deep-learning-house-loan-project

April 22, 2024

1 House Loan Data Analysis

Description For safe and secure lending experience, it's important to analyze the past data. In this project, you have to build a deep learning model to predict the chance of default for future loans using the historical data. As you will see, this dataset is highly imbalanced and includes a lot of features that make this problem more challenging.

Objective: Create a model that predicts whether or not an applicant will be able to repay a loan using historical data.

Domain: Finance

Analysis to be done: Perform data preprocessing and build a deep learning prediction model.

Steps to be done:

Load the dataset that is given to you Check for null values in the dataset Print percentage of default to payer of the dataset for the TARGET column Balance the dataset if the data is imbalanced Plot the balanced data or imbalanced data Encode the columns that is required for the model Calculate Sensitivity as a metrice Calculate area under receiver operating characteristics curve

[66]:
```
import pandas as pd
import numpy  as np
import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import roc_curve
from sklearn.preprocessing    import LabelEncoder
from sklearn.impute           import SimpleImputer
from sklearn.preprocessing    import StandardScaler
from sklearn.model_selection  import train_test_split
from sklearn.metrics          import accuracy_score
from imblearn.over_sampling   import SMOTE
import matplotlib.pyplot as plt
import matplotlib
%matplotlib inline
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import accuracy_score ,classification_report,␣
  ↪confusion_matrix
# ANN Modules
```

```python
import keras
from keras.models       import Sequential
from keras.layers       import Dense, Dropout
from tensorflow.keras.optimizers import RMSprop,Adam
```

1. Load the dataset that is given to you

[4]:
```python
df=pd.read_csv("/content/drive/MyDrive/data_project_folder/loan_data_project.
 ↪csv")
df= df.drop(['SK_ID_CURR'],axis=1)
df.head()
```

[4]:
```
   TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR FLAG_OWN_REALTY  \
0       1         Cash loans           M            N               Y
1       0         Cash loans           F            N               N
2       0    Revolving loans           M            Y               Y
3       0         Cash loans           F            N               Y
4       0         Cash loans           M            N               Y

   CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  AMT_GOODS_PRICE  \
0             0          202500.0    406597.5      24700.5         351000.0
1             0          270000.0   1293502.5      35698.5        1129500.0
2             0           67500.0    135000.0       6750.0         135000.0
3             0          135000.0    312682.5      29686.5         297000.0
4             0          121500.0    513000.0      21865.5         513000.0

   … FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20 FLAG_DOCUMENT_21  \
0  …                0                0                0                0
1  …                0                0                0                0
2  …                0                0                0                0
3  …                0                0                0                0
4  …                0                0                0                0

  AMT_REQ_CREDIT_BUREAU_HOUR  AMT_REQ_CREDIT_BUREAU_DAY  \
0                        0.0                        0.0
1                        0.0                        0.0
2                        0.0                        0.0
3                        NaN                        NaN
4                        0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         NaN                        NaN
4                         0.0                        0.0
```

```
   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                         1.0
1                        0.0                         0.0
2                        0.0                         0.0
3                        NaN                         NaN
4                        0.0                         0.0

[5 rows x 121 columns]
```

[5]:
```
df = df[pd.notnull(df['EMERGENCYSTATE_MODE'])]
#EMERGENCYSTATE_MODE--> this column contains around 145755 of missing values in␣
↪it
```

[6]:
```
df.shape
```

[6]: (161756, 121)

[7]:
```
df = df.loc[df['CODE_GENDER'] != 'XNA']
```

[8]:
```
df['NAME_TYPE_SUITE'] = df['NAME_TYPE_SUITE'].replace(np.nan,'Other_C')
df['NAME_FAMILY_STATUS'] = df['NAME_FAMILY_STATUS'].replace('Unknown',␣
↪'Married')
df['OCCUPATION_TYPE'] = df['OCCUPATION_TYPE'].replace(np.nan,'Others')
df['WALLSMATERIAL_MODE'] = df['WALLSMATERIAL_MODE'].replace(np.nan,'Others')
df['HOUSETYPE_MODE'] = df['HOUSETYPE_MODE'].replace(np.nan,'Unkown')
df['FONDKAPREMONT_MODE'] = df['FONDKAPREMONT_MODE'].replace(np.nan,'not␣
↪available')
```

[9]:
```
df = df[pd.notnull(df['AMT_REQ_CREDIT_BUREAU_YEAR'])]
```

[10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 141359 entries, 0 to 307510
Columns: 121 entries, TARGET to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(40), object(16)
memory usage: 131.6+ MB
```

2. Encode the columns that is required for the model ### Lable encoding

[11]:
```
labels = df.describe(include=['object']).columns.values
labels
```

[11]:
```
array(['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
       'FLAG_OWN_REALTY', 'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE',
       'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE',
       'OCCUPATION_TYPE', 'WEEKDAY_APPR_PROCESS_START',
       'ORGANIZATION_TYPE', 'FONDKAPREMONT_MODE', 'HOUSETYPE_MODE',
```

```
'WALLSMATERIAL_MODE', 'EMERGENCYSTATE_MODE'], dtype=object)
```

[12]:
```
le = LabelEncoder()
for lab in labels:
    le.fit(df[lab].values)
    df[lab] = le.transform(df[lab])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 141359 entries, 0 to 307510
Columns: 121 entries, TARGET to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(56)
memory usage: 131.6 MB
```

3. Check for null values in the dataset

[13]:
```
null_column = df.columns[df.isnull().any()]
print('Percentage of nan values :       %')
print()
print(df[null_column].isnull().sum()/df.shape[0]*100)
```

```
Percentage of nan values :       %

AMT_ANNUITY                    0.003537
AMT_GOODS_PRICE                0.076401
OWN_CAR_AGE                   66.835504
CNT_FAM_MEMBERS                0.000707
EXT_SOURCE_1                  53.918746
EXT_SOURCE_2                   0.181099
EXT_SOURCE_3                   7.437093
APARTMENTS_AVG                 6.336349
BASEMENTAREA_AVG              21.041462
YEARS_BEGINEXPLUATATION_AVG    2.606130
YEARS_BUILD_AVG               36.207104
COMMONAREA_AVG                42.638955
ELEVATORS_AVG                 11.141137
ENTRANCES_AVG                  5.554652
FLOORSMAX_AVG                  4.435515
FLOORSMIN_AVG                 38.816771
LANDAREA_AVG                  22.631739
LIVINGAPARTMENTS_AVG          39.747734
LIVINGAREA_AVG                 5.292199
NONLIVINGAPARTMENTS_AVG       41.785100
NONLIVINGAREA_AVG             14.723505
APARTMENTS_MODE                6.336349
BASEMENTAREA_MODE             21.041462
YEARS_BEGINEXPLUATATION_MODE   2.606130
YEARS_BUILD_MODE              36.207104
```

```
COMMONAREA_MODE                42.638955
ELEVATORS_MODE                 11.141137
ENTRANCES_MODE                  5.554652
FLOORSMAX_MODE                  4.435515
FLOORSMIN_MODE                 38.816771
LANDAREA_MODE                  22.631739
LIVINGAPARTMENTS_MODE          39.747734
LIVINGAREA_MODE                 5.292199
NONLIVINGAPARTMENTS_MODE       41.785100
NONLIVINGAREA_MODE             14.723505
APARTMENTS_MEDI                 6.336349
BASEMENTAREA_MEDI              21.041462
YEARS_BEGINEXPLUATATION_MEDI    2.606130
YEARS_BUILD_MEDI               36.207104
COMMONAREA_MEDI                42.638955
ELEVATORS_MEDI                 11.141137
ENTRANCES_MEDI                  5.554652
FLOORSMAX_MEDI                  4.435515
FLOORSMIN_MEDI                 38.816771
LANDAREA_MEDI                  22.631739
LIVINGAPARTMENTS_MEDI          39.747734
LIVINGAREA_MEDI                 5.292199
NONLIVINGAPARTMENTS_MEDI       41.785100
NONLIVINGAREA_MEDI             14.723505
TOTALAREA_MODE                  1.631308
OBS_30_CNT_SOCIAL_CIRCLE        0.384128
DEF_30_CNT_SOCIAL_CIRCLE        0.384128
OBS_60_CNT_SOCIAL_CIRCLE        0.384128
DEF_60_CNT_SOCIAL_CIRCLE        0.384128
dtype: float64
```

[14]:
```
df = df.
↪drop(['EXT_SOURCE_1','OWN_CAR_AGE','COMMONAREA_AVG','FLOORSMIN_AVG','LIVINGAPARTMENTS_AVG',
↪axis=1)

#since these columns contains more tham 39% of nan values
```

[15]:
```
df.shape
```

[15]: (141359, 107)

[16]:
```
df = df[pd.notnull(df['AMT_ANNUITY'])]
```

1.0.1 Imputing the missing values

[17]:
```
imp1 = SimpleImputer(missing_values= np.nan, strategy='mean')
imp2 = SimpleImputer(missing_values= np.nan, strategy='median')
```

[18]:
```
df[['AMT_GOODS_PRICE','EXT_SOURCE_2',
    'EXT_SOURCE_3','APARTMENTS_AVG',
    'BASEMENTAREA_AVG','YEARS_BEGINEXPLUATATION_AVG',
    'YEARS_BUILD_AVG','ELEVATORS_AVG',
    'ENTRANCES_AVG','FLOORSMAX_AVG',
    'LANDAREA_AVG','LIVINGAREA_AVG',
    'NONLIVINGAREA_AVG','APARTMENTS_MODE',
    'BASEMENTAREA_MODE','YEARS_BEGINEXPLUATATION_MODE',
    'YEARS_BUILD_MODE','ELEVATORS_MODE','ENTRANCES_MODE',
    'FLOORSMAX_MODE','LANDAREA_MODE','LIVINGAREA_MODE',
    'NONLIVINGAREA_MODE','APARTMENTS_MEDI',
    'BASEMENTAREA_MEDI','BASEMENTAREA_MEDI',
    'YEARS_BEGINEXPLUATATION_MEDI','YEARS_BUILD_MEDI',
    'ELEVATORS_MEDI','ENTRANCES_MEDI','FLOORSMAX_MEDI',
    'LANDAREA_MEDI','LIVINGAREA_MEDI',
    'NONLIVINGAREA_MEDI','TOTALAREA_MODE',]]              = imp1.
 ↪fit_transform(df[['AMT_GOODS_PRICE','EXT_SOURCE_2',
                                                                    ␣
 ↪  'EXT_SOURCE_3','APARTMENTS_AVG',
                                                                    ␣
 ↪  'BASEMENTAREA_AVG','YEARS_BEGINEXPLUATATION_AVG',
                                                                    ␣
 ↪  'YEARS_BUILD_AVG','ELEVATORS_AVG',
                                                                    ␣
 ↪  'ENTRANCES_AVG','FLOORSMAX_AVG',
                                                                    ␣
 ↪  'LANDAREA_AVG','LIVINGAREA_AVG',
                                                                    ␣
 ↪  'NONLIVINGAREA_AVG','APARTMENTS_MODE',
                                                                    ␣
 ↪  'BASEMENTAREA_MODE','YEARS_BEGINEXPLUATATION_MODE',
                                                                    ␣
 ↪  'YEARS_BUILD_MODE','ELEVATORS_MODE','ENTRANCES_MODE',
                                                                    ␣
 ↪  'FLOORSMAX_MODE','LANDAREA_MODE','LIVINGAREA_MODE',
                                                                    ␣
 ↪  'NONLIVINGAREA_MODE','APARTMENTS_MEDI',
                                                                    ␣
 ↪  'BASEMENTAREA_MEDI','BASEMENTAREA_MEDI',
                                                                    ␣
 ↪  'YEARS_BEGINEXPLUATATION_MEDI','YEARS_BUILD_MEDI',
```

```
↪ 'ELEVATORS_MEDI','ENTRANCES_MEDI','FLOORSMAX_MEDI',
↪ 'LANDAREA_MEDI','LIVINGAREA_MEDI',
↪ 'NONLIVINGAREA_MEDI','TOTALAREA_MODE',]]  )
```

[19]:
```
df[['CNT_FAM_MEMBERS','OBS_30_CNT_SOCIAL_CIRCLE',
    'DEF_30_CNT_SOCIAL_CIRCLE','OBS_60_CNT_SOCIAL_CIRCLE',
    'OBS_60_CNT_SOCIAL_CIRCLE','DEF_60_CNT_SOCIAL_CIRCLE',]] = imp2.
↪fit_transform(df[['CNT_FAM_MEMBERS','OBS_30_CNT_SOCIAL_CIRCLE',
↪     'DEF_30_CNT_SOCIAL_CIRCLE','OBS_60_CNT_SOCIAL_CIRCLE',
↪     'OBS_60_CNT_SOCIAL_CIRCLE','DEF_60_CNT_SOCIAL_CIRCLE',]])
```

[20]:
```
null_columns=df.columns[df.isnull().any()]
print('Percentage of nan values :       %')
print()
print(df[null_columns].isnull().sum()/df.shape[0]*100)
```

```
Percentage of nan values :       %

Series([], dtype: float64)
```

1.0.2 Finding column with zero variance

[21]:
```
var = df.var()[df.var()==0].index.values
print(var)
```

```
['FLAG_MOBIL' 'FLAG_DOCUMENT_2']
```

[22]:
```
df = df.drop(['FLAG_DOCUMENT_2','FLAG_MOBIL'],axis=1)

#since this column contains only one categorical variable, ie zero variance
```

[23]:
```
class_counts = df.TARGET.value_counts()

print('Counts of Class 0 :',class_counts[0])
print('Counts of Class 1 :',class_counts[1])
print()
print('Propotion ---> ',round(class_counts[0]/len(df.TARGET)*100),':
↪',round(class_counts[1]/len(df.TARGET)*100))
```

```
Counts of Class 0 : 131840
Counts of Class 1 : 9514
```

```
Propotion --->  93 : 7
```

[24]:
```
sc = StandardScaler()
df[['AMT_INCOME_TOTAL','AMT_ANNUITY',
   'AMT_CREDIT','AMT_GOODS_PRICE',
   'DAYS_BIRTH','DAYS_EMPLOYED',
   'DAYS_REGISTRATION','DAYS_ID_PUBLISH',
   'DAYS_LAST_PHONE_CHANGE']]              = sc.
 ↪fit_transform(df[['AMT_INCOME_TOTAL','AMT_ANNUITY',
                                                                             ␣
 ↪'AMT_CREDIT','AMT_GOODS_PRICE',
                                                                             ␣
 ↪'DAYS_BIRTH','DAYS_EMPLOYED',
                                                                             ␣
 ↪'DAYS_REGISTRATION','DAYS_ID_PUBLISH',
                                                                             ␣
 ↪'DAYS_LAST_PHONE_CHANGE']])
```

4. Print percentage of default to payer of the dataset for the TARGET column

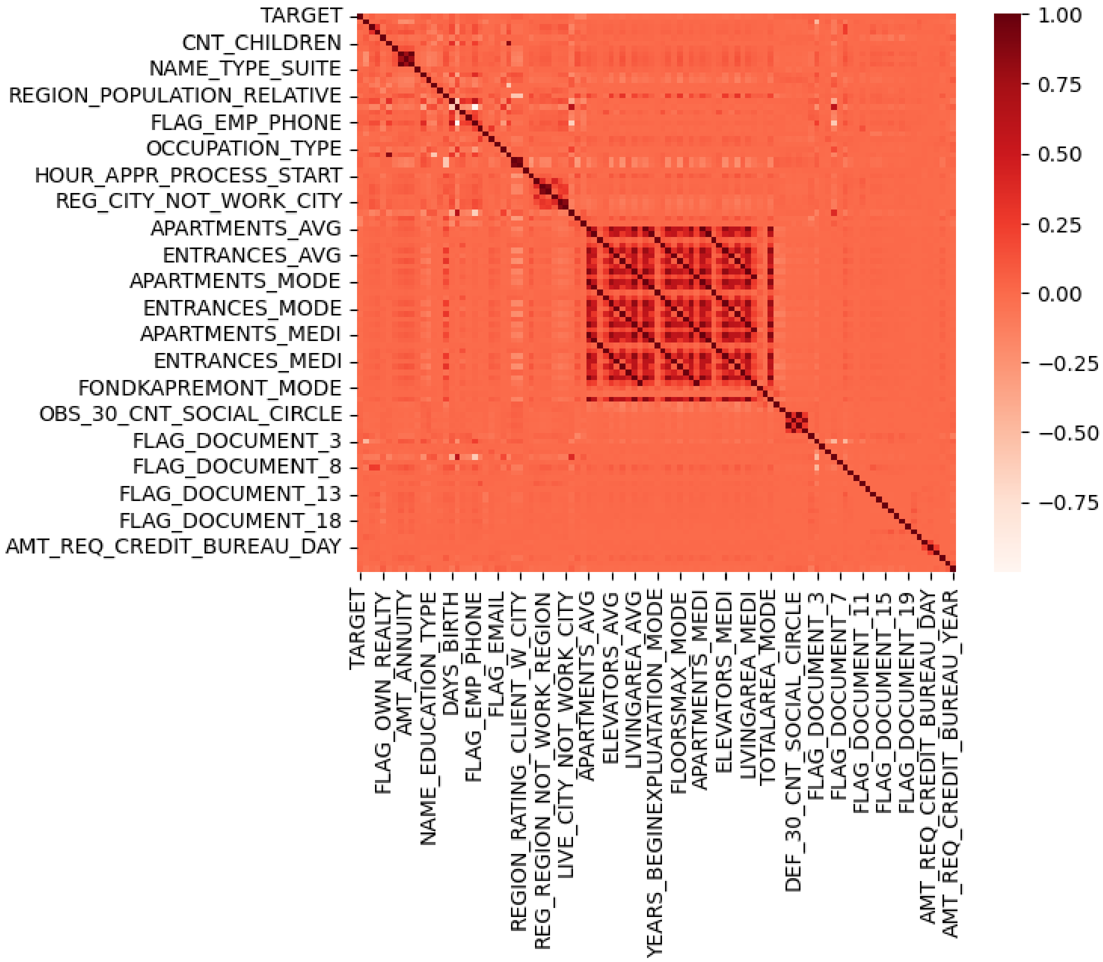
[60]:
```
defaulters=(df.TARGET==1).sum()
payers=(df.TARGET==0).sum()
percentage_of_default_payer= (defaulters/payers)*100
print("% of default to payer: ", percentage_of_default_payer)
```

```
% of default to payer:  7.216322815533981
```

1.0.3 Finding the highly correlated columns in dataset

[25]:
```
corr = df.corr()
```

[26]:
```
import seaborn as sns
sns.heatmap(corr, annot=False, cmap=plt.cm.Reds)
plt.show()
```



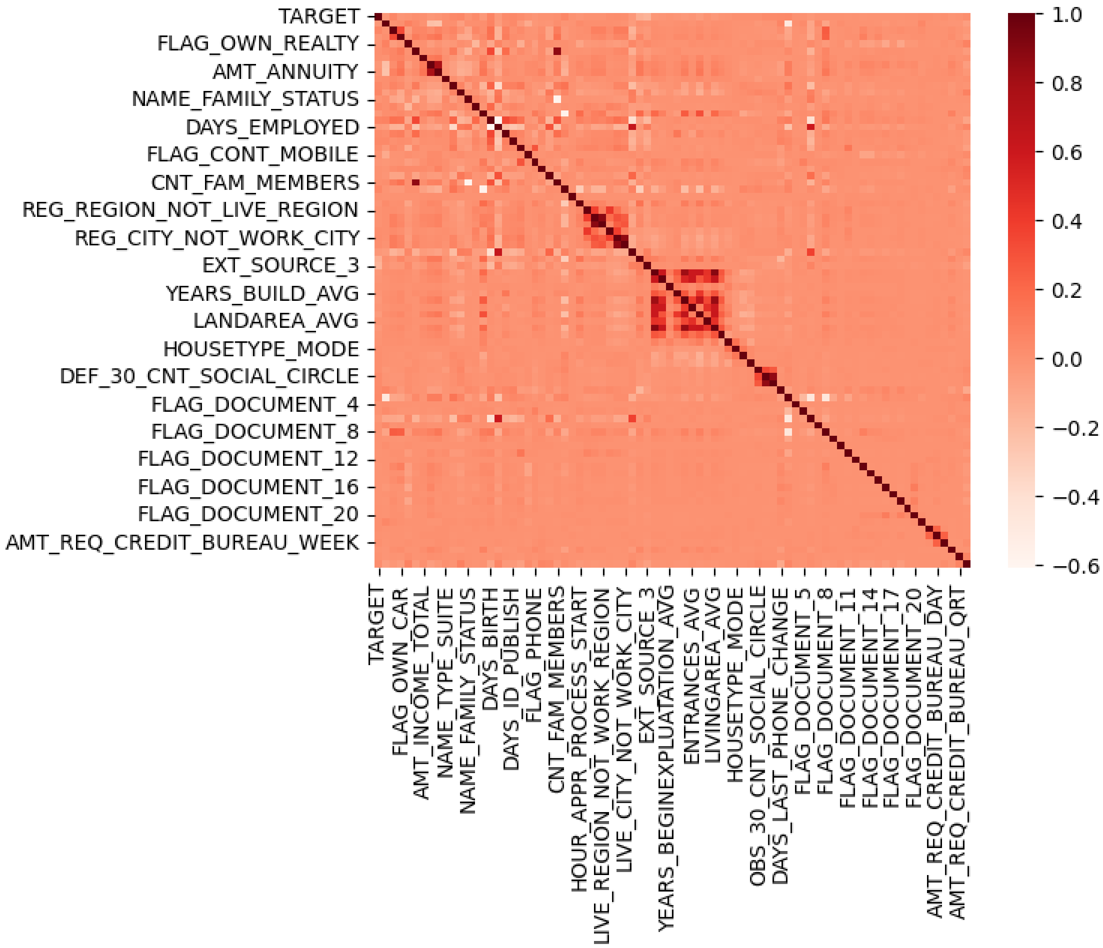
[27]:
```python
corr_matrix = df.corr().abs()
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape),k=1).astype(np.
 ↪bool_))
to_drop = [col for col in upper.columns if any(upper[col]>0.90)]
to_drop
```

[27]:
```
['AMT_GOODS_PRICE',
 'FLAG_EMP_PHONE',
 'REGION_RATING_CLIENT_W_CITY',
 'APARTMENTS_MODE',
 'BASEMENTAREA_MODE',
 'YEARS_BEGINEXPLUATATION_MODE',
 'YEARS_BUILD_MODE',
 'ELEVATORS_MODE',
 'ENTRANCES_MODE',
 'FLOORSMAX_MODE',
 'LANDAREA_MODE',
```

```
 'LIVINGAREA_MODE',
 'NONLIVINGAREA_MODE',
 'APARTMENTS_MEDI',
 'BASEMENTAREA_MEDI',
 'YEARS_BEGINEXPLUATATION_MEDI',
 'YEARS_BUILD_MEDI',
 'ELEVATORS_MEDI',
 'ENTRANCES_MEDI',
 'FLOORSMAX_MEDI',
 'LANDAREA_MEDI',
 'LIVINGAREA_MEDI',
 'NONLIVINGAREA_MEDI',
 'TOTALAREA_MODE',
 'OBS_60_CNT_SOCIAL_CIRCLE']
```

[28]:
```
df = df.drop(df[to_drop], axis=1)
```

[29]:
```
corr = df.corr()
sns.heatmap(corr, annot=False, cmap=plt.cm.Reds)
plt.show()
```



1.0.4 Splitting data in Hold out method

[30]:
```
x = df.drop('TARGET',axis=1)
y = df.TARGET
```

[31]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y,test_size= 0.2,␣
↪random_state= 10, stratify=y)
print(x_train.shape)
print(y_train.shape)
print()
print(y_train.value_counts())
```

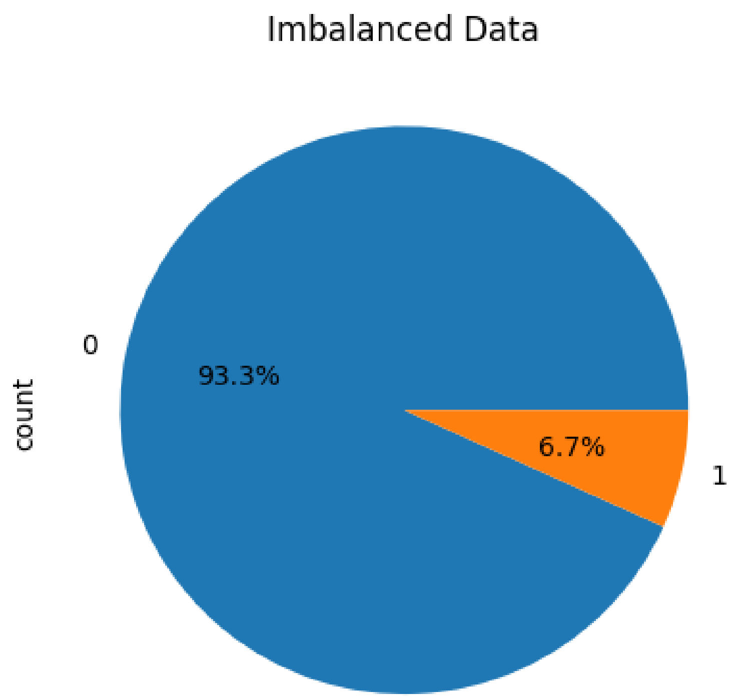
```
(113083, 79)
(113083,)

TARGET
0    105472
1      7611
Name: count, dtype: int64
```

5. Plot the balanced data or imbalanced data

[63]:
```
print(y.value_counts())
y.value_counts().plot(kind="pie",autopct="%1.1f%%")
plt.title("Imbalanced Data")
```

```
TARGET
0    131840
1      9514
Name: count, dtype: int64
```

[63]:
```
Text(0.5, 1.0, 'Imbalanced Data')
```



[32]:
```
smt = SMOTE(random_state= 10, n_jobs=-1,sampling_strategy='all' )
#sampling_strategy='minority' ----> resample only the minority class;
#sampling_strategy='not minority' ----> resample all classes but the minority␣
↪class;
#sampling_strategy='not majority' ----> resample all classes but the majority␣
↪class;
#sampling_strategy='all' ----> resample all classes;
#sampling_strategy='auto' ----> equivalent to 'not majority'.
```

[64]:
```
x_train, y_train = smt.fit_resample(x_train,y_train)
```

[34]:
```
print(x_train.shape)
print(y_train.shape)
```

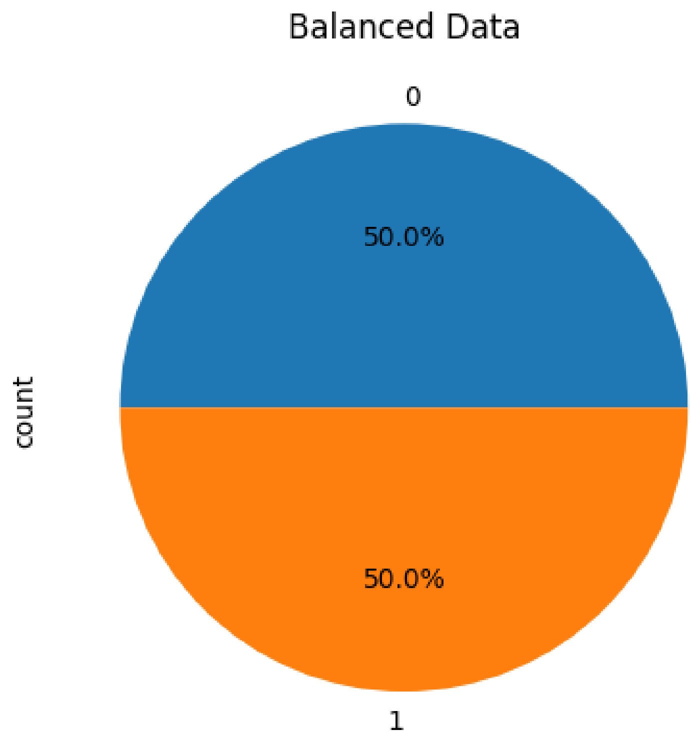
```
(210944, 79)
(210944,)
```

[65]:
```
print(y_train.value_counts())
y_train.value_counts().plot(kind="pie",autopct="%1.1f%%")
plt.title("Balanced Data")
```

```
TARGET
```

```
0    105472
1    105472
Name: count, dtype: int64
```

[65]: Text(0.5, 1.0, 'Balanced Data')



1.0.5 Building NN model

[35]:
```
model = Sequential()
model.add(Dense(units= 53,activation = 'relu',input_dim=79)) # first hidden and␣
  ↪first input layer
model.add(Dropout(0.2))
model.add(Dense(units= 53,activation = 'relu')) # second hidden layer
model.add(Dropout(0.2))
model.add(Dense(units= 1,activation = 'sigmoid')) # output layer
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 53)                4240
```

```
 dropout (Dropout)           (None, 53)                0

 dense_1 (Dense)             (None, 53)                2862

 dropout_1 (Dropout)         (None, 53)                0

 dense_2 (Dense)             (None, 1)                 54

=================================================================
Total params: 7156 (27.95 KB)
Trainable params: 7156 (27.95 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[36]:
```
model.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy'])
```

[44]:
```
history= model.
 ↪fit(x_train,y_train,batch_size=10,epochs=5,validation_data=(x_test,y_test))
```

```
Epoch 1/5
21095/21095 [==============================] - 60s 3ms/step - loss: 0.3233 -
accuracy: 0.8622 - val_loss: 0.3927 - val_accuracy: 0.8405
Epoch 2/5
21095/21095 [==============================] - 57s 3ms/step - loss: 0.3227 -
accuracy: 0.8628 - val_loss: 0.3415 - val_accuracy: 0.8679
Epoch 3/5
21095/21095 [==============================] - 56s 3ms/step - loss: 0.3228 -
accuracy: 0.8629 - val_loss: 0.3726 - val_accuracy: 0.8553
Epoch 4/5
21095/21095 [==============================] - 56s 3ms/step - loss: 0.3236 -
accuracy: 0.8624 - val_loss: 0.3628 - val_accuracy: 0.8632
Epoch 5/5
21095/21095 [==============================] - 53s 3ms/step - loss: 0.3207 -
accuracy: 0.8620 - val_loss: 0.3431 - val_accuracy: 0.8701
```

[45]:
```
score = model.evaluate(x_test,y_test)
```

```
884/884 [==============================] - 1s 2ms/step - loss: 0.3431 -
accuracy: 0.8701
```

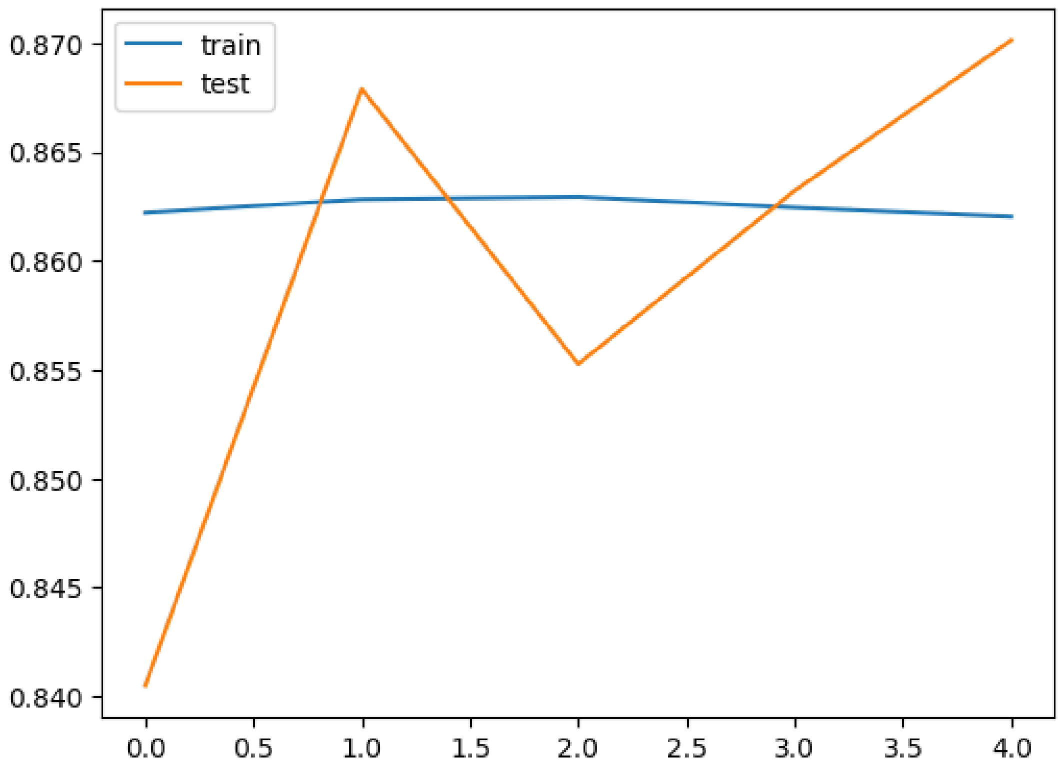
[46]:
```
print('Test loss : ', score[0])
print('Test accuracy : ', score[1])
```

```
Test loss :  0.34306642413139343
Test accuracy :  0.870114266872406
```

[47]:
```
y_pred_train=model.predict(x_train)
y_test_train=model.predict(x_test)
```

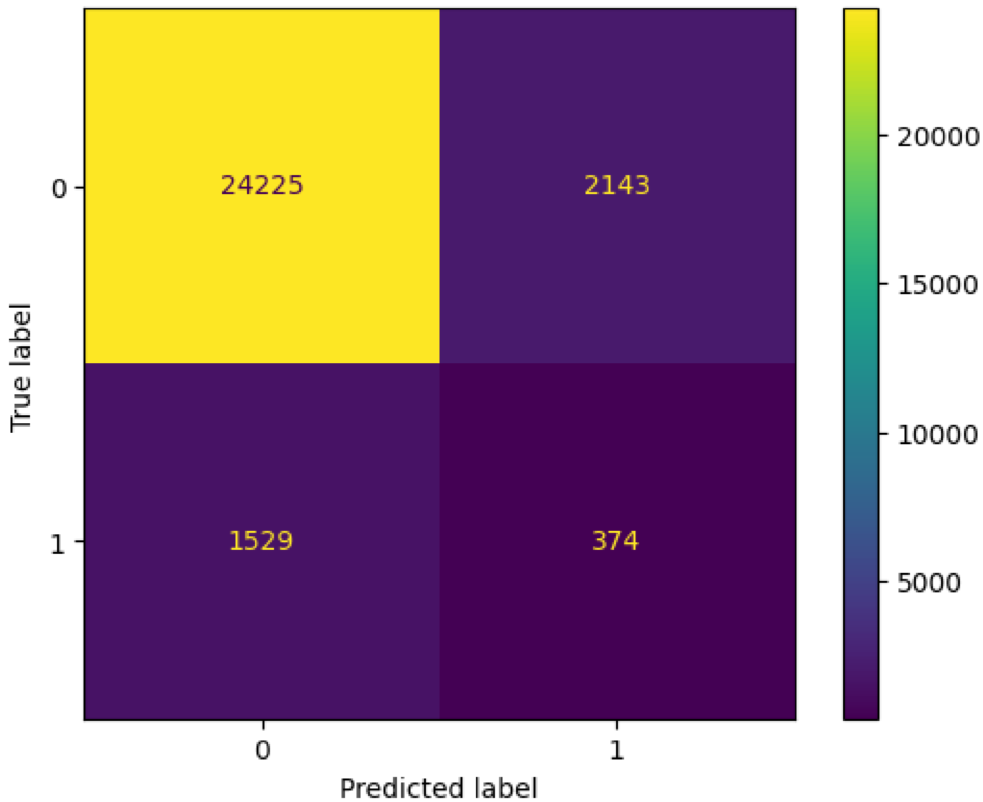
```
6592/6592 [==============================] - 14s 2ms/step
884/884 [==============================] - 1s 1ms/step
```

[48]:
```
plt.plot(history.history['accuracy'], label='train')
plt.plot(history.history['val_accuracy'], label='test')
plt.legend()
plt.show()
```



[55]:
```
conmat=confusion_matrix(y_test,pred)
disp=ConfusionMatrixDisplay(confusion_matrix=conmat)
disp.plot()
```

[55]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7c3f687f5ff0>
```



7. Calculate Sensitivity as a metrice.

```
[56]: print("Accuracy Score: ",accuracy_score(y_test,pred))
print("Classification Report: \n",classification_report(y_test,pred))
print("confusion matrix: \n",confusion_matrix(y_test,pred))
```

```
Accuracy Score:  0.8701142513529766
Classification Report:
               precision    recall  f1-score   support

           0       0.94      0.92      0.93     26368
           1       0.15      0.20      0.17      1903

    accuracy                           0.87     28271
   macro avg       0.54      0.56      0.55     28271
weighted avg       0.89      0.87      0.88     28271

confusion matrix:
 [[24225  2143]
 [ 1529   374]]
```

8. Calculate area under receiver operating characteristics curv

[58]:

```
fpr,tpr,thresholds=roc_curve(pred,y_test)
print(fpr)
print("\n")
print(tpr)
print("\n")
print(thresholds)
```

```
[0.         0.05936942 1.        ]


[0.         0.14858959 1.        ]


[2 1 0]
```