In [91]:
```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report,roc_auc_score,roc_curve
from sklearn.preprocessing import StandardScaler
```

In [5]:
```
bank_data=pd.read_csv('bank-full.csv',sep=';')
bank_data
```

Out[5]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previo
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
45206	51	technician	married	tertiary	no	825	no	no	cellular	17	nov	977	3	-1	
45207	71	retired	divorced	primary	no	1729	no	no	cellular	17	nov	456	2	-1	
45208	72	retired	married	secondary	no	5715	no	no	cellular	17	nov	1127	5	184	
45209	57	blue-collar	married	secondary	no	668	no	no	telephone	17	nov	508	4	-1	
45210	37	entrepreneur	married	secondary	no	2971	no	no	cellular	17	nov	361	2	188	

45211 rows × 17 columns

In [6]:
```
bank_data.shape
```

Out[6]: (45211, 17)

In [7]:
```
bank_data.dtypes
```

Out[7]:
```
age           int64
job          object
marital      object
education    object
default      object
balance       int64
housing      object
loan         object
contact      object
day           int64
month        object
duration      int64
campaign      int64
pdays         int64
previous      int64
poutcome     object
y            object
dtype: object
```

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

Out[8]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

In [10]:
```
bank_data.drop(labels=['day','month'],axis=1,inplace= True)
```

In [11]:
```
bank_data
```

Out[11]:

	age	job	marital	education	default	balance	housing	loan	contact	duration	campaign	pdays	previous	poutcome
0	58	management	married	tertiary	no	2143	yes	no	unknown	261	1	-1	0	unknowr
1	44	technician	single	secondary	no	29	yes	no	unknown	151	1	-1	0	unknowr
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	76	1	-1	0	unknowr
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	92	1	-1	0	unknowr
4	33	unknown	single	unknown	no	1	no	no	unknown	198	1	-1	0	unknowr
...	...	...	...	...	...	...	...	...	...	...	...	...	...	..
45206	51	technician	married	tertiary	no	825	no	no	cellular	977	3	-1	0	unknowr
45207	71	retired	divorced	primary	no	1729	no	no	cellular	456	2	-1	0	unknowr
45208	72	retired	married	secondary	no	5715	no	no	cellular	1127	5	184	3	success
45209	57	blue-collar	married	secondary	no	668	no	no	telephone	508	4	-1	0	unknowr
45210	37	entrepreneur	married	secondary	no	2971	no	no	cellular	361	2	188	11	othei

45211 rows × 15 columns

In [32]:
```
label=LabelEncoder() # initialize the labelencoder
```

In [33]:
```
bank_data['job']=label.fit_transform(bank_data.job)
bank_data['marital']=label.fit_transform(bank_data.marital)
bank_data['education']=label.fit_transform(bank_data.education)
bank_data['default']=label.fit_transform(bank_data.default)
bank_data['housing']=label.fit_transform(bank_data.housing)
bank_data['loan']=label.fit_transform(bank_data.loan)
bank_data['contact']=label.fit_transform(bank_data.contact)
bank_data['poutcome']=label.fit_transform(bank_data.poutcome)
bank_data['y']=label.fit_transform(bank_data.y)
bank_data
```

Out[33]:

	age	job	marital	education	default	balance	housing	loan	contact	duration	campaign	pdays	previous	poutcome	y
0	58	4	1	2	0	2143	1	0	2	261	1	-1	0	3	0
1	44	9	2	1	0	29	1	0	2	151	1	-1	0	3	0
2	33	2	1	1	0	2	1	1	2	76	1	-1	0	3	0
3	47	1	1	3	0	1506	1	0	2	92	1	-1	0	3	0
4	33	11	2	3	0	1	0	0	2	198	1	-1	0	3	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	51	9	1	2	0	825	0	0	0	977	3	-1	0	3	1
45207	71	5	0	0	0	1729	0	0	0	456	2	-1	0	3	1
45208	72	5	1	1	0	5715	0	0	0	1127	5	184	3	2	1
45209	57	1	1	1	0	668	0	0	1	508	4	-1	0	3	0
45210	37	2	1	1	0	2971	0	0	0	361	2	188	11	1	0

45211 rows × 15 columns

Model Building

train_test_split

In [69]:
```
x=bank_data.drop(labels='y',axis=1)
y=bank_data[['y']]
```

In [70]:
```
x.shape,y.shape
```

Out[70]: ((45211, 14), (45211, 1))

In [71]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_state=12,shuffle=True)
```

In [72]:
```
x_train.shape,y_train.shape
```

Out[72]: ((36168, 14), (36168, 1))

In [73]:
```
x_test.shape,y_test.shape
```

Out[73]: ((9043, 14), (9043, 1))

Model Training

In [74]:
```
logistic_model=LogisticRegression(class_weight={0:1,1:3})
logistic_model.fit(x_train,y_train)
```

Out[74]: LogisticRegression(class_weight={0: 1, 1: 3})

In [75]:
```
logistic_model.coef_
```

Out[75]:
```
array([[-5.14267274e-03,  1.35419281e-02, -2.03510893e-01,
         5.15737466e-02, -1.79714676e-02,  3.34419526e-05,
        -6.76447444e-01, -2.06152383e-01, -7.12039454e-01,
         4.49086858e-03, -1.22753876e-01, -1.09376973e-03,
         6.03475565e-02, -3.97480919e-01]])
```

In [76]:
```
logistic_model.intercept_
```

Out[76]: array([-0.21267153])

Model Test

training accuracy

In [77]:
```
y_pred_train=logistic_model.predict(x_train)
```

In [78]:
```
accuracy_score(y_train,y_pred_train)
```

Out[78]:
```
0.8687237336872373
```

In [79]:
```
confusion_matrix(y_train,y_pred_train)
```

Out[79]:
```
array([[29425,  2504],
       [ 2244,  1995]], dtype=int64)
```

In [80]:
```
print(classification_report(y_train,y_pred_train))
```

```
              precision    recall  f1-score   support

           0       0.93      0.92      0.93     31929
           1       0.44      0.47      0.46      4239

    accuracy                           0.87     36168
   macro avg       0.69      0.70      0.69     36168
weighted avg       0.87      0.87      0.87     36168
```

ROC CURVE || AOC CURVE

In [83]:
```
roc_curve(y, logistic_model.predict_proba (x)[:,1])
```

Out[83]:
```
(array([0.00000000e+00, 2.50488452e-05, 5.00976905e-05, ...,
        9.91483393e-01, 9.91483393e-01, 1.00000000e+00]),
 array([0.        , 0.        , 0.        , ..., 0.99981093, 1.        ,
        1.        ]),
 array([1.99999999e+00, 9.99999995e-01, 9.99999899e-01, ...,
        7.24527904e-03, 7.19420380e-03, 1.69755773e-05]))
```

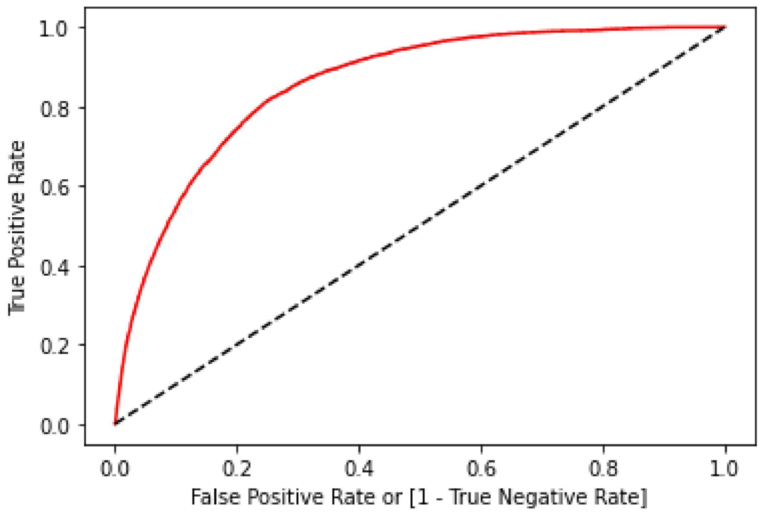
In [86]:
```
fpr, tpr, thresholds = roc_curve(y, logistic_model.predict_proba (x)[:,1])

auc = roc_auc_score(y_train,y_pred_train)
print(auc)

plt.plot(fpr, tpr, color='red', label='logit model ( area  = %0.2f)'%auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
plt.ylabel('True Positive Rate')
```

```
0.6961029311385486
```

Out[86]:
```
Text(0, 0.5, 'True Positive Rate')
```



training accuracy

In [64]:
```
y_pred_test=logistic_model.predict(x_test)
```

In [65]:
```
accuracy_score(y_test,y_pred_test)
```

Out[65]:
```
0.8727192303439124
```

Model Optimization

In [97]:
```
std_scaler=StandardScaler()
scaled_x=std_scaler.fit_transform(x)
scaled_x
```

Out[97]:
```
array([[ 1.60696496, -0.10381968, -0.27576178, ..., -0.41145311,
        -0.25194037,  0.44489814],
       [ 0.28852927,  1.42400783,  1.3683719 , ..., -0.41145311,
        -0.25194037,  0.44489814],
       [-0.74738448, -0.71495069, -0.27576178, ..., -0.41145311,
        -0.25194037,  0.44489814],
       ...,
       [ 2.92540065,  0.20174582, -0.27576178, ...,  1.43618859,
         1.05047333, -0.56617504],
       [ 1.51279098, -1.02051619, -0.27576178, ..., -0.41145311,
        -0.25194037,  0.44489814],
       [-0.37068857, -0.71495069, -0.27576178, ...,  1.4761376 ,
         4.52357654, -1.57724822]])
```

In [98]:
```
x_train,x_test,y_train,y_test=train_test_split(scaled_x,y,test_size=0.20,random_state=12,shuffle=True)
```

In [99]:
```
logistic_model.fit(x_train,y_train)
```

Out[99]:
```
LogisticRegression(class_weight={0: 1, 1: 3})
```

In [102]:
```
scly_pred_train=logistic_model.predict(x_train)
```

In [104]:
```
accuracy_score(y_train,scly_pred_train)
```

Out[104]:
```
0.8779031187790312
```

In [105]:
```
confusion_matrix(y_train,scly_pred_train)
```

Out[105]:
```
array([[29532,  2397],
       [ 2019,  2220]], dtype=int64)
```

In [106]:
```
print(classification_report(y_train,scly_pred_train))
```

```
              precision    recall  f1-score   support

           0       0.94      0.92      0.93     31929
           1       0.48      0.52      0.50      4239

    accuracy                           0.88     36168
   macro avg       0.71      0.72      0.72     36168
weighted avg       0.88      0.88      0.88     36168
```

In [111]:
```
scaly_pred_test=logistic_model.predict(x_test)
```

In [114]:
```
accuracy_score(y_test,scaly_pred_test)
```

Out[114]:
```
0.8822293486674776
```

In [ ]: