TITANIC SURVIVAL PREDICTION

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TASK NO 01

DATASET

CODE

RESULTS

Task

- Use the Titanic dataset to build a model that predicts whether a passenger on the Titanic survived or not. This is a classic beginner project with readily available data.
- The dataset typically used for this project contains information about individual passengers, such as their age, gender, ticket class, fare, cabin, and whether or not they survived.

Code

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
import seaborn as sns
import matplotlib.pyplot as plt


```

✓ 0.0s

```
df = pd.read_csv(r"C:\Users\Fjwu\Downloads\archive\tested.csv")
```

✓ 0.0s

```
df
```

✓ 0.2s

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
413	1305	0	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500	NaN	S

```
df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S

```
df.tail()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
413	1305	0	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500	NaN	S
414	1306	1	1	Oliva y Ocana, Dona. Fermina	female	39.0	0	0	PC 17758	108.9000	C105	C
415	1307	0	3	Saether, Mr. Simon Sivertsen	male	38.5	0	0	SOTON/O.Q. 3101262	7.2500	NaN	S
416	1308	0	3	Ware, Mr. Frederick	male	NaN	0	0	359309	8.0500	NaN	S
417	1309	0	3	Peter, Master. Michael J	male	NaN	1	1	2668	22.3583	NaN	C

```
df.shape
```

✓ 0.0s

```
(418, 12)
```

```
#data pre prossesing
# Handle missing values
df.dropna(subset=['Survived'], inplace=True)
df ['Age'].fillna(df ['Age'].median(), inplace=True)
df ['Embarked'].fillna(df ['Embarked'].mode()[0], inplace=True)

# Feature selection
features = ['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Embarked']
X = df [features]
X = pd.get_dummies(X, columns=['Sex', 'Embarked'], drop_first=True)
y = df ['Survived']

```

✓ 0.0s

```
#Split Data into Training and Testing Sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

```

0.0s

```
def summary(df):
    sum = pd.DataFrame(df.dtypes, columns=['dtypes'])
    sum['missing#'] = df.isna().sum().values
    sum['missing%'] = (df.isna().sum().values*100)/len(df)
    sum['uniques'] = df.nunique().values
    sum['count'] = df.count().values
    #sum['skew'] = df.skew().values
    desc = pd.DataFrame(df.describe().T)
    sum['min'] = desc['min']
    sum['max'] = desc['max']
    sum['mean'] = desc['mean']
    return sum

summary(df).style.background_gradient(cmap='twilight_shifted_r')
```

	dtypes	missing#	missing%	uniques	count	min	max	mean
PassengerId	int64	0	0.000000	418	418	892.000000	1309.000000	1100.500000
Survived	int64	0	0.000000	2	418	0.000000	1.000000	0.363636
Pclass	int64	0	0.000000	3	418	1.000000	3.000000	2.265550
Name	object	0	0.000000	418	418	nan	nan	nan
Sex	object	0	0.000000	2	418	nan	nan	nan
Age	float64	0	0.000000	79	418	0.170000	76.000000	29.599282
SibSp	int64	0	0.000000	7	418	0.000000	8.000000	0.447368
Parch	int64	0	0.000000	8	418	0.000000	9.000000	0.392344
Ticket	object	0	0.000000	363	418	nan	nan	nan
Fare	float64	1	0.239234	169	417	0.000000	512.329200	35.627188
Cabin	object	327	78.229665	76	91	nan	nan	nan
Embarked	object	0	0.000000	3	418	nan	nan	nan

```
df.drop(columns=['Cabin'], inplace=True)

```

0.0s

```
summary(df).style.background_gradient(cmap='twilight_shifted_r')
```

0.2s

	dtypes	missing#	missing%	uniques	count	min	max	mean
PassengerId	int64	0	0.000000	418	418	892.000000	1309.000000	1100.500000
Survived	int64	0	0.000000	2	418	0.000000	1.000000	0.363636
Pclass	int64	0	0.000000	3	418	1.000000	3.000000	2.265550
Name	object	0	0.000000	418	418	nan	nan	nan
Sex	object	0	0.000000	2	418	nan	nan	nan
Age	float64	0	0.000000	79	418	0.170000	76.000000	29.599282
SibSp	int64	0	0.000000	7	418	0.000000	8.000000	0.447368
Parch	int64	0	0.000000	8	418	0.000000	9.000000	0.392344
Ticket	object	0	0.000000	363	418	nan	nan	nan
Fare	float64	1	0.239234	169	417	0.000000	512.329200	35.627188
Embarked	object	0	0.000000	3	418	nan	nan	nan

```
1  df['Age'].fillna(df['Age'].mean(), inplace=True)
```
✓ 0.0s

```
1  df['Fare'].fillna(df['Fare'].mean(), inplace=True)
2
```
✓ 0.0s

```
1  summary(df).style.background_gradient(cmap='twilight_shifted_r')
```

	dtypes	missing#	missing%	uniques	count	min	max	mean
PassengerId	int64	0	0.000000	418	418	892.000000	1309.000000	1100.500000
Survived	int64	0	0.000000	2	418	0.000000	1.000000	0.363636
Pclass	int64	0	0.000000	3	418	1.000000	3.000000	2.265550
Name	object	0	0.000000	418	418	nan	nan	nan
Sex	object	0	0.000000	2	418	nan	nan	nan
Age	float64	0	0.000000	79	418	0.170000	76.000000	29.599282
SibSp	int64	0	0.000000	7	418	0.000000	8.000000	0.447368
Parch	int64	0	0.000000	8	418	0.000000	9.000000	0.392344
Ticket	object	0	0.000000	363	418	nan	nan	nan
Fare	float64	0	0.000000	170	418	0.000000	512.329200	35.627188
Embarked	object	0	0.000000	3	418	nan	nan	nan

```
1  df.drop(columns=['PassengerId', 'Name'], inplace=True)
```
✓ 0.0s

```
1  summary(df).style.background_gradient(cmap='twilight_shifted_r')
```
✓ 0.1s

	dtypes	missing#	missing%	uniques	count	min	max	mean
Survived	int64	0	0.000000	2	418	0.000000	1.000000	0.363636
Pclass	int64	0	0.000000	3	418	1.000000	3.000000	2.265550
Sex	object	0	0.000000	2	418	nan	nan	nan
Age	float64	0	0.000000	79	418	0.170000	76.000000	29.599282
SibSp	int64	0	0.000000	7	418	0.000000	8.000000	0.447368
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Ticket	object	0	0.000000	363	418	nan	nan	nan
Fare	float64	0	0.000000	170	418	0.000000	512.329200	35.627188
Embarked	object	0	0.000000	3	418	nan	nan	nan

```
1  df['Ticket'].sample(10)
```

✓ 0.0s

```
397        13567
243         3470
75        113503
354    C.A. 2315
68          2543
5           7538
34         13236
84        240261
300       347079
67        113796
Name: Ticket, dtype: object
```

```
1  df.drop(columns=['Ticket'], inplace=True)
```

✓ 0.0s

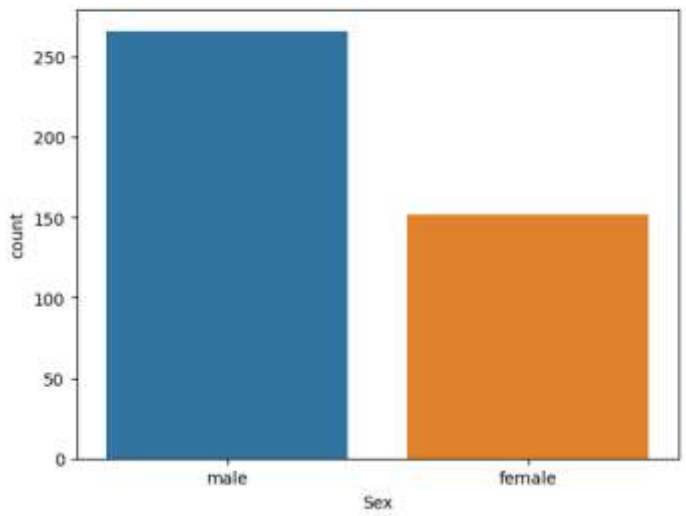
```
1  summary(df).style.background_gradient(cmap='twilight_shifted_r')
2
```

	dtypes	missing#	missing%	uniques	count	min	max	mean
Survived	int64	0	0.000000	2	418	0.000000	1.000000	0.363636
Pclass	int64	0	0.000000	3	418	1.000000	3.000000	2.265550
Sex	object	0	0.000000	2	418	nan	nan	nan
Age	float64	0	0.000000	79	418	0.170000	76.000000	29.599282
SibSp	int64	0	0.000000	7	418	0.000000	8.000000	0.447368
Parch	int64	0	0.000000	8	418	0.000000	9.000000	0.392344
Fare	float64	0	0.000000	170	418	0.000000	512.329200	35.627188
Embarked	object	0	0.000000	3	418	nan	nan	nan

```
1  sns.countplot(x=df['Sex'])
```

✓ 0.5s

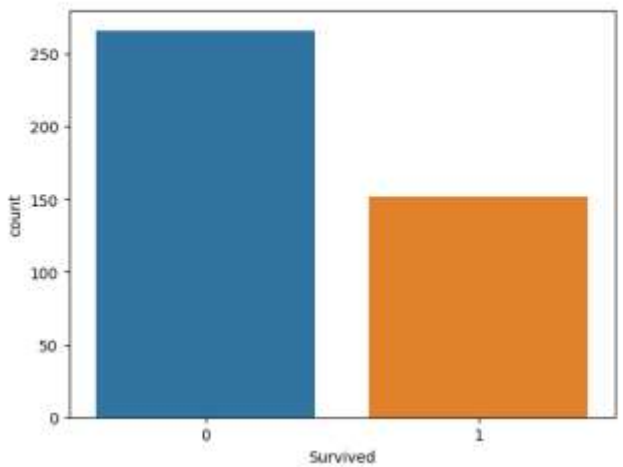
```
<Axes: xlabel='Sex', ylabel='count'>
```




```
1  sns.countplot(x=df['Survived'])
```

✓ 0.3s

```
<Axes: xlabel='Survived', ylabel='count'>
```




```
1  from sklearn.preprocessing import LabelEncoder  # Import LabelEncoder from scikit-learn
2
3  le = LabelEncoder()
4  columns_to_encode = ['Sex', 'Embarked']
5
6  for column in columns_to_encode:
7      df[column] = le.fit_transform(df[column])
8
9  # Now 'Sex' and 'Embarked' columns are encoded
10
```

✓ 0.0s

```
1  le = LabelEncoder()
2  columnsle=['Sex', 'Embarked']
3  for i in columnsle:
4      df[i] = le.fit_transform(df[i])
```

✓ 0.0s

```
1  summary(df).style.background_gradient(cmap='twilight_shifted_r')
2
```

	dtypes	missing#	missing%	uniques	count	min	max	mean
Survived	int64	0	0.000000	2	418	0.000000	1.000000	0.363636
Pclass	int64	0	0.000000	3	418	1.000000	3.000000	2.265550
Sex	int64	0	0.000000	2	418	0.000000	1.000000	0.636364
Age	float64	0	0.000000	79	418	0.170000	76.000000	29.599282
SibSp	int64	0	0.000000	7	418	0.000000	8.000000	0.447368
Parch	int64	0	0.000000	8	418	0.000000	9.000000	0.392344
Fare	float64	0	0.000000	170	418	0.000000	512.329200	35.627188
Embarked	int64	0	0.000000	3	418	0.000000	2.000000	1.401914

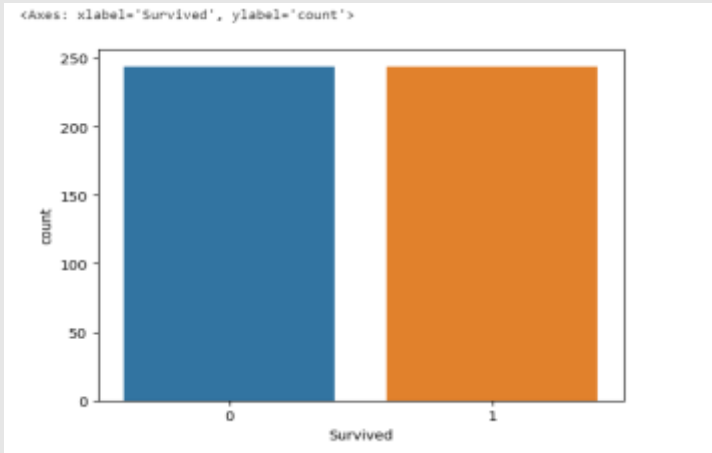
```
x = df.drop(columns=['Survived'])
y = df['Survived']
```
✓ 0.0s

```
pip install imbalanced-learn

```
✓ 9.3s

```
from imblearn.combine import SMOTETomek
smt=SMOTETomek()
x,y=smt.fit_resample(x,y)
```
✓ 0.7s

```
sns.countplot(x=y)
```
✓ 0.4s




```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=123)
```
✓ 0.0s

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier

# Now you can use DecisionTreeClassifier, RandomForestClassifier, and GradientBoostingClassifier in your code
dtree = DecisionTreeClassifier()
rf = RandomForestClassifier()
gb = GradientBoostingClassifier()

```
✓ 0.0s

```
from sklearn.ensemble import AdaBoostClassifier  # Import AdaBoostClassifier from scikit-learn
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression

# Now you can use AdaBoostClassifier, KNeighborsClassifier, and LogisticRegression in your code
ada = AdaBoostClassifier()
knn = KNeighborsClassifier()
lr = LogisticRegression()

```
✓ 0.0s

```
dtree = DecisionTreeClassifier()
rf = RandomForestClassifier()
gb = GradientBoostingClassifier()
ada = AdaBoostClassifier()
knn = KNeighborsClassifier()
lr = LogisticRegression()
```
✓ 0.0s

```
dtree.fit(x_train, y_train)
rf.fit(x_train, y_train)
gb.fit(x_train, y_train)
ada.fit(x_train, y_train)
knn.fit(x_train, y_train)
lr.fit(x_train, y_train)
```
✓ 0.0s

```
c:\Users\F%a\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\linear_model\_logistic.
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(
```

▾ LogisticRegression
LogisticRegression()

```
pdtreetr = dtree.predict(x_train)
pdtreete = dtree.predict(x_test)

prftr = rf.predict(x_train)
prfte = rf.predict(x_test)

pgbtr = gb.predict(x_train)
pgbte = gb.predict(x_test)

padatr = ada.predict(x_train)
padate = ada.predict(x_test)

pknntr = knn.predict(x_train)
pknnte = knn.predict(x_test)
```

```
print(acc_report(y_train, pdtreetr))
print(acc_report(y_test, pdtreete))
```

```
the accuracy of the model is  1.0
Confusion Matrix:
[[194   0]
 [  0 196]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       194
           1       1.00      1.00      1.00       196

    accuracy                           1.00       390
   macro avg       1.00      1.00      1.00       390
weighted avg       1.00      1.00      1.00       390

None
the accuracy of the model is  1.0
Confusion Matrix:
[[50  0]
 [ 0 48]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        50
           1       1.00      1.00      1.00        48

...
   macro avg       1.00      1.00      1.00        98
```

```
print(acc_report(y_train, prftr))
print(acc_report(y_test, prfte))
```

```
the accuracy of the model is  1.0
Confusion Matrix:
[[194   0]
 [  0 196]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       194
           1       1.00      1.00      1.00       196

    accuracy                           1.00       390
   macro avg       1.00      1.00      1.00       390
weighted avg       1.00      1.00      1.00       390

None
the accuracy of the model is  1.0
Confusion Matrix:
[[50  0]
 [ 0 48]]
Classification Report:
              precision    recall  f1-score   support
```

```
print(acc_report(y_train, pgbtr))
print(acc_report(y_test, pgbte))
```

```
the accuracy of the model is  1.0
Confusion Matrix:
[[194   0]
 [  0 196]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       194
           1       1.00      1.00      1.00       196

    accuracy                           1.00       390
   macro avg       1.00      1.00      1.00       390
weighted avg       1.00      1.00      1.00       390

None
the accuracy of the model is  1.0
Confusion Matrix:
[[50  0]
 [ 0 48]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        50
           1       1.00      1.00      1.00        48

...
```

```
print(acc_report(y_train, padatr))
print(acc_report(y_test, padate))
```

```
the accuracy of the model is  1.0
Confusion Matrix:
[[194   0]
 [  0 196]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       194
           1       1.00      1.00      1.00       196

    accuracy                           1.00       390
   macro avg       1.00      1.00      1.00       390
weighted avg       1.00      1.00      1.00       390

None
the accuracy of the model is  1.0
Confusion Matrix:
[[50  0]
 [ 0 48]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        50
           1       1.00      1.00      1.00        48

...
   macro avg       1.00      1.00      1.00        98
weighted avg       1.00      1.00      1.00        98
```

```
print(acc_report(y_train, pknntr))
print(acc_report(y_test, pknnte))
```

```
he accuracy of the model is  0.8564102564102564
onfusion Matrix:
[158  36]
 20 176]]
lassification Report:
              precision    recall  f1-score   support

           0       0.89      0.81      0.85       194
           1       0.83      0.90      0.86       196

    accuracy                           0.86       390
   macro avg       0.86      0.86      0.86       390
eighted avg       0.86      0.86      0.86       390

one
he accuracy of the model is  0.7142857142857143
onfusion Matrix:
[32 18]
[10 38]]
lassification Report:
              precision    recall  f1-score   support

           0       0.76      0.64      0.70        50
           1       0.68      0.79      0.73        48
```