In [1]:

```
import pandas as pd
import seaborn as sns
```

In [2]:

```
data_set=pd.read_csv('Fraud_check.csv')
data_set.head()
```

Out[2]:

	Undergrad	Marital.Status	Taxable.Income	City.Population	Work.Experience	Urban
0	NO	Single	68833	50047	10	YES
1	YES	Divorced	33700	134075	18	YES
2	NO	Married	36925	160205	30	YES
3	YES	Single	50190	193264	15	YES
4	NO	Married	81002	27533	28	NO

Inital investigation

In [3]:

```
data_set.shape
```

Out[3]:

```
(600, 6)
```

In [4]:

```
data_set.dtypes
```

Out[4]:

```
Undergrad          object
Marital.Status     object
Taxable.Income      int64
City.Population     int64
Work.Experience     int64
Urban              object
dtype: object
```

In [5]:

```
data_set.isnull().sum()
```

Out[5]:

```
Undergrad          0
Marital.Status     0
Taxable.Income     0
City.Population    0
Work.Experience    0
Urban              0
dtype: int64
```

Number of features and records in the given data set is 6 and 600 respesctively

There is no null values in the data set

The categorical data can be converted into numeric data type by using encoder so that the model can learn the things more easily

Data preprocessing

In [7]:

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
```

In [8]:

```
data_set['Undergrad']=le.fit_transform(data_set['Undergrad'])
data_set['Marital.Status']=le.fit_transform(data_set['Marital.Status'])
data_set['Urban']=le.fit_transform(data_set['Urban'])
data_set.dtypes
```

Out[8]:

```
Undergrad          int32
Marital.Status     int32
Taxable.Income     int64
City.Population    int64
Work.Experience    int64
Urban              int32
dtype: object
```

In [9]:

```
data_set.insert(6,'tax_category','')
data_set
```

Out[9]:

	Undergrad	Marital.Status	Taxable.Income	City.Population	Work.Experience	Urban	tax_ca
0	0	2	68833	50047	10	1	
1	1	0	33700	134075	18	1	
2	0	1	36925	160205	30	1	
3	1	2	50190	193264	15	1	
4	0	1	81002	27533	28	0	
...	...	...	...	...	...	...	
595	1	0	76340	39492	7	1	
596	1	0	69967	55369	2	1	
597	0	0	47334	154058	0	1	
598	1	1	98592	180083	17	0	
599	0	0	96519	158137	16	0	

600 rows × 7 columns

In [10]:

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

Converting taxable income to category of 0 and 1

In [15]:

```
for i in range(0,len(data_set['tax_category']),1):
    if data_set['Taxable.Income'][i]<=30000:
        data_set['tax_category'][i]='1'
    else:
        data_set['tax_category'][i]='0'
```

In [16]:

```
data_set['tax_category'].unique()
```

Out[16]:

```
array([0, 1])
```

In [17]:

```
data_set['tax_category']=data_set['tax_category'].astype(int)
```

In [18]:

```
data_set.dtypes
```

Out[18]:

```
Undergrad          int32
Marital.Status     int32
Taxable.Income     int64
City.Population    int64
Work.Experience    int64
Urban              int32
tax_category       int32
dtype: object
```

Model building

In [19]:

```
x=data_set.loc[:,('Undergrad','Marital.Status','City.Population','Work.Experience','Urban')
y=data_set['tax_category']
```

In [20]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2)
```

Model training

In [21]:

```
from sklearn.tree import DecisionTreeClassifier
dt_model=DecisionTreeClassifier()
```

In [22]:

```
dt_model.fit(x_train,y_train)
```

Out[22]:

```
DecisionTreeClassifier()
```

Model testing

In [23]:

```
y_pred_train=dt_model.predict(x_train)
y_pred_test=dt_model.predict(x_test)
```

Model Evaluation

In [24]:

```
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score,roc_auc_s
```

In [25]:

```
print(classification_report(y_train,y_pred_train))
print(classification_report(y_test,y_pred_test))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       385
           1       1.00      1.00      1.00        95

    accuracy                           1.00       480
   macro avg       1.00      1.00      1.00       480
weighted avg       1.00      1.00      1.00       480

              precision    recall  f1-score   support

           0       0.73      0.77      0.75        91
           1       0.12      0.10      0.11        29

    accuracy                           0.61       120
   macro avg       0.43      0.44      0.43       120
weighted avg       0.58      0.61      0.60       120
```

In [26]:

```
print(accuracy_score(y_train,y_pred_train))
print(accuracy_score(y_test,y_pred_test))
```

```
1.0
0.6083333333333333
```

In [27]:

```
print(confusion_matrix(y_train,y_pred_train))
print(confusion_matrix(y_test,y_pred_test))
```

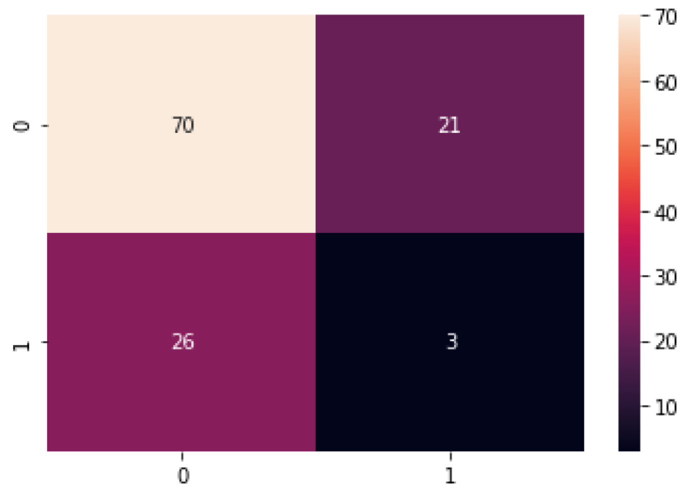
```
[[385   0]
 [  0  95]]
[[70 21]
 [26  3]]
```

In [68]:

```
confusion_matrix_test=confusion_matrix(y_test,y_pred_test)
sns.heatmap(confusion_matrix_test,annot=True)
```

Out[68]:

```
<AxesSubplot:>
```



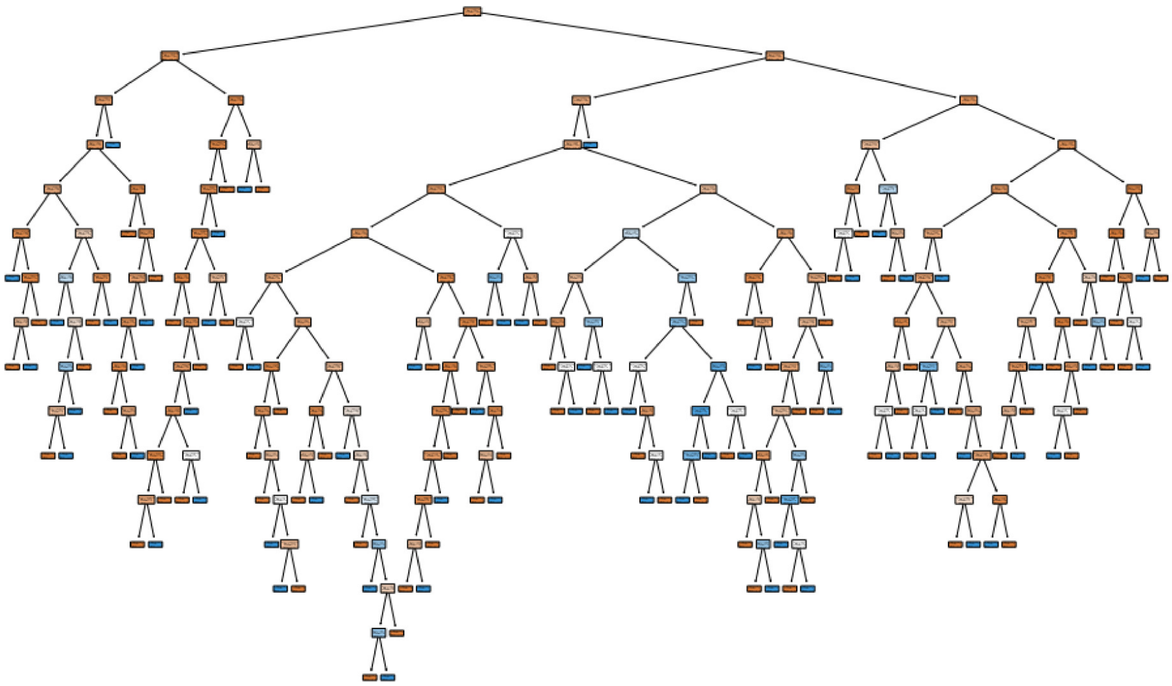
In [28]:

```
auc_train = roc_auc_score(y_train, y_pred_train)
print('auc value for train data',auc_train)
auc_test= roc_auc_score(y_test, y_pred_test)
print('auc value for test data',auc_test)
```

```
auc value for train data 1.0
auc value for test data 0.43633952254641906
```

In [29]:

```
import matplotlib.pyplot as plt
from sklearn import tree
plt.figure(figsize=(16,10))
tree.plot_tree(dt_model,rounded=True,filled=True)
plt.show()
```



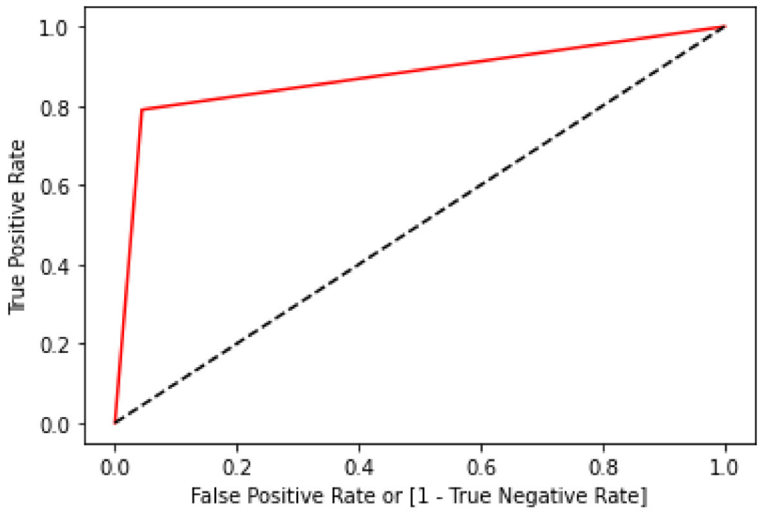
In [30]:

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

plt.plot(fpr, tpr, color='red')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
plt.ylabel('True Positive Rate')

auc_test= roc_auc_score(y_test, y_pred_test)
print('auc value for test data',auc_test)
```

```
auc value for test data 0.43633952254641906
```



GridSearchCV

In [31]:

```
from sklearn.model_selection import GridSearchCV
grid_model=GridSearchCV(estimator = dt_model,param_grid={'criterion':['entropy','gini'],
                                                       'max_depth':[2,4,8,10],
                                                        'min_samples_split':[2,4,6,8],
                                                        'min_samples_leaf':[1,2,3,4]})
grid_model.fit(x_train,y_train)
print(grid_model.best_params_)
print(grid_model.best_score_)
```

```
{'criterion': 'entropy', 'max_depth': 2, 'min_samples_leaf': 2, 'min_samples
_split': 2}
0.8020833333333334
```

In [32]:

```
from sklearn.tree import DecisionTreeClassifier
dt_model_tweak=DecisionTreeClassifier(criterion='entropy',max_depth=2)
```

In [33]:

```
dt_model_tweak.fit(x_train,y_train)
```

Out[33]:

```
DecisionTreeClassifier(criterion='entropy', max_depth=2)
```

In [34]:

```
y_pred_train_tweak=dt_model_tweak.predict(x_train)
y_pred_test_tweak=dt_model_tweak.predict(x_test)
```

In [35]:

```
print(classification_report(y_test,y_pred_test_tweak))
```

```
              precision    recall  f1-score   support

           0       0.76      1.00      0.86        91
           1       0.00      0.00      0.00        29

    accuracy                           0.76       120
   macro avg       0.38      0.50      0.43       120
weighted avg       0.58      0.76      0.65       120
```

In [36]:

```
print(accuracy_score(y_test,y_pred_test_tweak))
```

```
0.7583333333333333
```

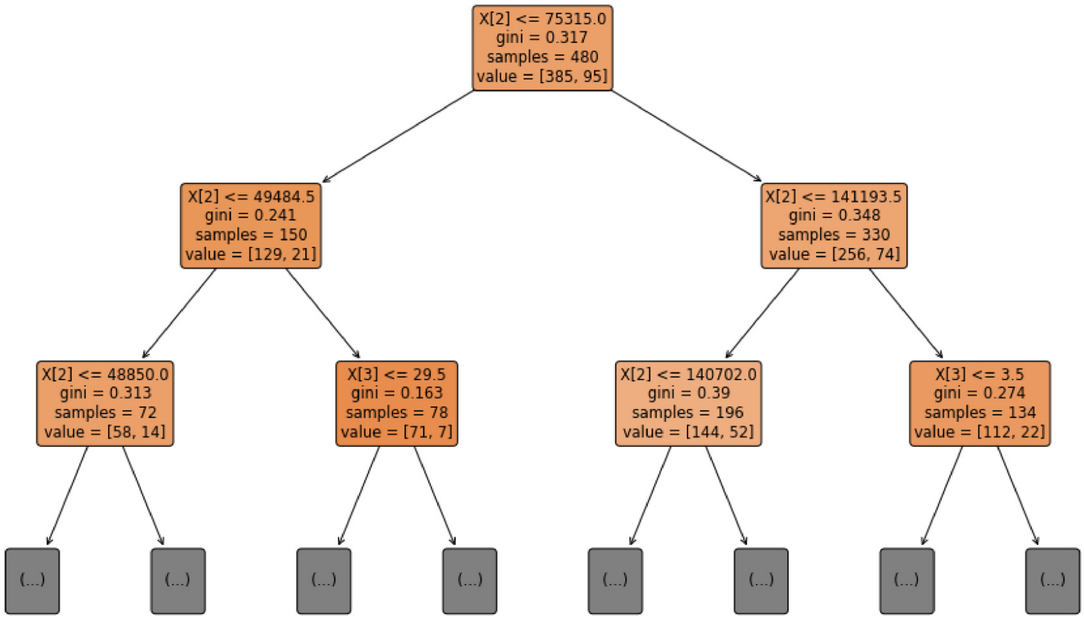
In [37]:

```
auc_test= roc_auc_score(y_test, y_pred_test_tweak)
print('auc value for test data',auc_test)
```

```
auc value for test data 0.5
```

In [38]:

```
from sklearn import tree
plt.figure(figsize=(16,10))
tree.plot_tree(dt_model,rounded=True,filled=True,max_depth=2)
plt.show()
```



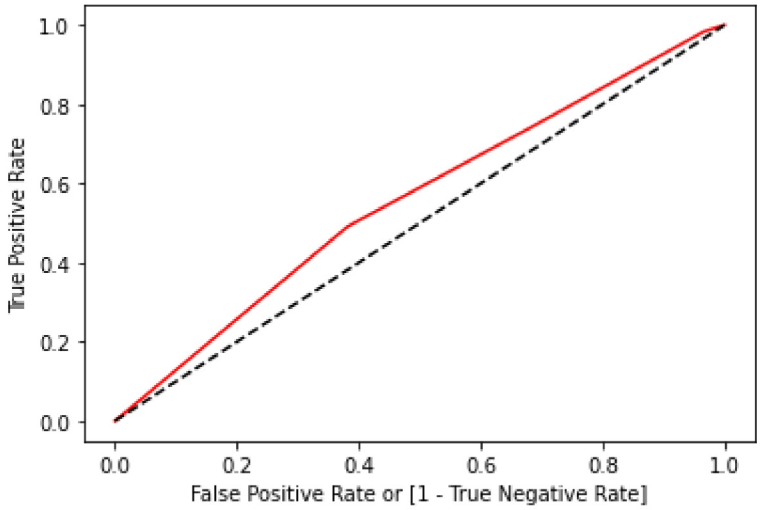
In [39]:

```
import matplotlib.pyplot as plt
fpr, tpr, thresholds = roc_curve(y,dt_model_tweak.predict_proba (x)[:,1])

plt.plot(fpr, tpr, color='red')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
plt.ylabel('True Positive Rate')

auc_test= roc_auc_score(y_test, y_pred_test_tweak)
print('auc value for test data',auc_test)
```

```
auc value for test data 0.5
```



Check for data imbalance

In [40]:

```
data_set['tax_category'].value_counts()
```

Out[40]:

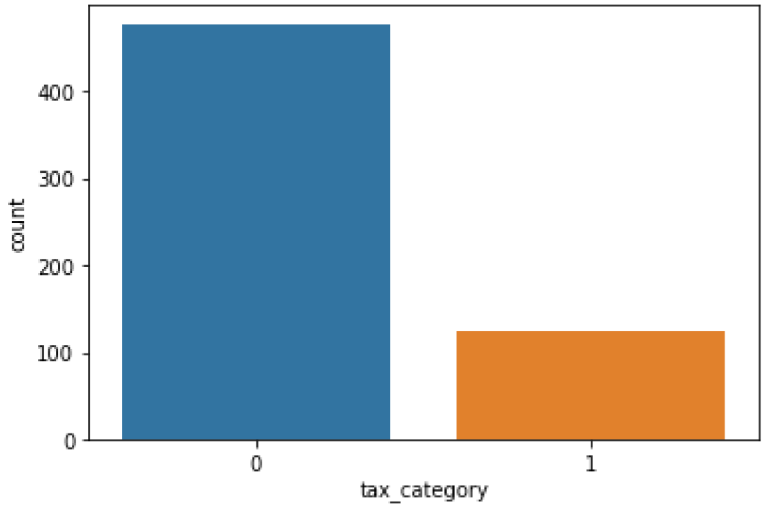
```
0    476
1    124
Name: tax_category, dtype: int64
```

In [54]:

```
sns.countplot(data_set['tax_category'])
```

Out[54]:

```
<AxesSubplot:xlabel='tax_category', ylabel='count'>
```



Countplot clearly shows that, the data are highly imbalanced, it may affect the accuaracy of the model

It need to be balanced for obtaining best model

Data balancing by adjusting class weights

In [72]:

```
dt_model_imb=DecisionTreeClassifier(class_weight={0:1,1:5}).fit(x_train,y_train)
```

In [73]:

```
y_pred=dt_model_imb.predict(x_test)
```

In [74]:

```
print(accuracy_score(y_test,y_pred))
```

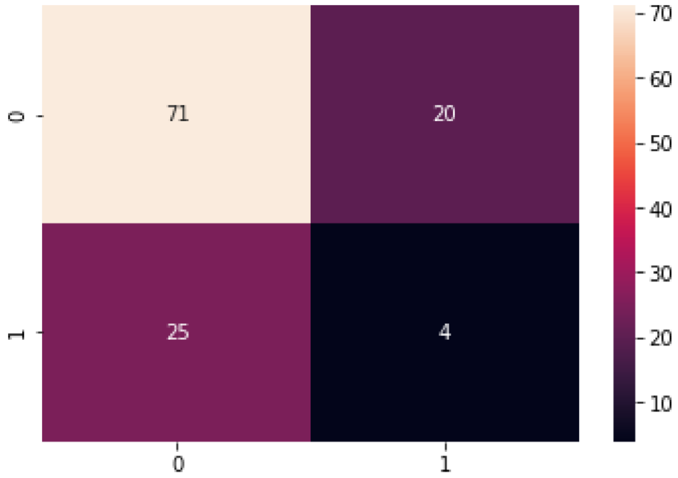
```
0.625
```

In [75]:

```
confusion_matrix_test=confusion_matrix(y_test,y_pred)
sns.heatmap(confusion_matrix_test,annot=True)
```

Out[75]:

```
<AxesSubplot:>
```



Data balancing - SMOTE

In [58]:

```
!pip install imblearn
```

```
Requirement already satisfied: imblearn in c:\users\rooba\anaconda3\lib\site
-packages (0.0)
Requirement already satisfied: imbalanced-learn in c:\users\rooba\anaconda3
\lib\site-packages (from imblearn) (0.8.0)
Requirement already satisfied: numpy>=1.13.3 in c:\users\rooba\anaconda3\lib
\site-packages (from imbalanced-learn->imblearn) (1.20.1)
Requirement already satisfied: joblib>=0.11 in c:\users\rooba\anaconda3\lib
\site-packages (from imbalanced-learn->imblearn) (1.0.1)
Requirement already satisfied: scikit-learn>=0.24 in c:\users\rooba\anaconda
3\lib\site-packages (from imbalanced-learn->imblearn) (0.24.1)
Requirement already satisfied: scipy>=0.19.1 in c:\users\rooba\anaconda3\lib
\site-packages (from imbalanced-learn->imblearn) (1.6.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\rooba\anacon
da3\lib\site-packages (from scikit-learn>=0.24->imbalanced-learn->imblearn)
(2.1.0)
```

In [59]:

```
from imblearn.over_sampling import SMOTE
```

In [60]:

```
smote=SMOTE(sampling_strategy='minority')
```

In [61]:

```
x_sm,y_sm=smote.fit_resample(x,y)
```

In [62]:

```
x_train_sm,x_test_sm,y_train_sm,y_test_sm=train_test_split(x_sm,y_sm,test_size=0.2)
```

In [63]:

```
dt_model_smote=DecisionTreeClassifier().fit(x_train_sm,y_train_sm)
```

In [64]:

```
y_pred_smote=dt_model_smote.predict(x_test_sm)
```

In [65]:

```
print(accuracy_score(y_test_sm,y_pred_smote))
```

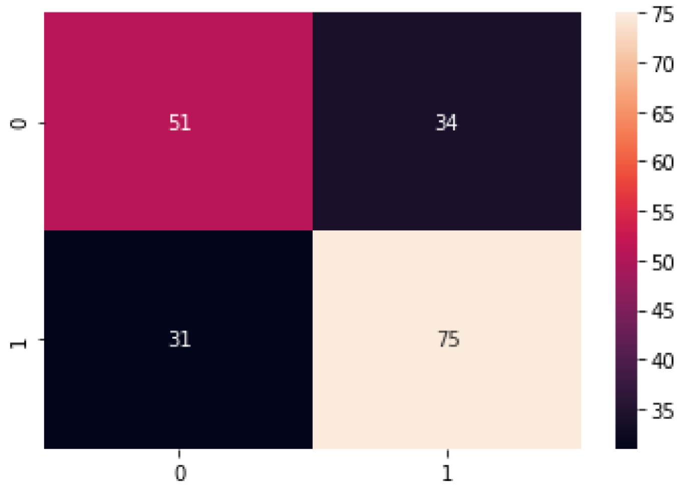
```
0.6596858638743456
```

In [71]:

```
confusion_matrix_test=confusion_matrix(y_test_sm,y_pred_smote)
sns.heatmap(confusion_matrix_test,annot=True)
```

Out[71]:

```
<AxesSubplot:>
```



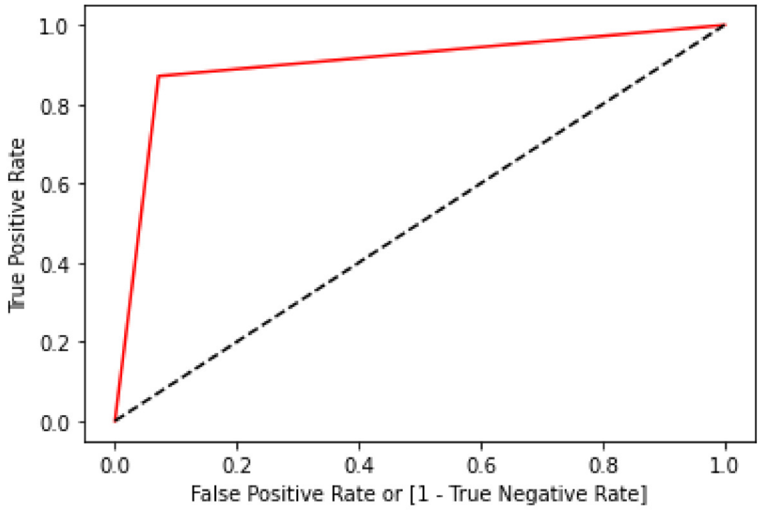
In [66]:

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

plt.plot(fpr, tpr, color='red')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
plt.ylabel('True Positive Rate')

auc_test= roc_auc_score(y_test_sm, y_pred_smote)
print('auc value for test data',auc_test)
```

```
auc value for test data 0.6537735849056603
```



The result clearly shows that accuarcy gets improved by balancing the data