albert    male  27.0      0      0
4  Hirvonen, Mrs. Alexander (Helga E Lindqvist)  female  22.0      1      1

    Ticket     Fare Cabin Embarked
0   330911   7.8292   NaN        Q
1   363272   7.0000   NaN        S
2   240276   9.6875   NaN        Q
3   315154   8.6625   NaN        S
```

```
4  3101298  12.2875   NaN        S
```

[ ]:
```
df.tail()
```

[ ]:
```
     PassengerId  Survived  Pclass                          Name     Sex  \
413         1305         0       3            Spector, Mr. Woolf    male
414         1306         1       1  Oliva y Ocana, Dona. Fermina  female
415         1307         0       3  Saether, Mr. Simon Sivertsen    male
416         1308         0       3           Ware, Mr. Frederick    male
417         1309         0       3      Peter, Master. Michael J    male

      Age  SibSp  Parch              Ticket      Fare Cabin Embarked
413   NaN      0      0           A.5. 3236    8.0500   NaN        S
414  39.0      0      0            PC 17758  108.9000  C105        C
415  38.5      0      0  SOTON/O.Q. 3101262    7.2500   NaN        S
416   NaN      0      0              359309    8.0500   NaN        S
417   NaN      1      1                2668   22.3583   NaN        C
```

[ ]:
```
df.shape
```

[ ]:
```
(418, 12)
```

[ ]:
```
df.dtypes
```

[ ]:
```
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
```

[ ]:
```
df.describe().T
```

[ ]:
```
             count         mean         std     min       25%       50%  \
PassengerId  418.0  1100.500000  120.810458  892.00  996.2500  1100.5000
Survived     418.0     0.363636    0.481622    0.00    0.0000    0.0000
Pclass       418.0     2.265550    0.841838    1.00    1.0000    3.0000
Age          332.0    30.272590   14.181209    0.17   21.0000   27.0000
SibSp        418.0     0.447368    0.896760    0.00    0.0000    0.0000
Parch        418.0     0.392344    0.981429    0.00    0.0000    0.0000
```

```
Fare         417.0    35.627188    55.907576     0.00     7.8958     14.4542

                 75%        max
PassengerId  1204.75  1309.0000
Survived        1.00     1.0000
Pclass          3.00     3.0000
Age            39.00    76.0000
SibSp           1.00     8.0000
Parch           0.00     9.0000
Fare           31.50   512.3292
```

[ ]:
```
df.describe(include='object').T
```

[ ]:
```
         count unique               top freq
Name       418    418  Kelly, Mr. James    1
Sex        418      2              male  266
Ticket     418    363          PC 17608    5
Cabin       91     76   B57 B59 B63 B66    3
Embarked   418      3                 S  270
```

[ ]:
```
df.isna().sum()
```

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

[ ]:
```
df['Cabin'].value_counts()
```

[ ]:
```
B57 B59 B63 B66    3
B45                2
C89                2
C55 C57            2
A34                2
                  ..
E52                1
D30                1
E31                1
```

```
C62 C64            1
C105               1
Name: Cabin, Length: 76, dtype: int64
```

[ ]:
```python
#droping irrelavant column
df.drop(['PassengerId','Name','Ticket'],axis=1,inplace=True)
df
```

[ ]:
```
     Survived  Pclass     Sex   Age  SibSp  Parch      Fare Cabin Embarked
0           0       3    male  34.5      0      0    7.8292   NaN        Q
1           1       3  female  47.0      1      0    7.0000   NaN        S
2           0       2    male  62.0      0      0    9.6875   NaN        Q
3           0       3    male  27.0      0      0    8.6625   NaN        S
4           1       3  female  22.0      1      1   12.2875   NaN        S
..        …      …      …     …    …      …     …    …       …
413         0       3    male   NaN      0      0    8.0500   NaN        S
414         1       1  female  39.0      0      0  108.9000  C105        C
415         0       3    male  38.5      0      0    7.2500   NaN        S
416         0       3    male   NaN      0      0    8.0500   NaN        S
417         0       3    male   NaN      1      1   22.3583   NaN        C

[418 rows x 9 columns]
```

[ ]:
```python
df['Age']=df['Age'].fillna(df['Age'].mean())
df['Fare']=df['Fare'].fillna(df['Fare'].mode()[0])
```

[ ]:
```python
df.isna().sum()
```

[ ]:
```
Survived      0
Pclass        0
Sex           0
Age           0
SibSp         0
Parch         0
Fare          0
Cabin       327
Embarked      0
dtype: int64
```

[ ]:
```python
#drops the "Cabin" column from the DataFrame
df.drop(['Cabin'],axis=1,inplace=True)
```

[ ]:
```python
df.isna().sum()
```

[ ]:
```
Survived    0
Pclass      0
Sex         0
```

```
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Survived  418 non-null    int64  
 1   Pclass    418 non-null    int64  
 2   Sex       418 non-null    object 
 3   Age       418 non-null    float64
 4   SibSp     418 non-null    int64  
 5   Parch     418 non-null    int64  
 6   Fare      418 non-null    float64
 7   Embarked  418 non-null    object 
dtypes: float64(2), int64(4), object(2)
memory usage: 26.2+ KB
```

[ ]:
```
df.dtypes
```

[ ]:
```
Survived      int64
Pclass        int64
Sex          object
Age         float64
SibSp         int64
Parch         int64
Fare        float64
Embarked     object
dtype: object
```

DATA VISUALIZATION

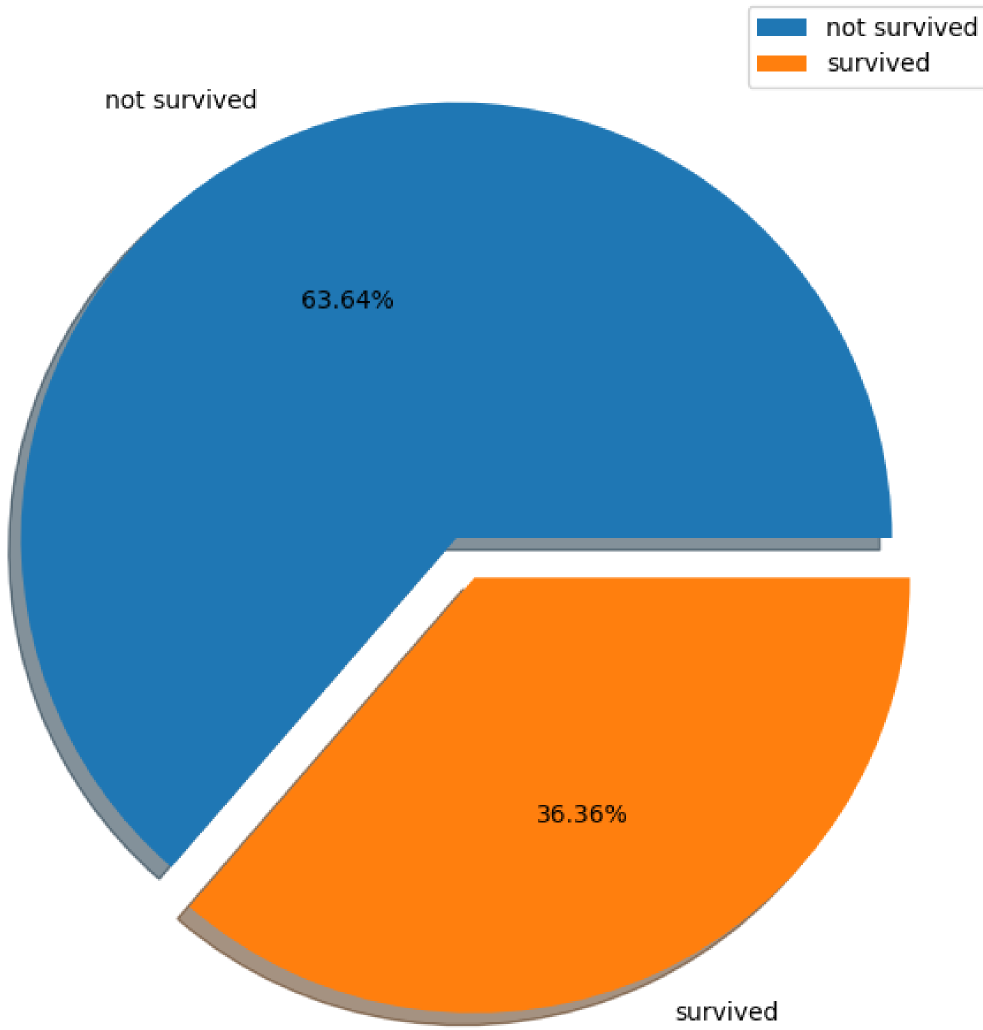
[ ]:
```
df['Survived'].value_counts()
```

[ ]:
```
0    266
1    152
Name: Survived, dtype: int64
```

[ ]:
```
plt.figure(figsize=(10,8))
label=['not survived','survived']
```

```
plt.pie(df['Survived'].value_counts(),labels=label,autopct='%1.
↪2f%%',explode=[0,0.1],shadow=True)
plt.legend()
```

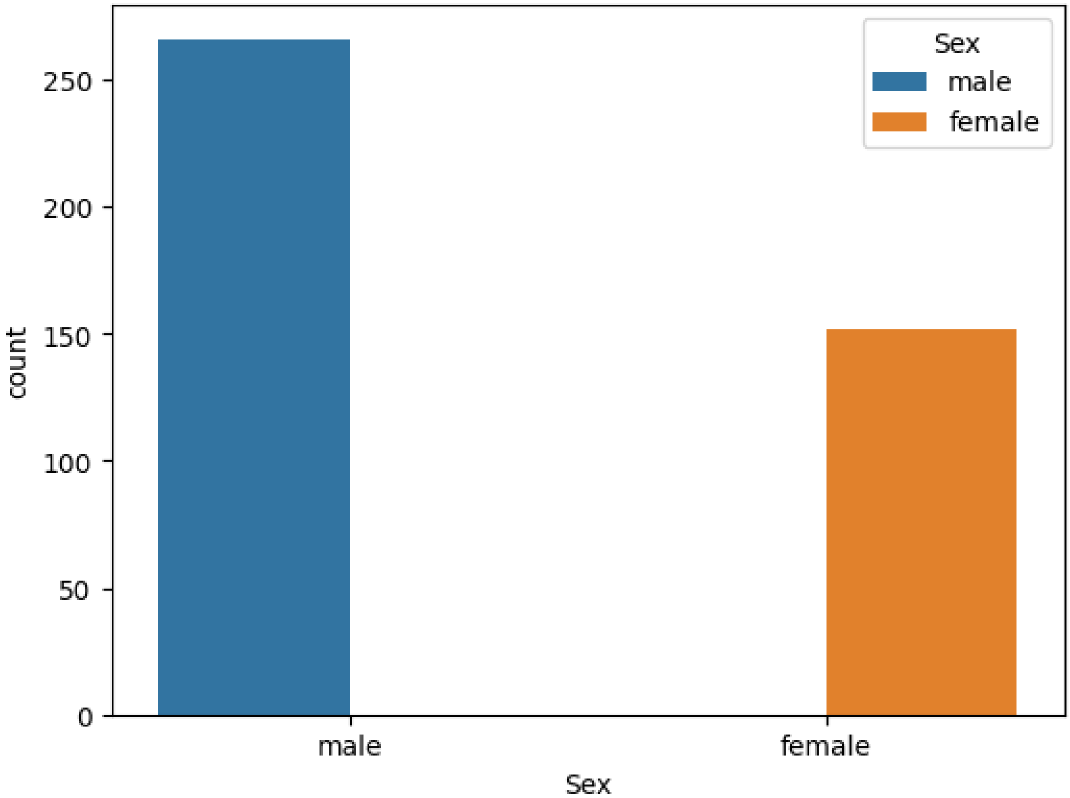
[ ]: <matplotlib.legend.Legend at 0x793198043010>




```
[ ]: df['Sex'].value_counts()
```

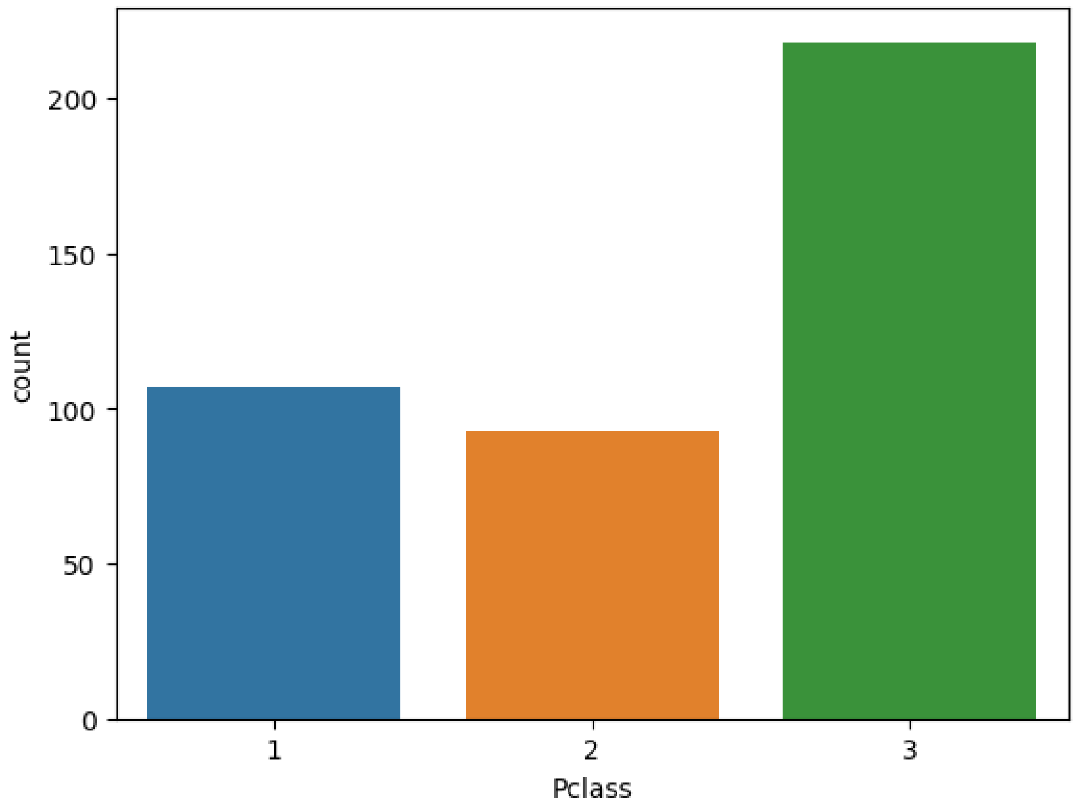
```
[ ]: male      266
     female    152
     Name: Sex, dtype: int64
```

[ ]:
```
color=['teal','green']
sns.countplot(x='Sex',data=df,hue='Sex')
plt.show()
```



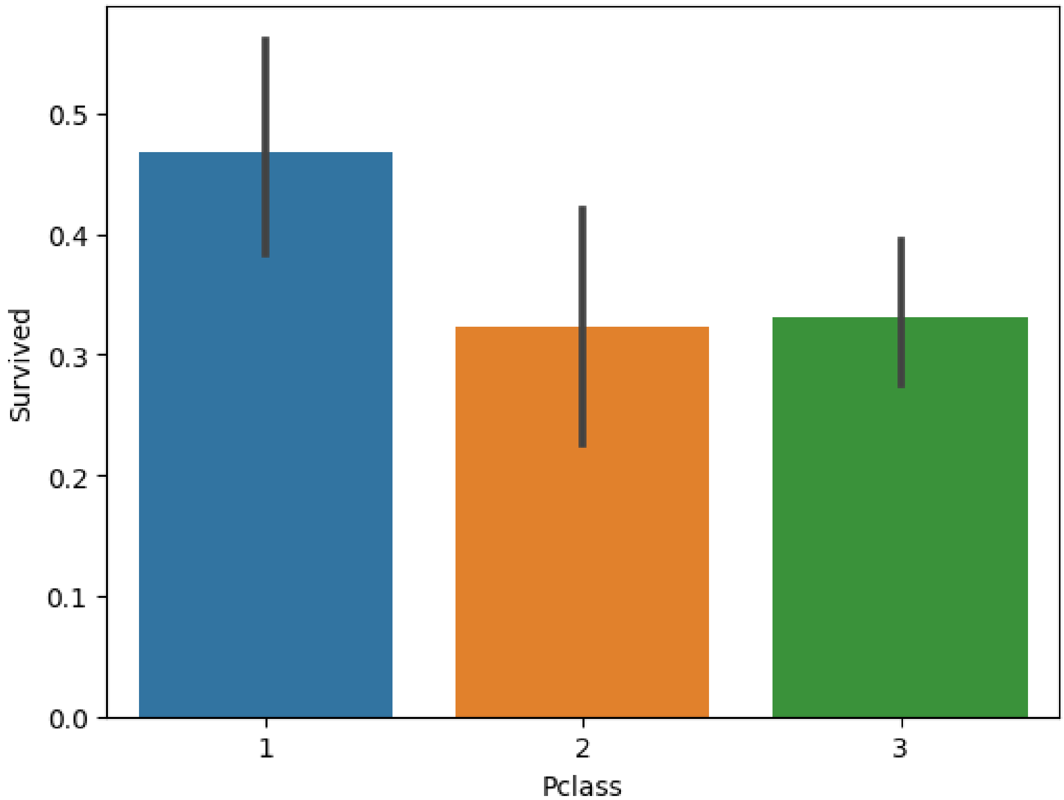
[ ]:
```
sns.countplot(x='Pclass',data=df)
```

[ ]: <Axes: xlabel='Pclass', ylabel='count'>



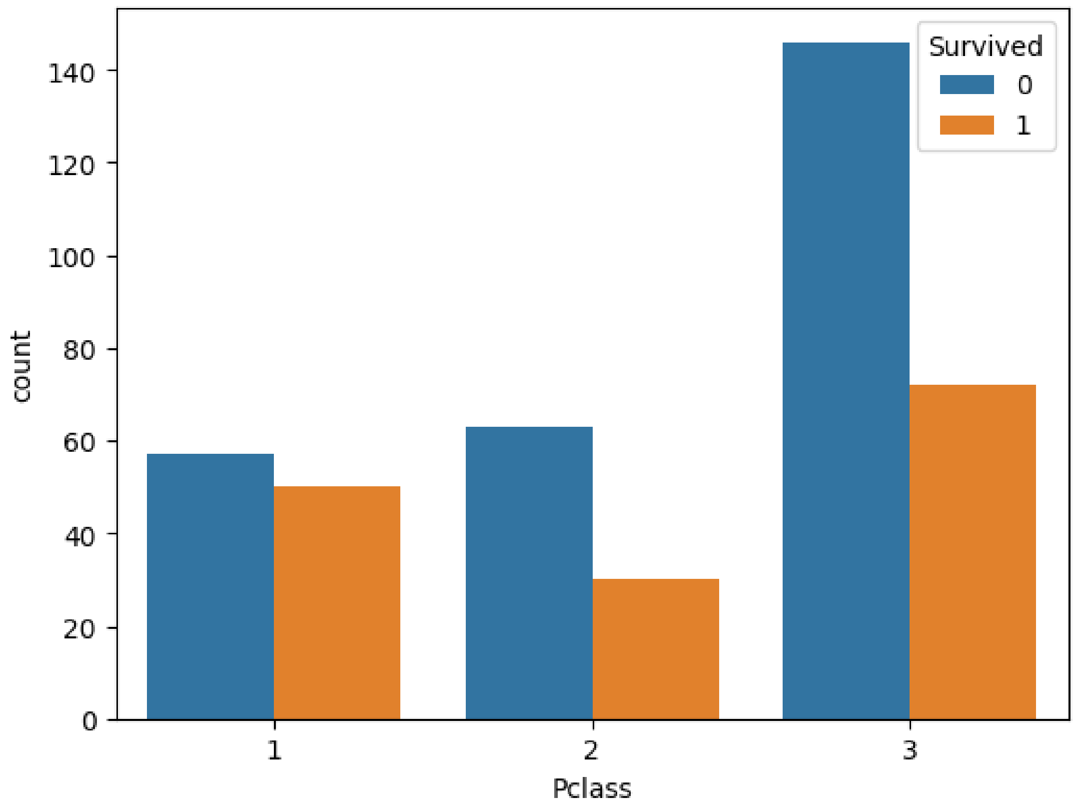

```
[ ]: sns.barplot(x=df['Pclass'],y=df['Survived'])
```

```
[ ]: <Axes: xlabel='Pclass', ylabel='Survived'>
```



[ ]:
```
sns.countplot(x='Pclass',data=df,hue='Survived')
```

[ ]: <Axes: xlabel='Pclass', ylabel='count'>



CORRELATION

[ ]:
```
df.corr()
```

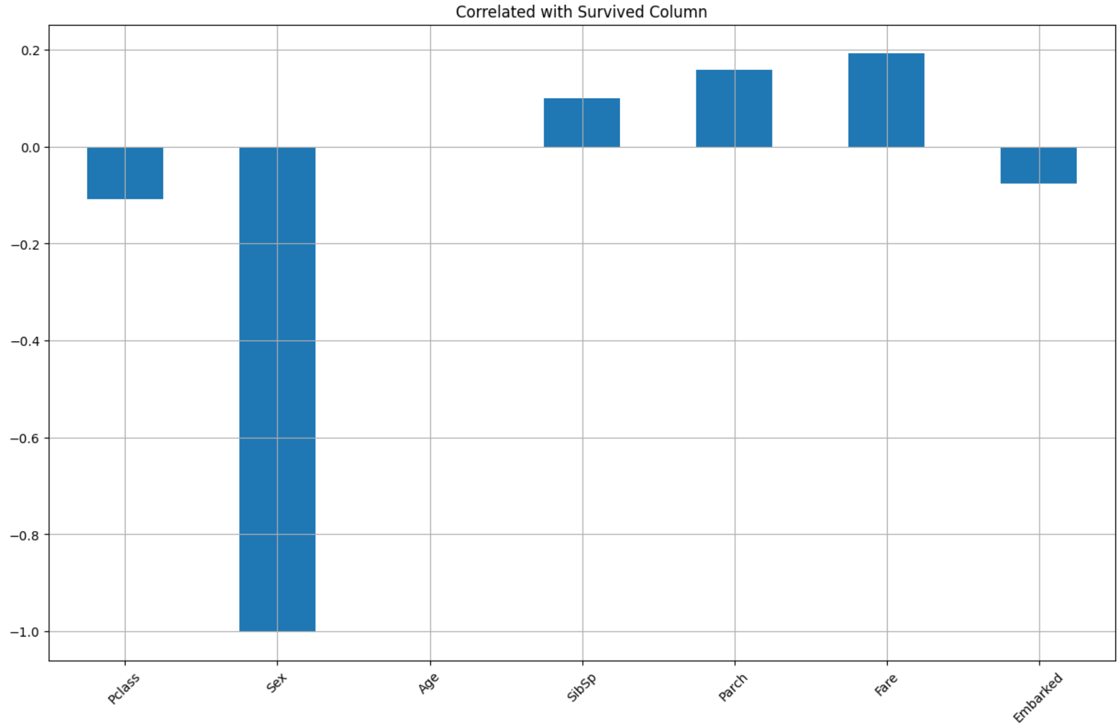
[ ]:

	Survived	Pclass	Age	SibSp	Parch	Fare
Survived	1.000000	-0.108615	-0.000011	0.099943	0.159120	0.192229
Pclass	-0.108615	1.000000	-0.440782	0.001087	0.018721	-0.577491
Age	-0.000011	-0.440782	1.000000	-0.079535	-0.045073	0.323839
SibSp	0.099943	0.001087	-0.079535	1.000000	0.306895	0.172034
Parch	0.159120	0.018721	-0.045073	0.306895	1.000000	0.230411
Fare	0.192229	-0.577491	0.323839	0.172034	0.230411	1.000000

[ ]:
```
plt.figure(figsize=(14,8))
sns.heatmap(df.corr(),annot=True)
plt.show()
```

[ ]:
```
df1=df.drop(columns='Survived')
df1.corrwith(df['Survived']).plot.bar(figsize=(15,9),title='Correlated with␣
↪Survived Column',rot=45,grid=True)
```

[ ]:
```
<Axes: title={'center': 'Correlated with Survived Column'}>
```



LABEL ENCODING

[ ]:
```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
df['Sex']=le.fit_transform(df['Sex'])
df['Embarked']=le.fit_transform(df['Embarked'])
df
```

[ ]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	1	34.50000	0	0	7.8292	1
1	1	3	0	47.00000	1	0	7.0000	2
2	0	2	1	62.00000	0	0	9.6875	1
3	0	3	1	27.00000	0	0	8.6625	2
4	1	3	0	22.00000	1	1	12.2875	2
..	…	…	…	…	…	…	…	…
413	0	3	1	30.27259	0	0	8.0500	2
414	1	1	0	39.00000	0	0	108.9000	0
415	0	3	1	38.50000	0	0	7.2500	2
416	0	3	1	30.27259	0	0	8.0500	2
417	0	3	1	30.27259	1	1	22.3583	0

[418 rows x 8 columns]

X AND Y SEPARATION

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

[ ]:
```
x
```

[ ]:
```
     Pclass  Sex       Age  SibSp  Parch      Fare  Embarked
0         3    1  34.50000      0      0    7.8292         1
1         3    0  47.00000      1      0    7.0000         2
2         2    1  62.00000      0      0    9.6875         1
3         3    1  27.00000      0      0    8.6625         2
4         3    0  22.00000      1      1   12.2875         2
..      …   …       …    …    …       …      …
413       3    1  30.27259      0      0    8.0500         2
414       1    0  39.00000      0      0  108.9000         0
415       3    1  38.50000      0      0    7.2500         2
416       3    1  30.27259      0      0    8.0500         2
417       3    1  30.27259      1      1   22.3583         0

[418 rows x 7 columns]
```

[ ]:
```
y
```

[ ]:
```
0      0
1      1
2      0
3      0
4      1
      ..
413    0
414    1
415    0
416    0
417    0
Name: Survived, Length: 418, dtype: int64
```

SPLITING IN TO TRAINING AND TESTING DATA

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

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
 ↪3,random_state=42)
```

FEATURE SCALING

[ ]:
```
from sklearn.preprocessing import StandardScaler
sd=StandardScaler()
x_train=sd.fit_transform(x_train)
x_test=sd.fit_transform(x_test)
```

[ ]:
```
from sklearn.metrics import␣
↪accuracy_score,classification_report,ConfusionMatrixDisplay
```

2 MODEL BUILDING AND EVALUATION

K Nearest Neighbor Classifier

SVC

LOGISTIC REGRESSION

DECISION TREE CLASSIFIER

RANDOM FOREST CLASSIFIER

1.KNN (K Nearest Neighbours)

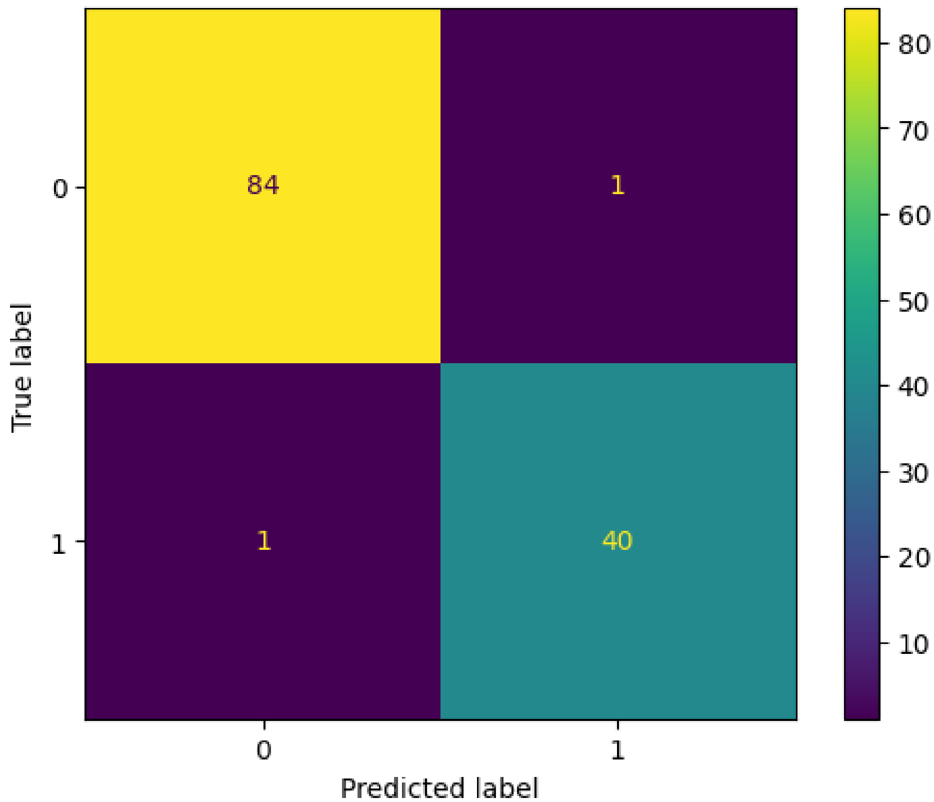
[ ]:
```
#model creation
from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=7)
knn.fit(x_train,y_train)
knn_pred=knn.predict(x_test)
```

[ ]:
```
#accuracy score
knn_acc=accuracy_score(y_test,knn_pred)
knn_acc
```

[ ]:
```
0.9841269841269841
```

[ ]:
```
#classification report and confusion matrix
print(classification_report(y_test,knn_pred))
print(ConfusionMatrixDisplay.from_predictions(y_test,knn_pred))
```

```
              precision    recall  f1-score   support

           0       0.99      0.99      0.99        85
           1       0.98      0.98      0.98        41

    accuracy                           0.98       126
   macro avg       0.98      0.98      0.98       126
weighted avg       0.98      0.98      0.98       126

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at
0x793198041150>
```



2.SVC (SUPPORT VECTOR CLASSIFIER)

[ ]:
```
#model creation
from sklearn.svm import SVC
model=SVC()
model.fit(x_train,y_train)
y_pred_svm=model.predict(x_test)
```

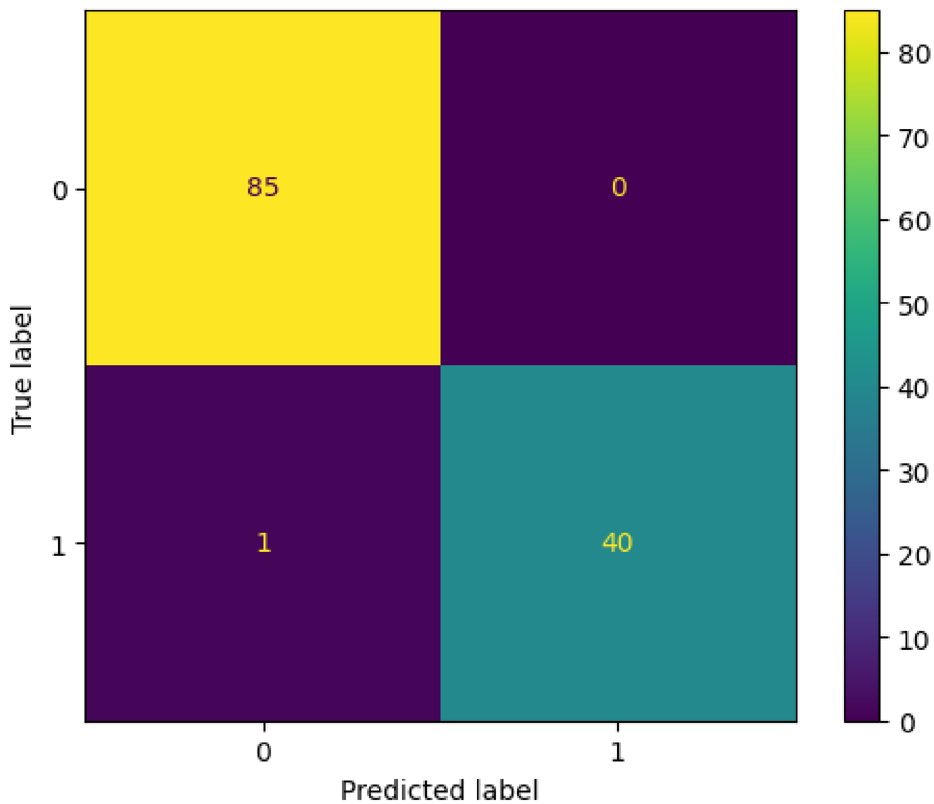
[ ]:
```
#accuracy score
svm_acc=(accuracy_score(y_test,y_pred_svm))
svm_acc
```

[ ]: 0.9920634920634921

[ ]:
```
print(classification_report(y_test,y_pred_svm))
print(ConfusionMatrixDisplay.from_predictions(y_test,y_pred_svm))
```

```
              precision    recall  f1-score   support

           0       0.99      1.00      0.99        85
           1       1.00      0.98      0.99        41
```

```
    accuracy                           0.99       126
   macro avg       0.99      0.99      0.99       126
weighted avg       0.99      0.99      0.99       126

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at
0x7931993cf670>
```



3.LOGISTIC REGRESSION

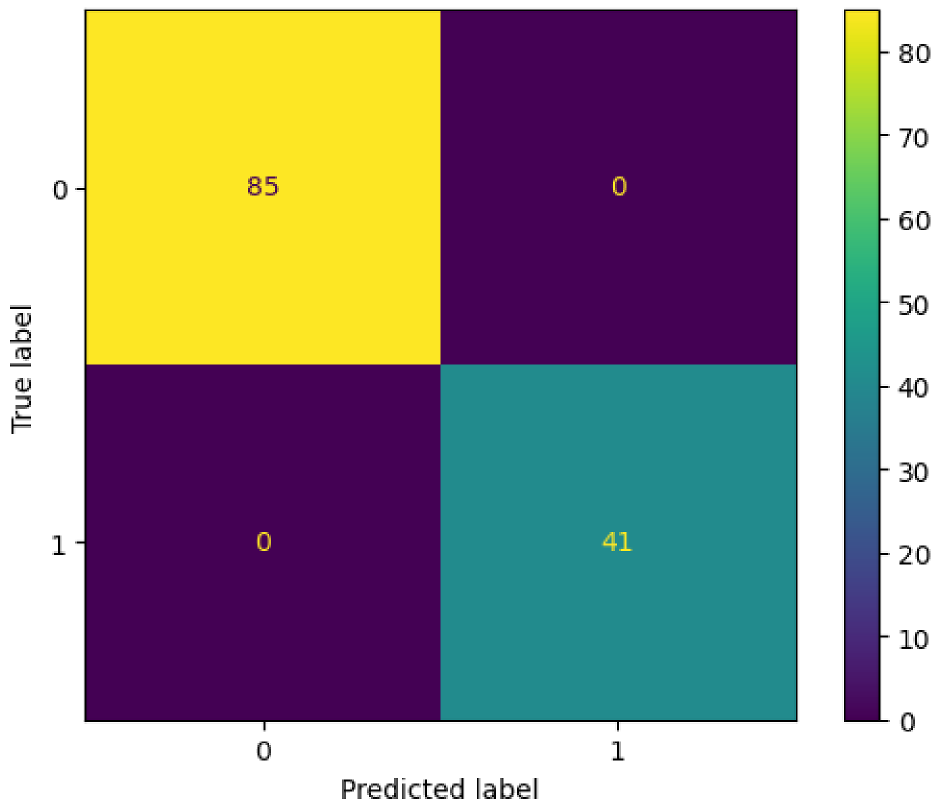
[ ]:
```
#model creation
from sklearn.linear_model import LogisticRegression
lg=LogisticRegression(random_state=42)
lg.fit(x_train,y_train)
y_pred_lg=lg.predict(x_test)
```

[ ]:
```
#accuracy score
lg_acc=(accuracy_score(y_test,y_pred_lg))
lg_acc
```

[ ]: 1.0

[ ]:
```
#classification report and confusion matrix
print(classification_report(y_test,y_pred_lg))
print(ConfusionMatrixDisplay.from_predictions(y_test,y_pred_lg))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        85
           1       1.00      1.00      1.00        41

    accuracy                           1.00       126
   macro avg       1.00      1.00      1.00       126
weighted avg       1.00      1.00      1.00       126

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at
0x793197fc9090>
```



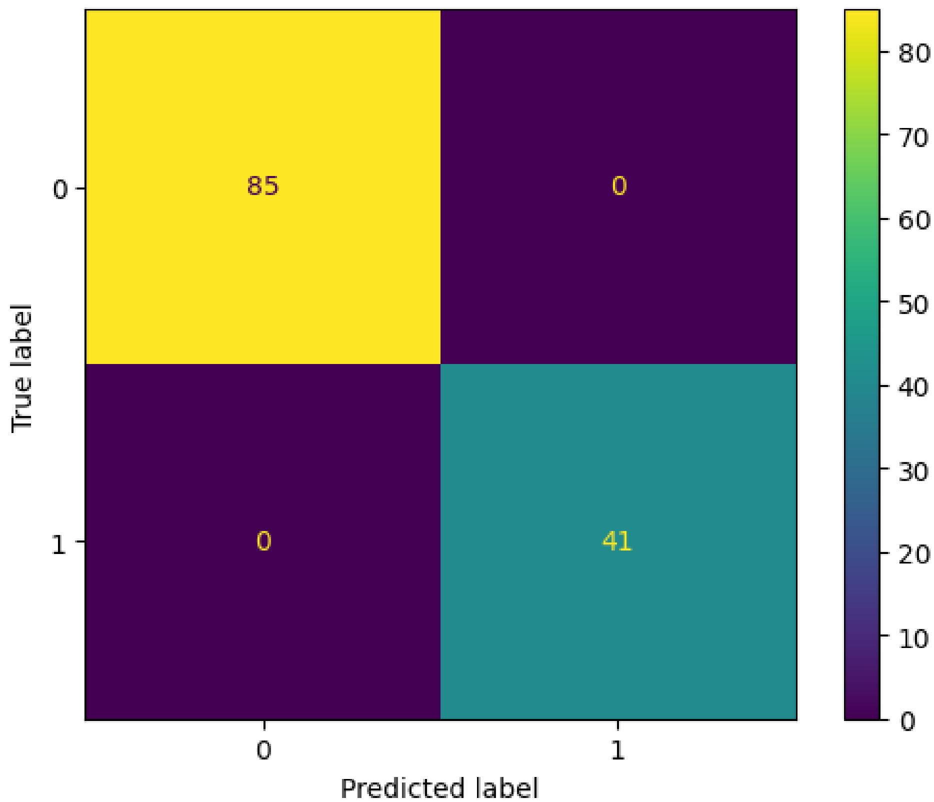
4.DECISION TREE CLASSIFIER

[ ]:
```
#model creation
from sklearn.tree import DecisionTreeClassifier
decision=DecisionTreeClassifier()
decision.fit(x_train,y_train)
```

```
y_pred_decision=decision.predict(x_test)
```

```
1.0
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        85
           1       1.00      1.00      1.00        41

    accuracy                           1.00       126
   macro avg       1.00      1.00      1.00       126
weighted avg       1.00      1.00      1.00       126
```

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at 0x793197d94af0>

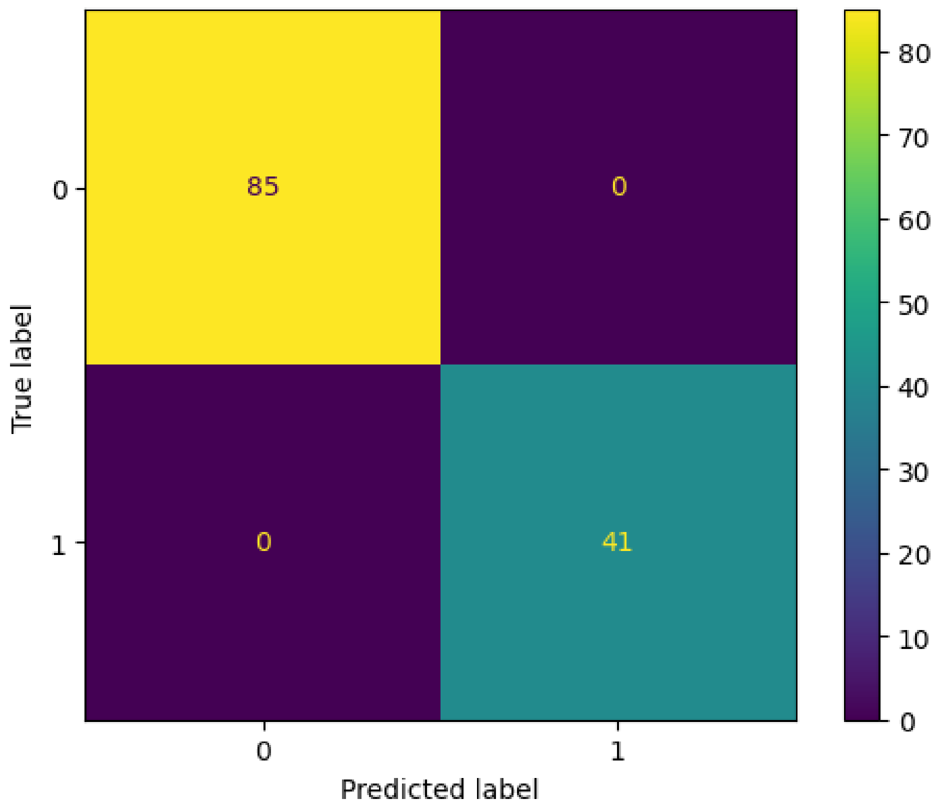


[ ]:
```
#accuracy score
dtree_acc=accuracy_score(y_test,y_pred_decision)
dtree_acc
```

[ ]: 1.0

[ ]:
```
#classification report and confusion matrix
print(classification_report(y_test,y_pred_decision))
print(ConfusionMatrixDisplay.from_predictions(y_test,y_pred_decision))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        85
           1       1.00      1.00      1.00        41

    accuracy                           1.00       126
   macro avg       1.00      1.00      1.00       126
weighted avg       1.00      1.00      1.00       126

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at
0x7931980425c0>
```



RANDOM FOREST CLASSIFIER

[ ]:
```
#model creation
from sklearn.ensemble import RandomForestClassifier
random=RandomForestClassifier(random_state=42)
random.fit(x_train,y_train)
```

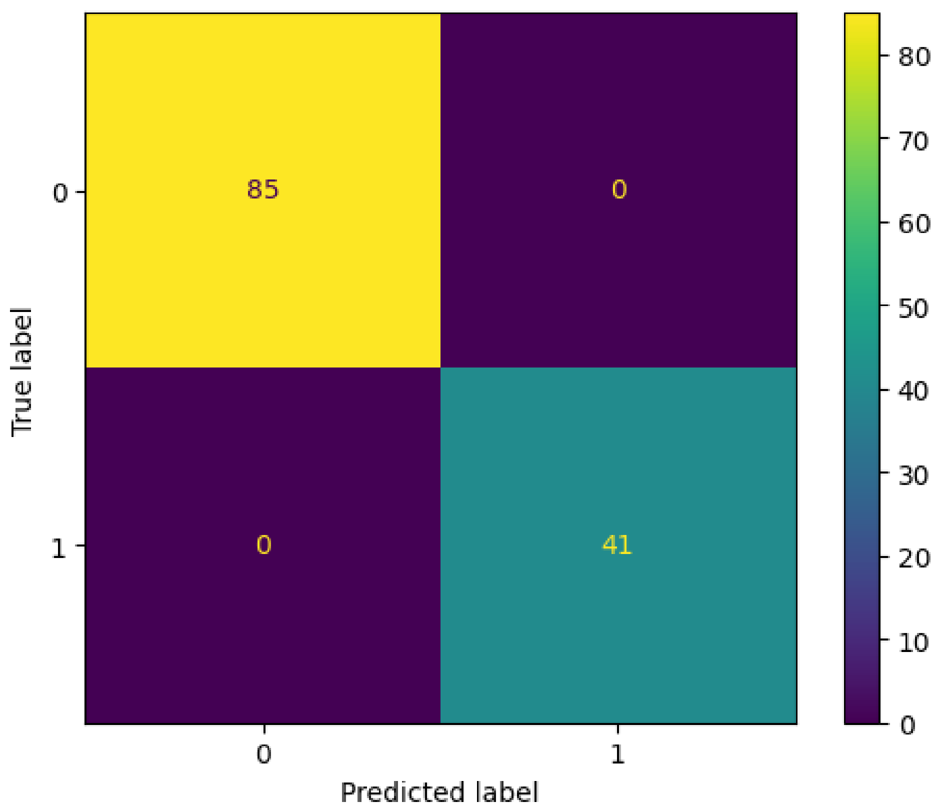
```
y_pred_random=random.predict(x_test)
```

[ ]:
```
#accuracy score
rf_acc=accuracy_score(y_test,y_pred_random)
rf_acc
```

[ ]: 1.0

[ ]:
```
#classification report and confusion matrix
print(classification_report(y_test,y_pred_random))
print(ConfusionMatrixDisplay.from_predictions(y_test,y_pred_random))
```

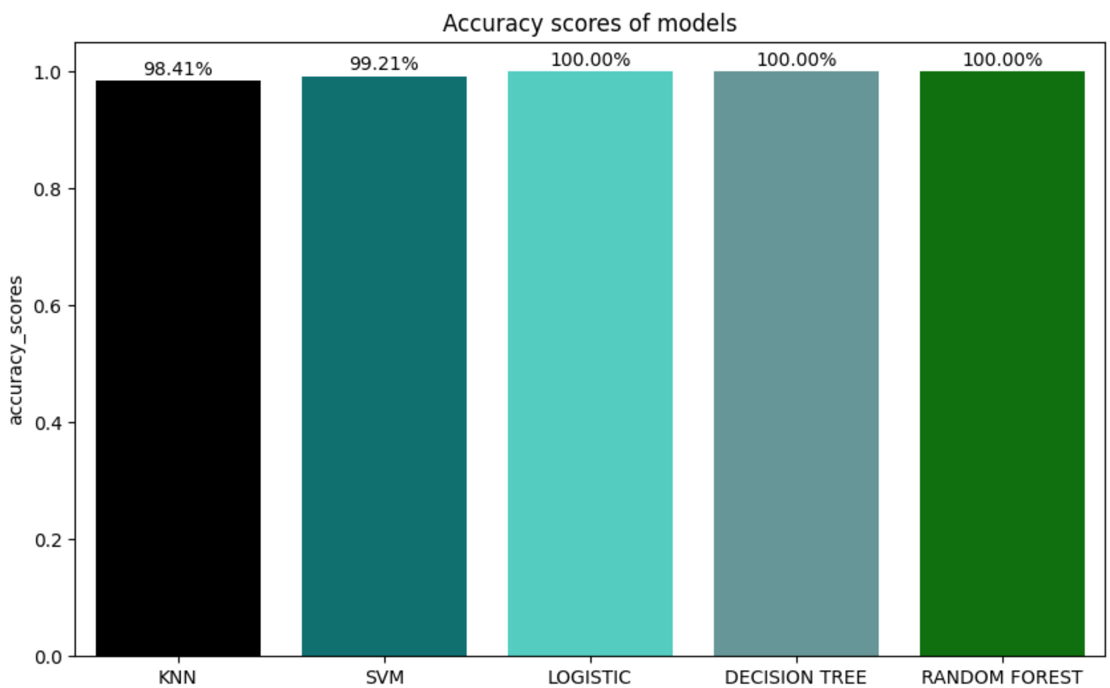
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        85
           1       1.00      1.00      1.00        41

    accuracy                           1.00       126
   macro avg       1.00      1.00      1.00       126
weighted avg       1.00      1.00      1.00       126

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at
0x793197762560>
```



[ ]:
```
model=['KNN','SVM','LOGISTIC','DECISION TREE','RANDOM FOREST']
accuracy_scores=[knn_acc,svm_acc,lg_acc,dtree_acc,rf_acc]
accuracy_scores
```

[ ]: [0.9841269841269841, 0.9920634920634921, 1.0, 1.0, 1.0]

[ ]:
```
color=['black','teal','turquoise','cadetblue','green']
plt.figure(figsize=(10,6))
sns.barplot(x=model,y=accuracy_scores,palette=color)
plt.ylabel('accuracy_scores')
plt.title('Accuracy scores of models')
# Adding percentage labels
for i, score in enumerate(accuracy_scores):
    plt.text(i, score +0.01, f'{score*100:.2f}%' , ha = 'center')
plt.show()
```



3 CONCLUSION

After a comprehensive analysis on the Titanic Survival Prediction dataset, multiple machine learning models were employed:

- **KNN**: 98.41% accuracy

- **SVM**: 99.21% accuracy
- **Logistic Regression**: 100% accuracy
- **Decision Tree**: 100% accuracy
- **Random Forest**: 100% accuracy

All models performed exceptionally well, achieving high accuracy scores. It's noteworthy that the Logistic Regression, Decision Tree, and Random Forest models achieved perfect accuracy, indicating robust predictive capabilities.