In [51]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns


import warnings
warnings.filterwarnings('ignore')


## Sklearn Library
from scipy.stats import uniform
from sklearn.metrics import accuracy_score , precision_score, recall_score, f1_score, roc_auc_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix
from sklearn.metrics import matthews_corrcoef
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
import sklearn.metrics as sm
```

In [2]:
```
df=pd.read_csv(r"C:\Users\DD\OneDrive\Desktop\ML PROJECTS\credit fraud\creditcard.csv")
```

In [3]:
```
df
```

Out[3]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798
...	...	...	...	...	...	...	...	...	...	...	...	...	
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.305334	1.914428	...	0.213454	0.111
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.294869	0.584800	...	0.214205	0.924
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.708417	0.432454	...	0.232045	0.578
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.679145	0.392087	...	0.265245	0.800
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.414650	0.486180	...	0.261057	0.643

284807 rows × 31 columns

In [4]:
```
df.info
```

Out[4]:
```
<bound method DataFrame.info of             Time         V1         V2        V3        V4        V5  \
0            0.0  -1.359807  -0.072781  2.536347  1.378155 -0.338321
1            0.0   1.191857   0.266151  0.166480  0.448154  0.060018
2            1.0  -1.358354  -1.340163  1.773209  0.379780 -0.503198
3            1.0  -0.966272  -0.185226  1.792993 -0.863291 -0.010309
4            2.0  -1.158233   0.877737  1.548718  0.403034 -0.407193
...          ...        ...        ...       ...       ...       ...
284802  172786.0 -11.881118  10.071785 -9.834783 -2.066656 -5.364473
284803  172787.0  -0.732789  -0.055080  2.035030 -0.738589  0.868229
284804  172788.0   1.919565  -0.301254 -3.249640 -0.557828  2.630515
284805  172788.0  -0.240440   0.530483  0.702510  0.689799 -0.377961
284806  172792.0  -0.533413  -0.189733  0.703337 -0.506271 -0.012546

             V6        V7        V8        V9  ...       V21       V22  \
0      0.462388  0.239599  0.098698  0.363787  ... -0.018307  0.277838
1     -0.082361 -0.078803  0.085102 -0.255425  ... -0.225775 -0.638672
2      1.800499  0.791461  0.247676 -1.514654  ...  0.247998  0.771679
3      1.247203  0.237609  0.377436 -1.387024  ... -0.108300  0.005274
4      0.095921  0.592941 -0.270533  0.817739  ... -0.009431  0.798278
...         ...       ...       ...       ...  ...       ...       ...
284802 -2.606837 -4.918215  7.305334  1.914428  ...  0.213454  0.111864
284803  1.058415  0.024330  0.294869  0.584800  ...  0.214205  0.924384
284804  3.031260 -0.296827  0.708417  0.432454  ...  0.232045  0.578229
284805  0.623708 -0.686180  0.679145  0.392087  ...  0.265245  0.800049
284806 -0.649617  1.577006 -0.414650  0.486180  ...  0.261057  0.643078

            V23       V24       V25       V26       V27       V28  Amount  \
0     -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053  149.62
1      0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724    2.69
2      0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752  378.66
3     -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458  123.50
4     -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153   69.99
...         ...       ...       ...       ...       ...       ...     ...
284802  1.014480 -0.509348  1.436807  0.250034  0.943651  0.823731    0.77
284803  0.012463 -1.016226 -0.606624 -0.395255  0.068472 -0.053527   24.79
284804 -0.037501  0.640134  0.265745 -0.087371  0.004455 -0.026561   67.88
284805 -0.163298  0.123205 -0.569159  0.546668  0.108821  0.104533   10.00
284806  0.376777  0.008797 -0.473649 -0.818267 -0.002415  0.013649  217.00

        Class
0           0
1           0
2           0
```

```
3         0
4         0
...     ...
284802    0
284803    0
284804    0
284805    0
284806    0

[284807 rows x 31 columns]>
```

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64  
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

In [7]:
```
df.isnull()
```

Out[7]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Am
0	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	F
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	F
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	F
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	F
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	F
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
284802	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	F
284803	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	F
284804	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	F
284805	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	F
284806	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	F

284807 rows × 31 columns

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

In [11]:
```
df['Class'].value_counts()
```

Out[11]:
```
Class
0    284315
1       492
Name: count, dtype: int64
```

In [12]:
```
# separating the data for analysis
legit = df[df.Class == 0]
fraud = df[df.Class == 1]
```

In [13]:
```
legit.head()
```

Out[13]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137

5 rows × 31 columns

In [14]:
```
fraud.head()
```

Out[14]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22
541	406.0	-2.312227	1.951992	-1.609851	3.997906	-0.522188	-1.426545	-2.537387	1.391657	-2.770089	...	0.517232	-0.035049
623	472.0	-3.043541	-3.157307	1.088463	2.288644	1.359805	-1.064823	0.325574	-0.067794	-0.270953	...	0.661696	0.435477
4920	4462.0	-2.303350	1.759247	-0.359745	2.330243	-0.821628	-0.075788	0.562320	-0.399147	-0.238253	...	-0.294166	-0.932391
6108	6986.0	-4.397974	1.358367	-2.592844	2.679787	-1.128131	-1.706536	-3.496197	-0.248778	-0.247768	...	0.573574	0.176968
6329	7519.0	1.234235	3.019740	-4.304597	4.732795	3.624201	-1.357746	1.713445	-0.496358	-1.282858	...	-0.379068	-0.704181

5 rows × 31 columns

In [15]:
```
# statistical measures of the data
legit.Amount.describe()
```

Out[15]:
```
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
max       25691.160000
Name: Amount, dtype: float64
```

In [16]:
```
fraud.Amount.describe()
```

Out[16]:
```
count     492.000000
mean      122.211321
std       256.683288
min         0.000000
25%         1.000000
50%         9.250000
75%       105.890000
max      2125.870000
Name: Amount, dtype: float64
```

In [17]:
```
# compare the values for both transactions
df.groupby('Class').mean()
```

Out[17]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V20	
Class													
0	94838.202258	0.008258	-0.006271	0.012171	-0.007860	0.005453	0.002419	0.009637	-0.000987	0.004467	...	-0.000644	-0.0
1	80746.806911	-4.771948	3.623778	-7.033281	4.542029	-3.151225	-1.397737	-5.568731	0.570636	-2.581123	...	0.372319	0.7

2 rows × 30 columns

sample

In [19]:
```
legit_sample = legit.sample(n=800)
```

In [20]:
```
new_dataset = pd.concat([legit_sample, fraud], axis=0)
```

In [21]:
```
new_dataset
```

Out[21]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V
256222	157591.0	-2.456527	2.457377	-0.278652	-1.334673	-0.388679	-0.391650	-0.056992	0.619518	1.626584	...	-0.380373	-0.6583
221908	142745.0	2.192551	-0.697003	-2.172062	-0.869045	-0.185080	-1.774343	0.265166	-0.576818	-0.790990	...	0.352996	0.8723
204906	135497.0	2.095278	-0.693180	-1.575512	-0.753739	-0.248853	-0.635268	-0.491066	-0.243448	-0.351194	...	0.123200	0.3245
178821	123796.0	-0.089165	0.807445	-0.169992	-0.959017	1.048850	-0.200202	0.876518	-0.042459	-0.201535	...	-0.263317	-0.6290
68959	53206.0	1.316849	-0.505091	0.660849	-0.788016	-0.970255	-0.376154	-0.728547	0.076743	-1.054445	...	-0.005768	-0.1273
...	...	...	...	...	...	...	...	...	...	...	...	...	
279863	169142.0	-1.927883	1.125653	-4.518331	1.749293	-1.566487	-2.010494	-0.882850	0.697211	-2.064945	...	0.778584	-0.3191
280143	169347.0	1.378559	1.289381	-5.004247	1.411850	0.442581	-1.326536	-1.413170	0.248525	-1.127396	...	0.370612	0.0282
280149	169351.0	-0.676143	1.126366	-2.213700	0.468308	-1.120541	-0.003346	-2.234739	1.210158	-0.652250	...	0.751826	0.8341
281144	169966.0	-3.113832	0.585864	-5.399730	1.817092	-0.840618	-2.943548	-2.208002	1.058733	-1.632333	...	0.583276	-0.2692
281674	170348.0	1.991976	0.158476	-2.583441	0.408670	1.151147	-0.096695	0.223050	-0.068384	0.577829	...	-0.164350	-0.2951

1292 rows × 31 columns

In [24]:
```
new_dataset['Class'].value_counts()
```

Out[24]:
```
Class
0    800
1    492
Name: count, dtype: int64
```

Train the model

In [25]:
```python
X = new_dataset.drop(columns='Class', axis=1)
Y = new_dataset['Class']
```

In [27]:
```python
X
```

Out[27]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V20	V
256222	157591.0	-2.456527	2.457377	-0.278652	-1.334673	-0.388679	-0.391650	-0.056992	0.619518	1.626584	...	0.712993	-0.3803
221908	142745.0	2.192551	-0.697003	-2.172062	-0.869045	-0.185080	-1.774343	0.265166	-0.576818	-0.790990	...	-0.031527	0.3529
204906	135497.0	2.095278	-0.693180	-1.575512	-0.753739	-0.248853	-0.635268	-0.491066	-0.243448	-0.351194	...	0.234644	0.1232
178821	123796.0	-0.089165	0.807445	-0.169992	-0.959017	1.048850	-0.200202	0.876518	-0.042459	-0.201535	...	0.000569	-0.2633
68959	53206.0	1.316849	-0.505091	0.660849	-0.788016	-0.970255	-0.376154	-0.728547	0.076743	-1.054445	...	0.030210	-0.0057
...	...	...	...	...	...	...	...	...	...	...	...	...	
279863	169142.0	-1.927883	1.125653	-4.518331	1.749293	-1.566487	-2.010494	-0.882850	0.697211	-2.064945	...	1.252967	0.7785
280143	169347.0	1.378559	1.289381	-5.004247	1.411850	0.442581	-1.326536	-1.413170	0.248525	-1.127396	...	0.226138	0.3706
280149	169351.0	-0.676143	1.126366	-2.213700	0.468308	-1.120541	-0.003346	-2.234739	1.210158	-0.652250	...	0.247968	0.7518
281144	169966.0	-3.113832	0.585864	-5.399730	1.817092	-0.840618	-2.943548	-2.208002	1.058733	-1.632333	...	0.306271	0.5832
281674	170348.0	1.991976	0.158476	-2.583441	0.408670	1.151147	-0.096695	0.223050	-0.068384	0.577829	...	-0.017652	-0.1643

1292 rows × 30 columns

In [28]:
```
Y
```

Out[28]:
```
256222    0
221908    0
204906    0
178821    0
68959     0
         ..
279863    1
280143    1
280149    1
281144    1
281674    1
Name: Class, Length: 1292, dtype: int64
```

In [29]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, stratify=Y, random_state=80)
```

In [30]:
```
print(X.shape, X_train.shape, X_test.shape)
```

```
(1292, 30) (1033, 30) (259, 30)
```

Modelbuilding

In [31]:
```
model=LogisticRegression()
```

In [32]:
```
model.fit(X_train,Y_train)
```

Out[32]:
```
▾ LogisticRegression
LogisticRegression()
```

In [33]:
```
model.coef_
```

Out[33]:
```
array([[-3.13211986e-05,  1.60897874e-01,  1.75202609e-01,
        -4.87694883e-01,  5.18734888e-01,  1.44712143e-01,
        -1.54600926e-01, -6.63488710e-02,  2.40804930e-02,
        -1.54601006e-01, -3.08508230e-01,  2.31229140e-01,
        -4.64667805e-01, -6.49880243e-02, -7.97302869e-01,
        -1.03700161e-01, -2.05438190e-01, -1.99380275e-01,
         1.56797814e-02, -1.88022527e-02,  1.02826591e-01,
         1.74783658e-01,  3.55219889e-02,  1.40924217e-02,
         1.54015796e-04, -3.31503607e-02, -4.30602551e-02,
        -1.71895557e-02,  6.36357850e-02,  1.54872525e-03]])
```

In [34]:
```
# accuracy on training data
X_train_prediction = model.predict(X_train)
training_data_accuracy = accuracy_score(X_train_prediction, Y_train)
```

In [35]:
```
print('Accuracy on Training data : ', training_data_accuracy*100)
```

```
Accuracy on Training data :  94.09486931268151
```

In [36]:
```
print('Accuracy on Training data : ', training_data_accuracy)
```

```
Accuracy on Training data :  0.9409486931268151
```

In [37]:
```
# accuracy on testing data
X_test_prediction = model.predict(X_test)
testing_data_accuracy = accuracy_score(X_test_prediction, Y_test)
```

In [39]:
```
print('Accuracy on Testing  data : ', training_data_accuracy*100)
```

```
Accuracy on Testing  data :  94.09486931268151
```

In [40]:
```
print('Accuracy on Testing  data : ', training_data_accuracy)
```

```
Accuracy on Testing  data :  0.9409486931268151
```

In [41]:
```
Trainpred = model.predict(X_train)
Testpred = model.predict(X_test)
```

In [43]:
```
print(sm.classification_report(Y_test,Testpred))
```

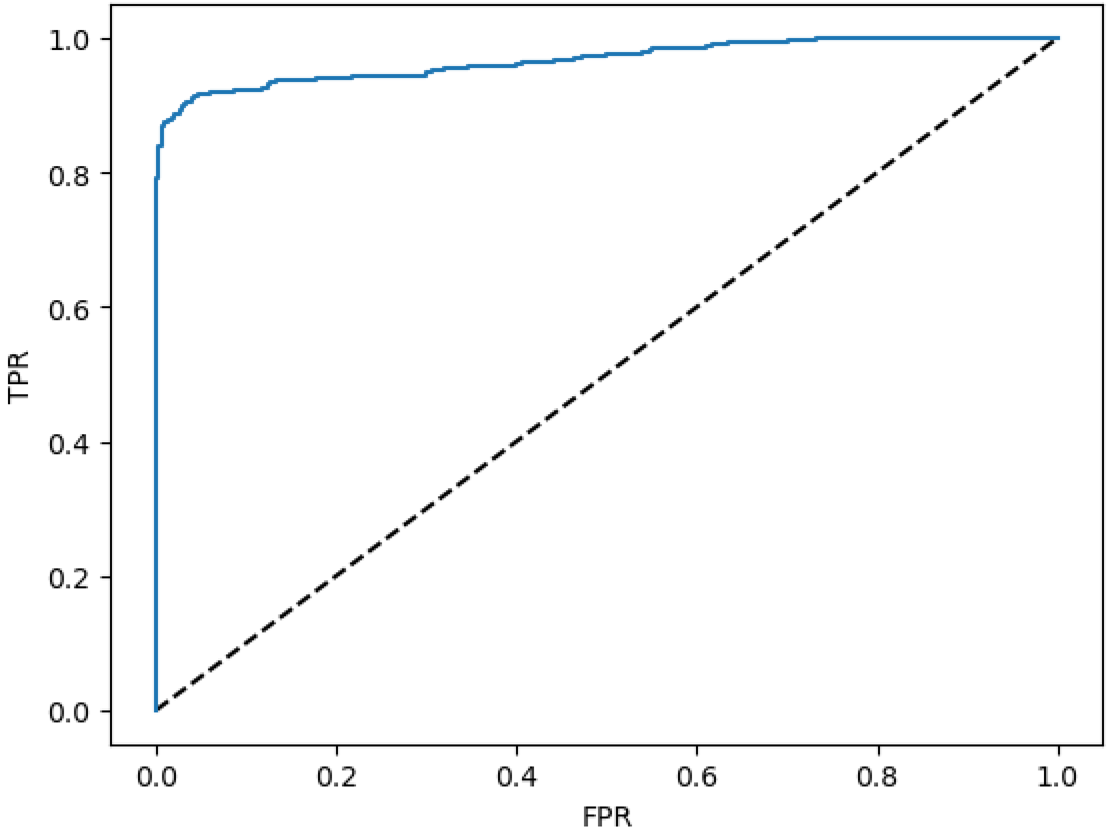
```
              precision    recall  f1-score   support

           0       0.94      0.95      0.95       160
           1       0.92      0.91      0.91        99

    accuracy                           0.93       259
   macro avg       0.93      0.93      0.93       259
weighted avg       0.93      0.93      0.93       259
```

AUC_ROC Curve

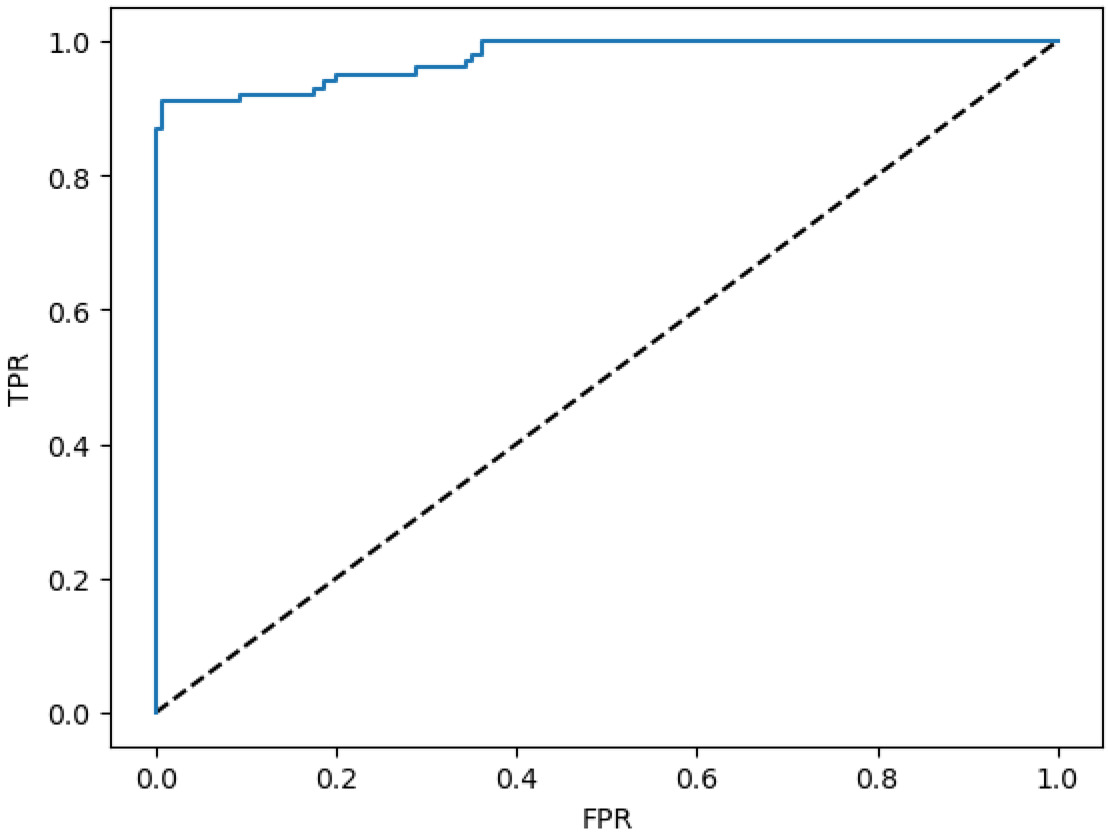
In [44]:
```
roc = model.predict_proba(X_train)[:,1]
fpr,tpr,threshold = sm.roc_curve(Y_train,roc)
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr, tpr, label='logistic')
plt.ylabel('TPR')
plt.xlabel('FPR')
plt.show()
```



In [46]:
```
sm.roc_auc_score(Y_train, roc)
```

Out[46]:
```
0.9673942430025445
```

In [45]:
```
roc1 = model.predict_proba(X_test)[:,1]
fpr,tpr,threshold = sm.roc_curve(Y_test,roc1)
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr, tpr, label='logistic')
plt.ylabel('TPR')
plt.xlabel('FPR')
plt.show()
```



In [48]:
```
sm.roc_auc_score(Y_test, roc1)
```

Out[48]:
```
0.9758838383838384
```

Grid search

In [49]:
```
param_grid = {
    'penalty':['l1','l2'],
    'C': [0.1,0.5,1,5,10],
    'solver': ['liblinear']
}
```

In [52]:
```
grid = GridSearchCV(estimator=model , param_grid=param_grid, cv=5)
```

In [53]:
```
grid.fit(X_train,Y_train)
```

Out[53]:
```
▸ GridSearchCV
▾ estimator: LogisticRegression
LogisticRegression()
    ▾ LogisticRegression
    LogisticRegression()
```

In [54]:
```
best_param = grid.best_params_
best_model = grid.best_estimator_
```

In [55]:
```
y_pred = best_model.predict(X_test)
```

In [56]:
```
acc = accuracy_score(Y_test,y_pred)
pre = precision_score(Y_test,y_pred)
rec = recall_score(Y_test,y_pred)
f1 = f1_score(Y_test,y_pred)
roc_auc = roc_auc_score(Y_test,y_pred)
```

In [57]:
```
print(f'''
Best param :{best_param}
Accuracy: {acc}
Precision: {pre}
Recall: {rec}
f1 score: {f1}
AUC-ROC: {roc_auc}
''')
```

```
Best param :{'C': 0.5, 'penalty': 'l1', 'solver': 'liblinear'}
Accuracy: 0.9536679536679536
Precision: 0.9578947368421052
Recall: 0.9191919191919192
f1 score: 0.9381443298969072
AUC-ROC: 0.9470959595959595
```

In [ ]:

In [ ]: