

Finance

import libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import (accuracy_score, classification_report,
                             fl_score,
                             roc_auc_score, roc_curve, auc, confusion_matrix, make_scorer)
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
import phik
import pickle
import math
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Dense, Input, Dropout,
BatchNormalization
from tensorflow.keras.regularizers import L1L2
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.ensemble import IsolationForest
from tensorflow.keras.optimizers import Adam, SGD, Adadelta, RMSprop
from tensorflow_addons.metrics import F1Score
from tensorflow.keras.utils import to_categorical
from keras_tuner import BayesianOptimization
```

Upload data

```
finance_train_df = pd.read_csv('train_data.csv')
finance_test_hidden_df = pd.read_csv('test_data_hidden.csv')
finance_test_df = pd.read_csv('test_data.csv')
```

Project Task: Week 1

df shapes

```
print(finance_train_df.shape)
print(finance_test_hidden_df.shape)
print(finance_test_df.shape)
```

```
(227845, 31)
(56962, 31)
(56962, 30)
```

```
# sample data
```

```
finance_train_df.head()
```

```
      Time      V1      V2      V3      V4      V5
V6 \
0  38355.0  1.043949  0.318555  1.045810  2.805989 -0.561113 -
0.367956
1  22555.0 -1.665159  0.808440  1.805627  1.903416 -0.821627
0.934790
2   2431.0 -0.324096  0.601836  0.865329 -2.138000  0.294663 -
1.251553
3   86773.0 -0.258270  1.217501 -0.585348 -0.875347  1.222481 -
0.311027
4  127202.0  2.142162 -0.494988 -1.936511 -0.818288 -0.025213 -
1.027245

      V7      V8      V9  ...      V21      V22      V23
V24 \
0  0.032736 -0.042333 -0.322674  ... -0.240105 -0.680315  0.085328
0.684812
1 -0.824802  0.975890  1.747469  ... -0.335332 -0.510994  0.035839
0.147565
2  1.072114 -0.334896  1.071268  ...  0.012220  0.352856 -0.341505 -
0.145791
3  1.073860 -0.161408  0.200665  ... -0.424626 -0.781158  0.019316
0.178614
4 -0.151627 -0.305750 -0.869482  ...  0.010115  0.021722  0.079463 -
0.480899

      V25      V26      V27      V28  Amount  Class
0  0.318620 -0.204963  0.001662  0.037894   49.67     0
1 -0.529358 -0.566950 -0.595998 -0.220086   16.94     0
2  0.094194 -0.804026  0.229428 -0.021623    1.00     0
3 -0.315616  0.096665  0.269740 -0.020635   10.78     0
4  0.023846 -0.279076 -0.030121 -0.043888   39.96     0
```

```
[5 rows x 31 columns]
```

We have 28 features (encoded-> result of PCA output), timestamp and amount with class labels (0,1) as froud and non-froud.

```
EDA
```

```
# info
```

```
finance_train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 227845 entries, 0 to 227844
```

```
Data columns (total 31 columns):
#   Column      Non-Null Count  Dtype
---  -
0   Time         227845 non-null   float64
1   V1           227845 non-null   float64
2   V2           227845 non-null   float64
3   V3           227845 non-null   float64
4   V4           227845 non-null   float64
5   V5           227845 non-null   float64
6   V6           227845 non-null   float64
7   V7           227845 non-null   float64
8   V8           227845 non-null   float64
9   V9           227845 non-null   float64
10  V10          227845 non-null   float64
11  V11          227845 non-null   float64
12  V12          227845 non-null   float64
13  V13          227845 non-null   float64
14  V14          227845 non-null   float64
15  V15          227845 non-null   float64
16  V16          227845 non-null   float64
17  V17          227845 non-null   float64
18  V18          227845 non-null   float64
19  V19          227845 non-null   float64
20  V20          227845 non-null   float64
21  V21          227845 non-null   float64
22  V22          227845 non-null   float64
23  V23          227845 non-null   float64
24  V24          227845 non-null   float64
25  V25          227845 non-null   float64
26  V26          227845 non-null   float64
27  V27          227845 non-null   float64
28  V28          227845 non-null   float64
29  Amount       227845 non-null   float64
30  Class        227845 non-null   int64
```

```
dtypes: float64(30), int64(1)
```

```
memory usage: 53.9 MB
```

```
finance_train_df.isna().all().sum()
```

```
0
```

```
finance_train_df.columns
```

```
Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9',
      'V10',
      'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19',
      'V20',
      'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28',
      'Amount',
      'Class'],
      dtype='object')
```

There is no missing values and we have numeric data present.

get statistical info

stats_data = finance_train_df.describe()

stats_data

	Time	V1	V2	V3	\
count	227845.000000	227845.000000	227845.000000	227845.000000	
mean	94752.853076	-0.003321	-0.001652	0.001066	
std	47500.410602	1.963028	1.661178	1.516107	
min	0.000000	-56.407510	-72.715728	-32.965346	
25%	54182.000000	-0.922851	-0.598040	-0.889246	
50%	84607.000000	0.012663	0.066665	0.182170	
75%	139340.000000	1.314821	0.804401	1.029449	
max	172792.000000	2.454930	22.057729	9.382558	

	V4	V5	V6	V7	\
count	227845.000000	227845.000000	227845.000000	227845.000000	
mean	-0.000374	0.000877	0.000770	-0.000035	
std	1.415061	1.367074	1.325341	1.220384	
min	-5.683171	-42.147898	-26.160506	-43.557242	
25%	-0.848884	-0.690811	-0.767803	-0.554761	
50%	-0.019309	-0.055243	-0.273025	0.040409	
75%	0.744822	0.610852	0.400298	0.570631	
max	16.875344	34.801666	22.529298	36.877368	

	V8	V9	...	V21	V22
\count	227845.000000	227845.000000	...	227845.000000	227845.000000
mean	0.001625	-0.000391	...	0.000563	0.001234
std	1.192648	1.097367	...	0.734187	0.724544
min	-73.216718	-13.434066	...	-34.830382	-10.933144
25%	-0.207838	-0.643365	...	-0.228031	-0.540792
50%	0.022928	-0.050932	...	-0.028807	0.008697
75%	0.327854	0.596671	...	0.186852	0.529535
max	20.007208	15.594995	...	27.202839	10.503090

	V23	V24	V25	V26	\
count	227845.000000	227845.000000	227845.000000	227845.000000	
mean	-0.001002	0.000254	0.000218	-0.001128	
std	0.625165	0.606012	0.521348	0.482314	

min	-44.807735	-2.836627	-10.295397	-2.604551
25%	-0.162264	-0.354099	-0.317450	-0.327910
50%	-0.011614	0.041212	0.016221	-0.053257
75%	0.147067	0.440051	0.351214	0.239885
max	22.528412	4.022866	6.070850	3.463246

	V27	V28	Amount	Class
count	227845.000000	227845.000000	227845.000000	227845.000000
mean	-0.000346	0.000498	88.522327	0.001729
std	0.400286	0.331184	248.100141	0.041548
min	-22.565679	-11.710896	0.000000	0.000000
25%	-0.070986	-0.053117	5.590000	0.000000
50%	0.001315	0.011216	22.000000	0.000000
75%	0.091105	0.078458	77.070000	0.000000
max	12.152401	33.847808	19656.530000	1.000000

[8 rows x 31 columns]

```
finance_train_df[finance_train_df['Class'] == 0].describe()
```

	Time	V1	V2	V3 \
count	227451.000000	227451.000000	227451.000000	227451.000000
mean	94778.158337	0.005102	-0.008137	0.013458
std	47497.567552	1.932798	1.645089	1.457120
min	0.000000	-56.407510	-72.715728	-32.965346
25%	54208.000000	-0.920154	-0.599136	-0.883556
50%	84617.000000	0.015404	0.064922	0.184336
75%	139354.000000	1.315404	0.801069	1.030604
max	172792.000000	2.454930	18.183626	9.382558

	V4	V5	V6	V7 \
count	227451.000000	227451.000000	227451.000000	227451.000000
mean	-0.008269	0.006550	0.003117	0.009964
std	1.398253	1.342508	1.322856	1.156654
min	-5.683171	-42.147898	-26.160506	-31.764946
25%	-0.850301	-0.688601	-0.766491	-0.552208
50%	-0.021897	-0.054227	-0.272081	0.041373
75%	0.739027	0.611240	0.401261	0.571178
max	16.875344	34.801666	22.529298	36.877368

	V8	V9	...	V21	V22
\					
count	227451.000000	227451.000000	...	227451.000000	227451.000000
mean	0.000961	0.004161	...	-0.000736	0.001222
std	1.154287	1.087586	...	0.712756	0.722077
min	-73.216718	-6.290730	...	-34.830382	-10.933144

25%	-0.207839	-0.640614	...	-0.228124	-0.540768
50%	0.022618	-0.049554	...	-0.029115	0.008584
75%	0.326785	0.597654	...	0.186010	0.529325
max	18.709255	15.594995	...	22.580675	10.503090

	V23	V24	V25	V26 \
count	227451.000000	227451.000000	227451.000000	227451.000000
mean	-0.000959	0.000431	0.000151	-0.001214
std	0.621716	0.606126	0.520723	0.482369
min	-44.807735	-2.836627	-10.295397	-2.604551
25%	-0.162080	-0.353897	-0.317450	-0.328061
50%	-0.011555	0.041289	0.016128	-0.053348
75%	0.146966	0.440280	0.351009	0.239648
max	22.528412	4.022866	6.070850	3.463246

	V27	V28	Amount	Class
count	227451.000000	227451.000000	227451.000000	227451.0
mean	-0.000628	0.000349	88.455144	0.0
std	0.396085	0.330667	248.066088	0.0
min	-22.565679	-11.710896	0.000000	0.0
25%	-0.071007	-0.053107	5.640000	0.0
50%	0.001194	0.011169	22.000000	0.0
75%	0.090640	0.078171	77.000000	0.0
max	12.152401	33.847808	19656.530000	0.0

[8 rows x 31 columns]

finance_train_df[finance_train_df['Class'] == 1].describe()

	Time	V1	V2	V3
V4 \				
count	394.000000	394.000000	394.000000	394.000000
mean	80144.459391	-4.865812	3.741947	-7.152669
std	46947.027931	6.948331	4.413446	7.239645
min	472.000000	-30.552380	-8.402154	-31.103685
25%	41250.500000	-5.972454	1.180534	-8.813291
50%	74647.500000	-2.331289	2.744670	-5.154274
75%	122960.500000	-0.442917	5.204418	-2.215501

max	170348.000000	2.132386	22.057729	2.250210	12.114672
-----	---------------	----------	-----------	----------	-----------

	V5	V6	V7	V8	V9	...
\						
count	394.000000	394.000000	394.000000	394.000000	394.000000	...
mean	-3.274295	-1.354128	-5.772326	0.384907	-2.628401	...
std	5.442972	1.930181	7.463612	7.306385	2.576605	...
min	-22.105532	-5.773192	-43.557242	-41.044261	-13.434066	...
25%	-4.801176	-2.492665	-8.589239	-0.169625	-3.880445	...
50%	-1.621234	-1.373933	-3.016983	0.615604	-2.179119	...
75%	0.065251	-0.356945	-1.009233	1.757590	-0.790027	...
max	11.095089	6.474115	5.802537	20.007208	3.353525	...

	V21	V22	V23	V24	V25	
V26 \						
count	394.000000	394.000000	394.000000	394.000000	394.000000	
mean	0.750538	0.008633	-0.025738	-0.101968	0.038909	
std	4.233532	1.609687	1.697116	0.526688	0.805024	
min	-22.797604	-8.887017	-19.254328	-2.028024	-4.781606	-
25%	0.040122	-0.554402	-0.339114	-0.436065	-0.318323	-
50%	0.615305	0.091214	-0.075809	-0.060737	0.076685	
75%	1.325559	0.623456	0.287309	0.291641	0.464751	
max	27.202839	8.361985	5.466230	1.091435	2.208209	

	V27	V28	Amount	Class
count	394.000000	394.000000	394.000000	394.0
mean	0.162197	0.086224	127.306523	1.0
std	1.438879	0.548258	264.533907	0.0
min	-7.263482	-1.552593	0.000000	1.0
25%	-0.009170	-0.116723	1.000000	1.0
50%	0.404295	0.147380	11.395000	1.0
75%	0.850654	0.387926	106.385000	1.0

```
max      3.052358      1.779364  2125.870000      1.0
```

```
[8 rows x 31 columns]
```

From the above statistical data, we can see, there are differences between both the class labels based on the mean, min & max values for different features and amount also. So these features can be useful.

Check all the latent features and parameters with their mean and standard deviation. Value are close to 0 centered (mean) with unit standard deviation

```
stats_data.iloc[1:3, 1:-2].T
```

	mean	std
V1	-0.003321	1.963028
V2	-0.001652	1.661178
V3	0.001066	1.516107
V4	-0.000374	1.415061
V5	0.000877	1.367074
V6	0.000770	1.325341
V7	-0.000035	1.220384
V8	0.001625	1.192648
V9	-0.000391	1.097367
V10	-0.000794	1.087268
V11	0.002083	1.021904
V12	0.000010	0.999581
V13	0.000080	0.995449
V14	0.000928	0.959575
V15	-0.000737	0.916011
V16	0.000433	0.875795
V17	-0.000007	0.851222
V18	-0.000831	0.838685
V19	-0.000191	0.812614
V20	0.000671	0.772535
V21	0.000563	0.734187
V22	0.001234	0.724544
V23	-0.001002	0.625165
V24	0.000254	0.606012
V25	0.000218	0.521348
V26	-0.001128	0.482314
V27	-0.000346	0.400286
V28	0.000498	0.331184

We can see most of the values of features (V1- V28) are having mean and std close to 0 and 1 respectively.

Check the class count for each class. It's a class Imbalance problem.

```
print('Class counts')
print(finance_train_df['Class'].value_counts())
print(finance_train_df['Class'].value_counts(normalize = True))
```



```
Class counts
0    227451
1       394
Name: Class, dtype: int64
0    0.998271
1    0.001729
Name: Class, dtype: float64

finance_train_df[finance_train_df['Amount'] <= 0].size

45477
```

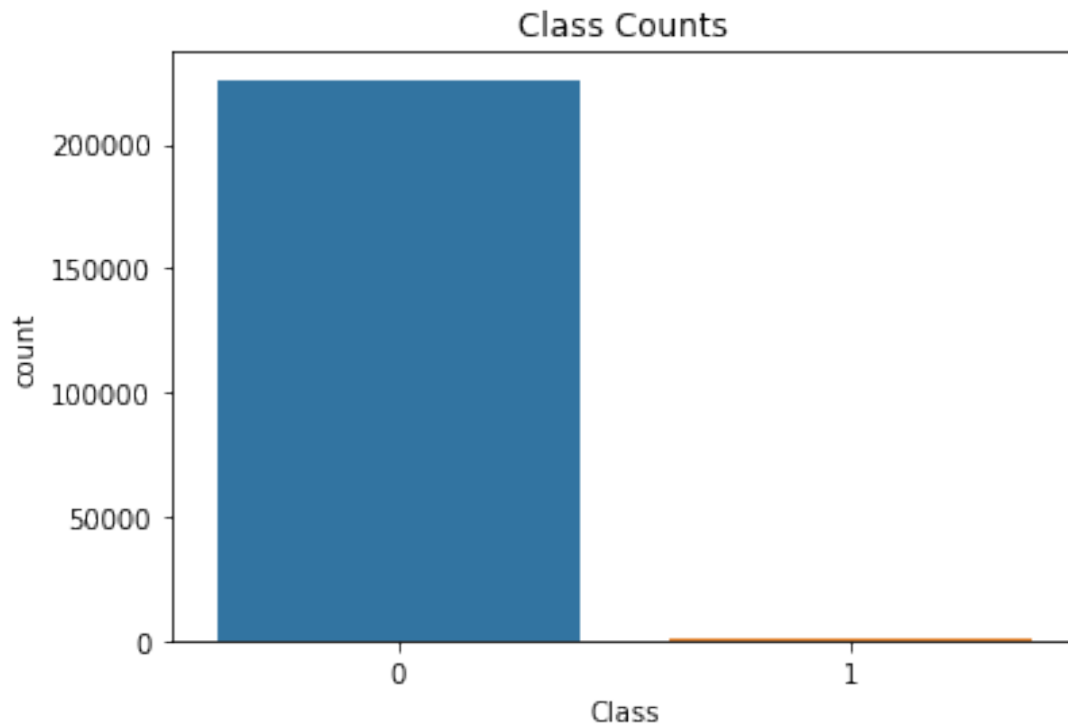
We have 45477 invalid data as well, lets get rid of them. (transactions can be made only with positive number amounts)

```
finance_train_df = finance_train_df[finance_train_df['Amount'] > 0]

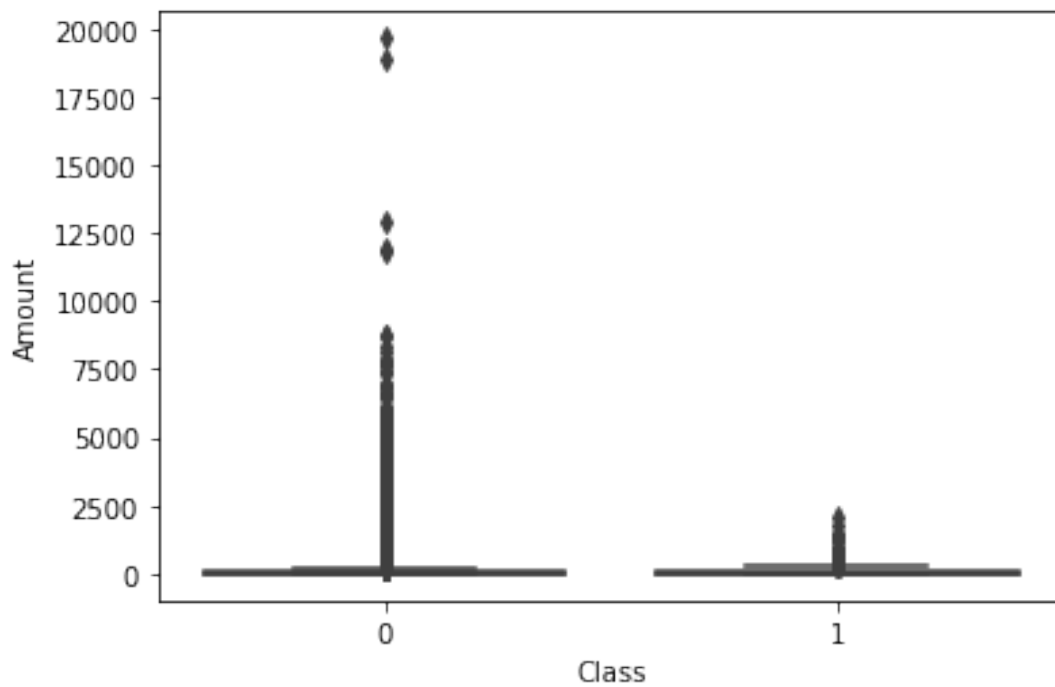
print('Class counts')
print(finance_train_df['Class'].value_counts())
print(finance_train_df['Class'].value_counts(normalize = True))

Class counts
0    226001
1       377
Name: Class, dtype: int64
0    0.998335
1    0.001665
Name: Class, dtype: float64

sns.countplot(x = finance_train_df['Class'])
plt.title('Class Counts')
plt.show()
```



```
sns.boxplot(x='Class', y='Amount', data=finance_train_df)  
plt.show()
```



```
finance_train_df.groupby('Class')['Amount'].sum() /  
finance_train_df['Amount'].sum()
```

```

Class
0      0.997513
1      0.002487
Name: Amount, dtype: float64

```

From the above result and plot, we can see, we have highly imbalanced data where non-fraud count is way higher than the number of frauds.

Also we have 99.8% non-fraudulent and 0.2% fraudulent transactions.

Find if there is any connection between Time, Amount, and the transaction being fraudulent.

Lets try some plotting to get some insights on the class, time and amount relationships.
 Lets try plotting on sample of data.

We can also try to find the relation between other encoded features and class labels.

```

class0_amt_med = finance_train_df[finance_train_df['Class'] == 0]
['Amount'].median()
class1_amt_med = finance_train_df[finance_train_df['Class'] == 1]
['Amount'].median()

```

```

print('Median amount for class 0 ', class0_amt_med)
print('Median amount for class 1 ', class1_amt_med)

```

```

Median amount for class 0  22.5
Median amount for class 1  18.0

```

```

finance_train_df.groupby('Class')['Amount'].describe()

```

	count	mean	std	min	25%	50%	75%
max							
Class							
0	226001.0	89.022663	248.759075	0.01	5.99	22.5	77.95
	19656.53						
1	377.0	133.047135	269.028423	0.01	1.00	18.0	112.45
	2125.87						

We can see, for class 1 (fraud), amount has comparatively higher mean value, but has less median (50%) value.

Lets sample the train data and proceed with further EDA.

```

sample_data = finance_train_df.sample(frac=1)

data0 = sample_data[sample_data['Class'] == 0][:500]
data1 = sample_data[sample_data['Class'] == 1]
data = pd.concat([data0, data1], axis=0)
print(data.shape)

```

```

(877, 31)

```

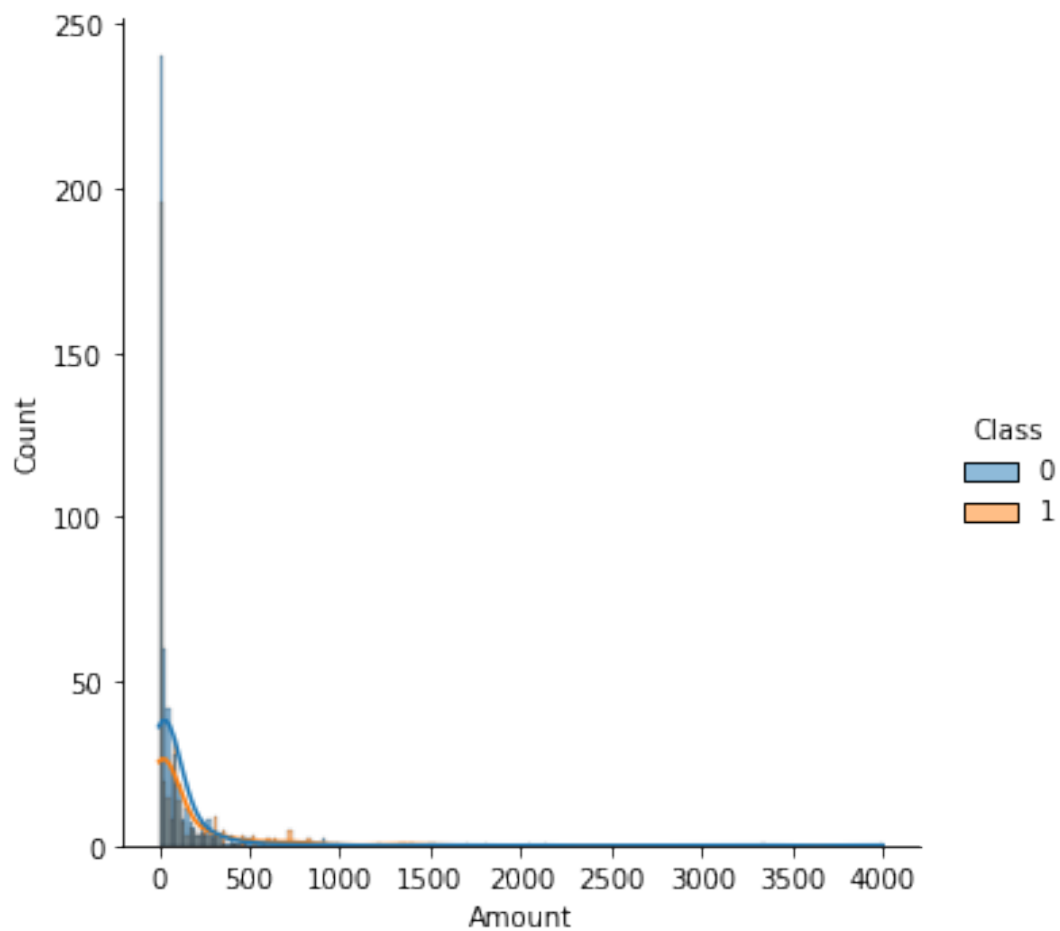
```
data['Class'].value_counts()
```

```
0    500
```

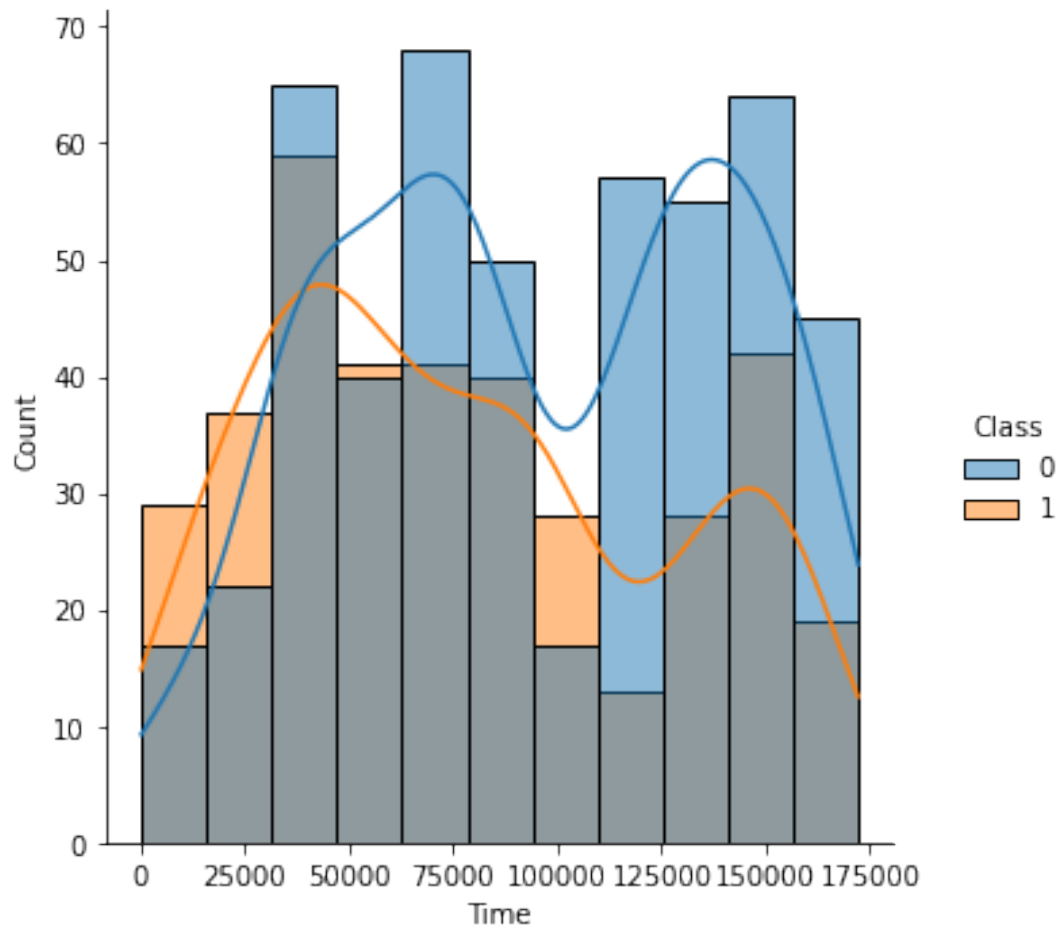
```
1    377
```

```
Name: Class, dtype: int64
```

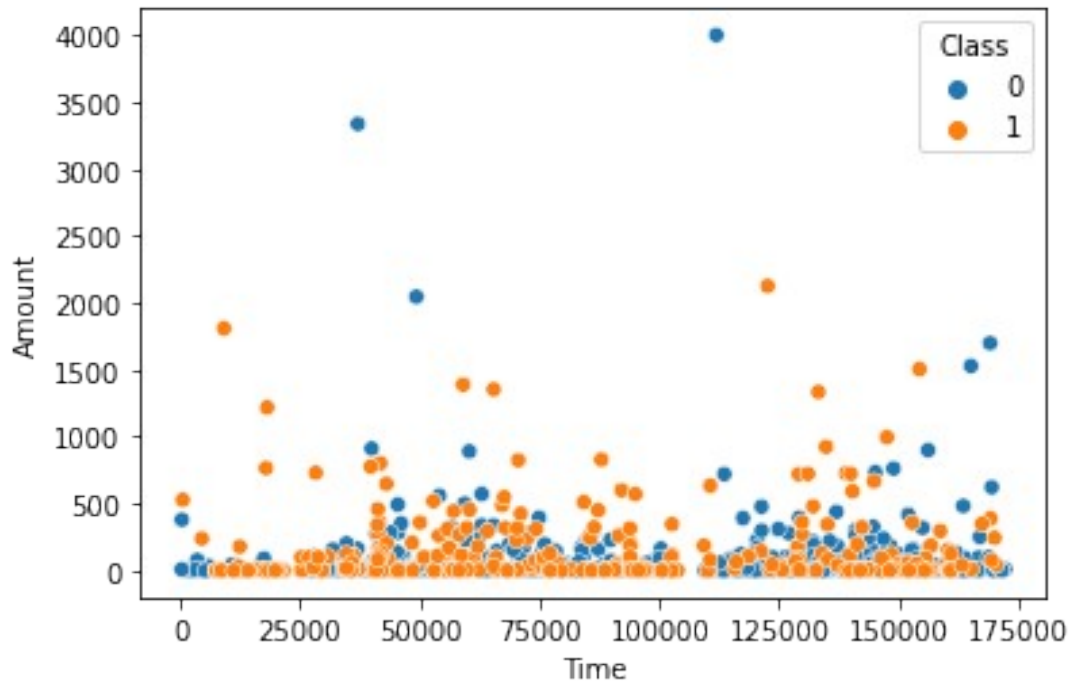
```
sns.displot(data, x= 'Amount', hue= 'Class', kde=True)  
plt.show()
```



```
sns.displot(data, x= 'Time', hue= 'Class', kde= True)  
plt.show()
```



```
sns.scatterplot(data=data, x="Time", y="Amount", hue="Class")  
plt.show()
```



From the above two plots, we cant find any specific relationship between the three data.

But from the scatterplot, we can see, most of the froud transactions have less amount, but still few of them has large amount.

Also, there are certain timestamps, where froud counts are more than the non-froud counts as compared to other timestamps.

```
corr = data.corr()['Class']['Amount']
corr
```

```
0.06042151045900016
```

We dont get much inference from the correlation. We can try phik library to get the relationship between class, time and amount.

```
corr = data.phik_matrix().loc['Class', ['Time', 'Amount',
'Class']].to_dict()
corr
```

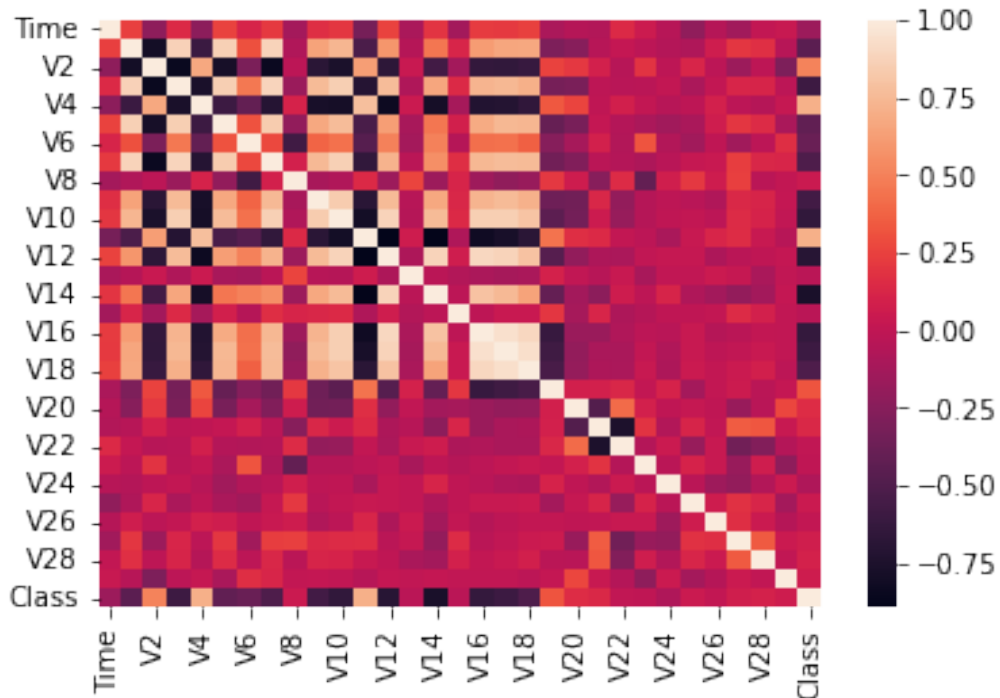
```
interval columns not set, guessing: ['Time', 'V1', 'V2', 'V3', 'V4',
'V5', 'V6', 'V7', 'V8', 'V9', 'V10', 'V11', 'V12', 'V13', 'V14',
'V15', 'V16', 'V17', 'V18', 'V19', 'V20', 'V21', 'V22', 'V23', 'V24',
'V25', 'V26', 'V27', 'V28', 'Amount', 'Class']
```

```
{'Time': 0.30580993495716885, 'Amount': 0.13369615362211948, 'Class':
1.0}
```

We can see, time got higher correlation value than amount for class labels.

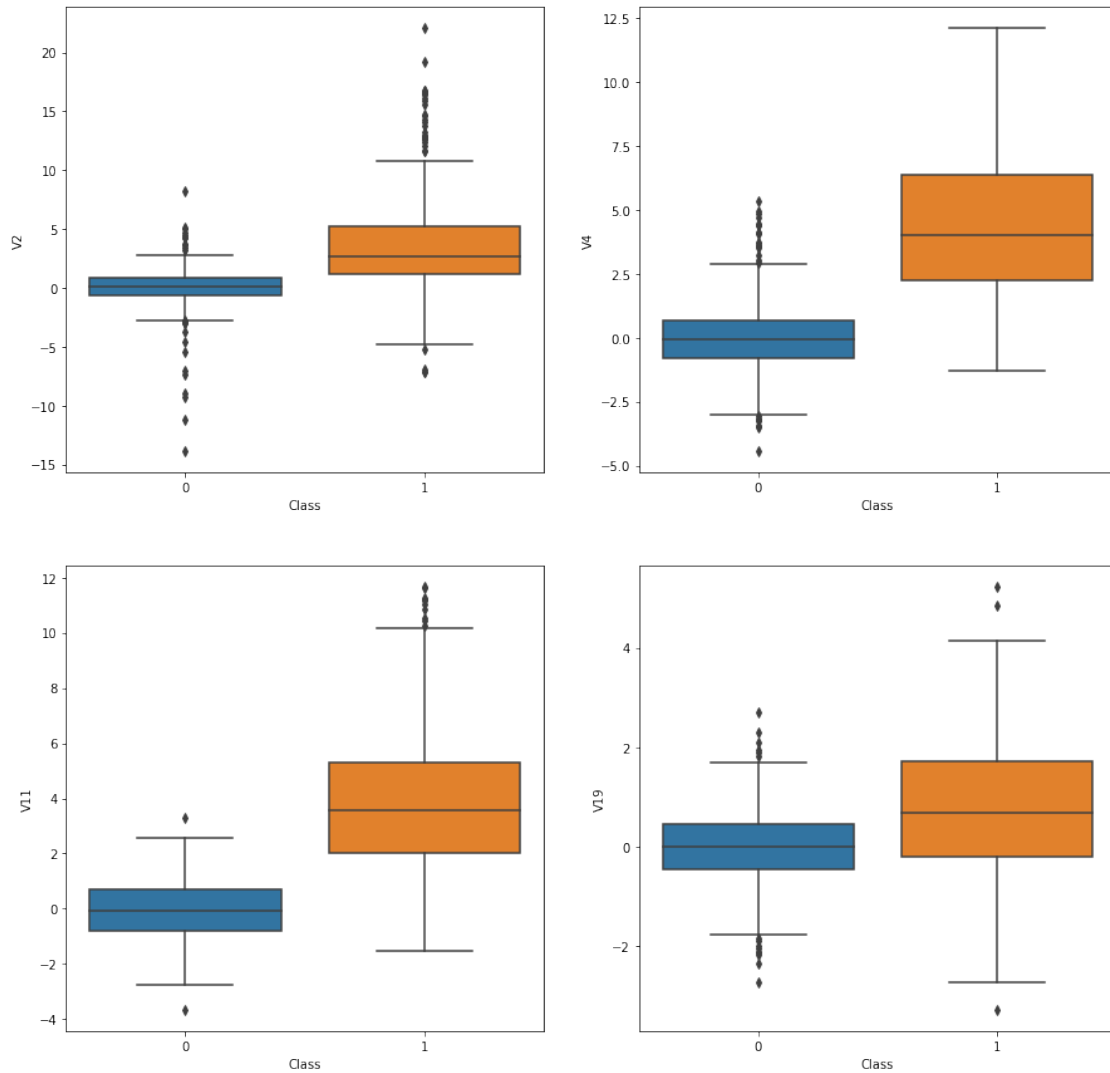
Lets find out the relationship between other features and class labels.

```
corr = data.corr()  
sns.heatmap(corr)  
plt.show()
```



All the features are correlated with each other and for amount, there are few possitively correlated features and some are negatively correlated.

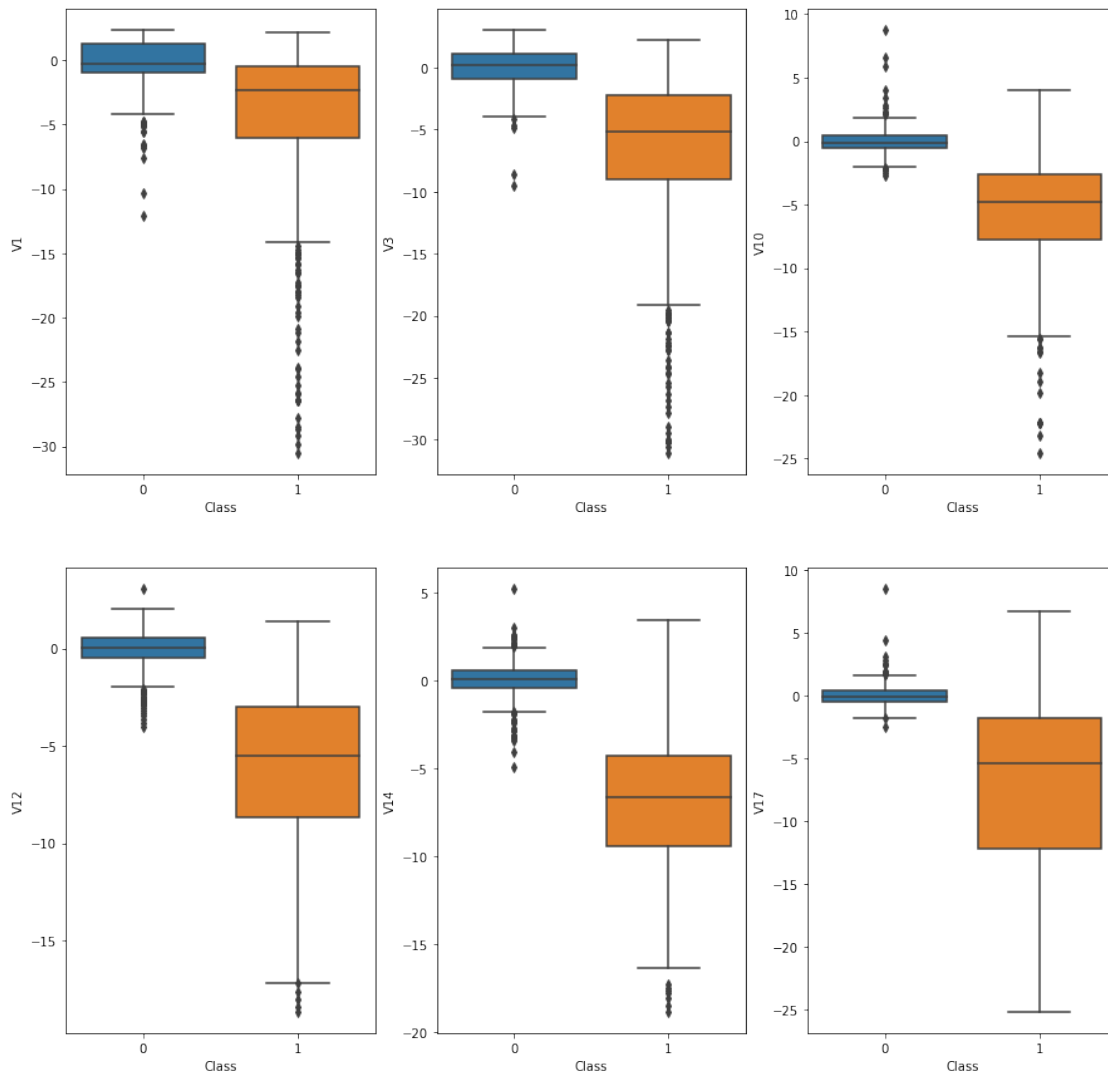
```
fig, ax = plt.subplots(2,2, figsize=(15,15))  
y = 0;  
for i, f in enumerate(['V2', 'V4', 'V11', 'V19']):  
    i, j = divmod(y, 2)  
    sns.boxplot(y=f, x= 'Class', data= data, ax= ax[i, j])  
    y += 1  
  
plt.show()
```



Above features are negatively correlated with the class label, so low value indicates class 0.

```
fig, ax = plt.subplots(2,3, figsize=(15,15))
y = 0;
for i, f in enumerate(['V1', 'V3', 'V10', 'V12', 'V14', 'V17']):
    i, j = divmod(y, 3)
    sns.boxplot(y=f, x= 'Class', data= data, ax= ax[i, j])
    y += 1

plt.show()
```

Above features are positively correlated with the class label. So higher value indicates class 0.

We can see, there are some features which properly classifies both the class labels.

So we can consider these useful features on modeling.

Now lets try to visualize the features with TSNE.

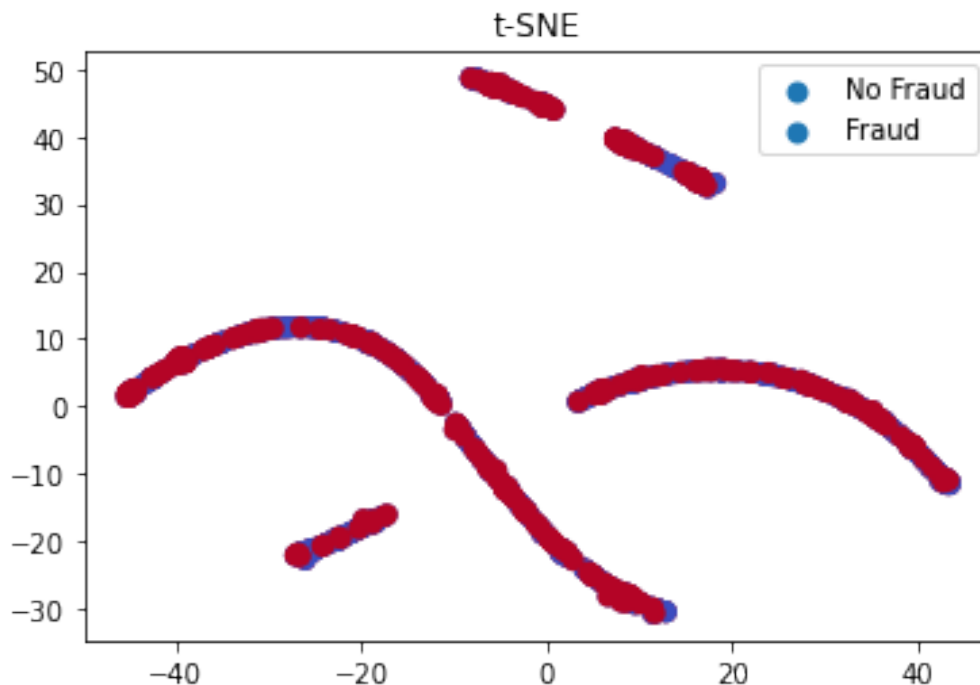
```
X = data.drop('Class', axis=1)
y = data['Class']

X_tsne = TSNE(n_components=2, random_state=42).fit_transform(X.values)
plt.scatter(X_tsne[:,0], X_tsne[:,1], c=(y == 0), cmap='coolwarm',
label='No Fraud', linewidths=2)
plt.scatter(X_tsne[:,0], X_tsne[:,1], c=(y == 1), cmap='coolwarm',
label='Fraud', linewidths=2)
plt.title('t-SNE')
```

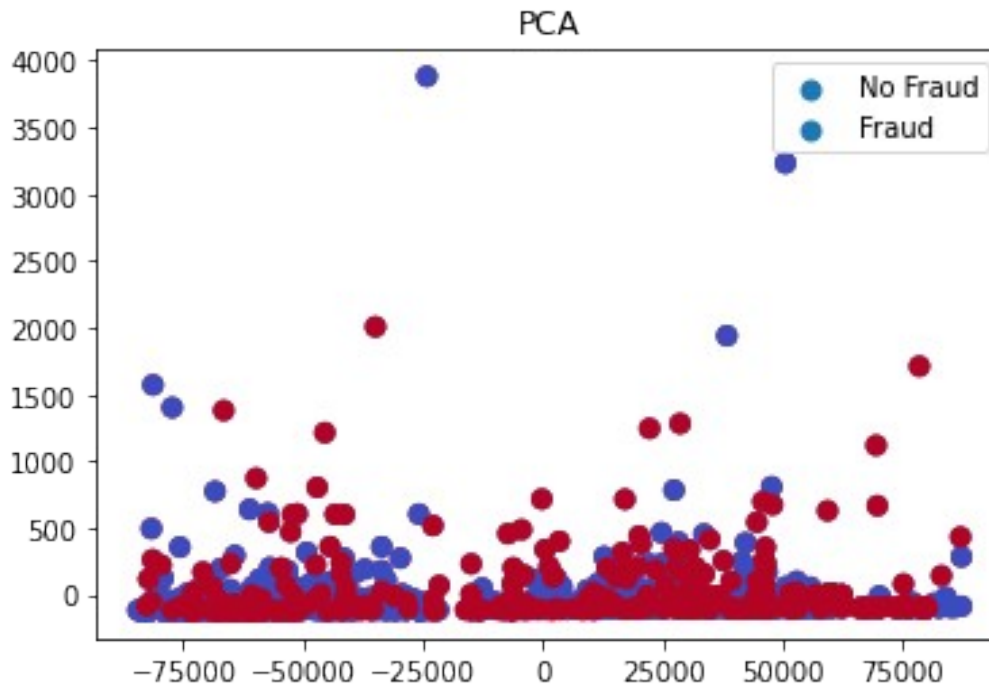
```
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/manifold/_t_sne.py:783:
FutureWarning: The default initialization in TSNE will change from
'random' to 'pca' in 1.2.
```

```
FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/manifold/_t_sne.py:793:
FutureWarning: The default learning rate in TSNE will change from
200.0 to 'auto' in 1.2.
FutureWarning,
```



```
X_pca = PCA(n_components=2, random_state=42).fit_transform(X.values)
plt.scatter(X_pca[:,0], X_pca[:,1], c=(y == 0), cmap='coolwarm',
label='No Fraud', linewidths=2)
plt.scatter(X_pca[:,0], X_pca[:,1], c=(y == 1), cmap='coolwarm',
label='Fraud', linewidths=2)
plt.title('PCA')
plt.legend()
plt.show()
```



Use techniques like undersampling or oversampling before running Naïve Bayes, Logistic Regression or SVM.

We can go for both oversampling and undersampling approach and compare the result. But before that, let's standardize the data as we have time and amount with higher scale than others.

```
train_X = finance_train_df.drop(['Class'], axis=1)
train_y = finance_train_df['Class']

test_X = finance_test_hidden_df.drop(['Class'], axis=1)
test_y = finance_test_hidden_df['Class']

stdsc = StandardScaler()

train_X = stdsc.fit_transform(train_X)
test_X = stdsc.transform(test_X)

train_y.reset_index(drop=True, inplace=True)

train_df = pd.DataFrame(train_X)
train_df.columns = finance_train_df.columns[:-1]
train_df['Class'] = train_y
train_df.to_pickle('finance_train.pkl')
```

Oversampling

```
osmp = RandomOverSampler(sampling_strategy='minority')
train_X_ovr, train_y_ovr = osmp.fit_resample(train_X, train_y)
```

```
print(train_X_ovr.shape)
print(train_y_ovr.shape)
print(train_y_ovr.value_counts())
```

```
(452002, 30)
(452002,)
0      226001
1      226001
Name: Class, dtype: int64
```

```
train_ovr_df = pd.DataFrame(train_X_ovr)
train_ovr_df.columns = finance_train_df.columns[:-1]
train_ovr_df['Class'] = train_y_ovr
```

```
train_ovr_df.shape

(452002, 31)
```

Undersampling

```
usmp = RandomUnderSampler(sampling_strategy=0.5)
train_X_udr, train_y_udr = usmp.fit_resample(train_X, train_y)
```

```
print(train_X_udr.shape)
print(train_y_udr.shape)
print(train_y_udr.value_counts())
```

```
(1131, 30)
(1131,)
0      754
1      377
Name: Class, dtype: int64
```

```
train_udr_df = pd.DataFrame(train_X_udr)
train_udr_df.columns = finance_train_df.columns[:-1]
train_udr_df['Class'] = train_y_udr
```

```
train_udr_df.shape

(1131, 31)
```

```
test_df = pd.DataFrame(test_X)
test_df.columns = finance_train_df.columns[:-1]
test_df['Class'] = test_y
```

```
test_df.shape

(56962, 31)
```

```
train_ovr_df.to_pickle('finance_ovr_train.pkl')
train_udr_df.to_pickle('finance_udr_train.pkl')
test_df.to_pickle('finance_test.pkl')
```

We have standardized, over and under sampled our data and saved it as pickle files for future purposes.

Following are the matrices for evaluating the model performance: Precision, Recall, F1-Score, AUC-ROC curve. Use F1-Score as the evaluation criteria for this project

```
def getPerformance(y_train, y_pred_train, y_test, y_pred_test, name):
    print('\nModel performance ' + name)
    print('\naccuracy score train', accuracy_score(y_train,
y_pred_train))
    print('accuracy score test', accuracy_score(y_test, y_pred_test))
    print('\nTrain classification report: ' + name + '\n')
    print(classification_report(y_train, y_pred_train))
    print('\nTest classification report: ' + name + '\n')
    print(classification_report(y_test, y_pred_test))
    print('\n')
    sns.heatmap(confusion_matrix(y_train, y_pred_train), annot= True,
cbar= False)
    plt.title('Train confusion matrix: ' + name)
    plt.show()
    sns.heatmap(confusion_matrix(y_test, y_pred_test), annot= True,
cbar= False)
    plt.title('Test confusion matrix: ' + name)
    plt.show()
    print('\nroc auc score train {}'.format(roc_auc_score(y_train,
y_pred_train)))
    fpr, tpr, th = roc_curve(y_train, y_pred_train)
    auc_val = auc(fpr, tpr)
    plt.title(name + ' Train Receiver Operating Characteristic Curve')
    plt.plot(fpr, tpr, label='area = {:.3f}'.format(auc_val))
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1], 'r--')
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()
    print('\nroc auc score test {}'.format(roc_auc_score(y_test,
y_pred_test)))
    fpr, tpr, th = roc_curve(y_test, y_pred_test)
    auc_val = auc(fpr, tpr)
    plt.title(name + ' Test Receiver Operating Characteristic Curve')
    plt.plot(fpr, tpr, label='area = {:.3f}'.format(auc_val))
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1], 'r--')
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()
```

Modeling Techniques

We can try out different models like naive bayes, svm, logistic regression and also three based models like random forest and xgboot with both the data (oversampled and undersampled). In addition to that we can do hyper-parameter tuning in parallel.

Before that lets upload our processed data.

```
train_ovr_df = pd.read_pickle('finance_ovr_train.pkl')
train_udr_df = pd.read_pickle('finance_udr_train.pkl')
test_df = pd.read_pickle('finance_test.pkl')
```

```
train_ovr_X = train_ovr_df.drop(['Class'], axis=1)
train_ovr_y = train_ovr_df['Class']
```

```
train_udr_X = train_udr_df.drop(['Class'], axis=1)
train_udr_y = train_udr_df['Class']
```

```
test_X = test_df.drop(['Class'], axis=1)
test_y = test_df['Class']
```

```
x_ovr_train, x_ovr_test, y_ovr_train, y_ovr_test =
train_test_split(train_ovr_X, train_ovr_y,
```

```
stratify= train_ovr_y,
```

```
test_size= 0.2, random_state= 0)
```

```
x_udr_train, x_udr_test, y_udr_train, y_udr_test =
train_test_split(train_udr_X, train_udr_y,
```

```
stratify= train_udr_y,
```

```
test_size= 0.2, random_state= 0)
```

```
print(x_ovr_train.shape)
print(x_ovr_test.shape)
print(y_ovr_train.shape)
print(y_ovr_test.shape)
```

```
(361601, 30)
(90401, 30)
(361601,)
(90401,)
```

```
print(x_udr_train.shape)
print(x_udr_test.shape)
print(y_udr_train.shape)
print(y_udr_test.shape)
```

```

(904, 30)
(227, 30)
(904,)
(227,)

print(test_X.shape)
print(test_y.shape)

(56962, 30)
(56962,)

def buildModel(model, params, x_train, y_train, x_test, y_test,
test_x, test_y, model_name):
    print('Building model ' + model_name + '.....')
    gs = GridSearchCV(model, params, refit=True,
scoring=make_scorer(f1_score , average='macro'))
    gs.fit(x_train, y_train)
    y_train_pred = gs.predict(x_train)
    y_test_pred = gs.predict(x_test)
    print('\nBest score ', gs.best_score_)
    print('Best param ', gs.best_params_)
    best_model = gs.best_estimator_
    print('Best model ', best_model)
    getPerformance(y_train, y_train_pred, y_test, y_test_pred,
model_name)
    test_y_pred = best_model.predict(test_X)
    print('\nTest accuracy score {} \n'.format(accuracy_score(test_y,
test_y_pred)))
    print('Classification report\n')
    print(classification_report(test_y, test_y_pred))
    print('\nCompleted for ' + model_name)
    print('Saving model as ' + model_name + '.pkl')
    pickle.dump(best_model, open(model_name + '.pkl', 'wb'))

```

Naive Bayes

Naive Bayes with over sampled data

```

gnb_ovr = GaussianNB()

gnb_params = {'var_smoothing': np.logspace(0,-9, num=100), 'priors':
[[0.5, 0.5], [0.25, 0.75], [0.75,0.25]]}

buildModel(gnb_ovr, gnb_params, x_ovr_train, y_ovr_train, x_ovr_test,
y_ovr_test, test_X, test_y, 'Oversampled GNB')

Building model Oversampled GNB.....

Best score  0.9189955854298983
Best param  {'priors': [0.25, 0.75], 'var_smoothing':
0.0006579332246575676}
Best model  GaussianNB(priors=[0.25, 0.75],

```

```
var_smoothing=0.0006579332246575676)
```

Model performance Oversampled GNB

```
accuracy score train 0.9192452454500956
```

```
accuracy score test 0.9205429143482926
```

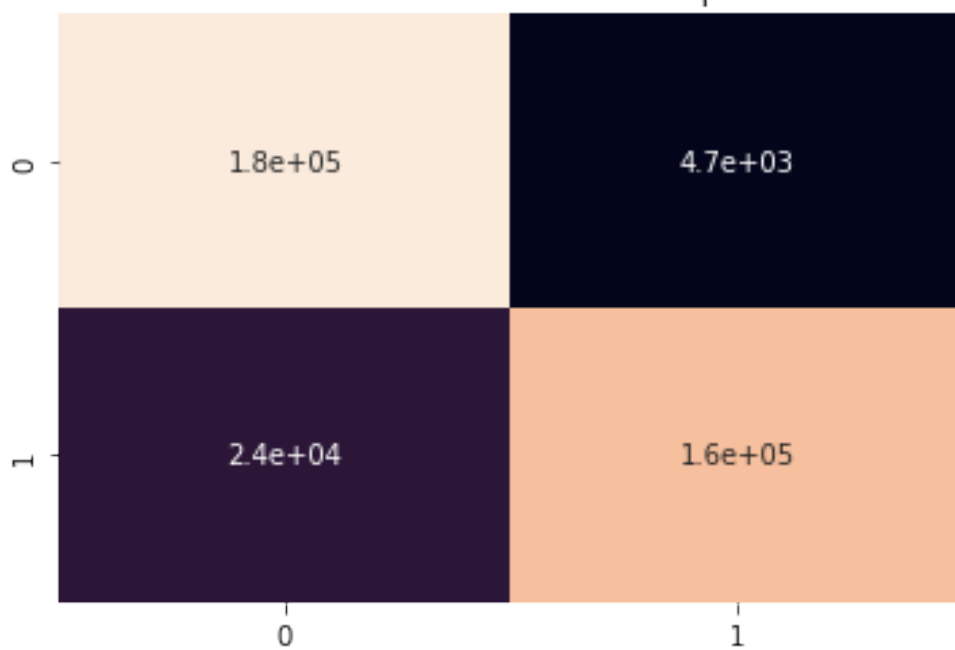
Train classification report: Oversampled GNB

	precision	recall	f1-score	support
0	0.88	0.97	0.92	180800
1	0.97	0.86	0.91	180801
accuracy			0.92	361601
macro avg	0.92	0.92	0.92	361601
weighted avg	0.92	0.92	0.92	361601

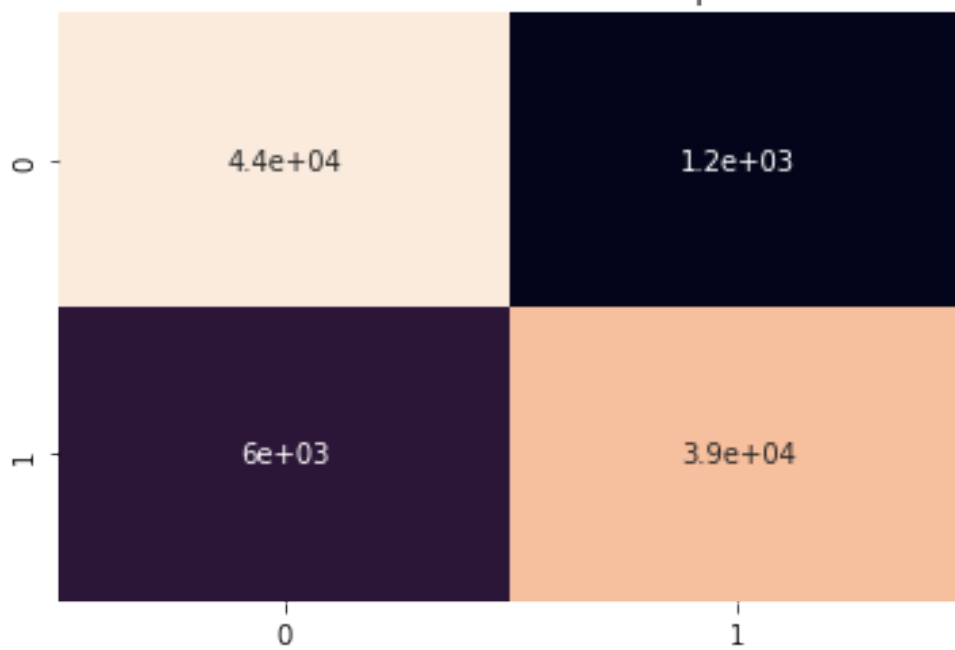
Test classification report: Oversampled GNB

	precision	recall	f1-score	support
0	0.88	0.97	0.92	45201
1	0.97	0.87	0.92	45200
accuracy			0.92	90401
macro avg	0.93	0.92	0.92	90401
weighted avg	0.93	0.92	0.92	90401

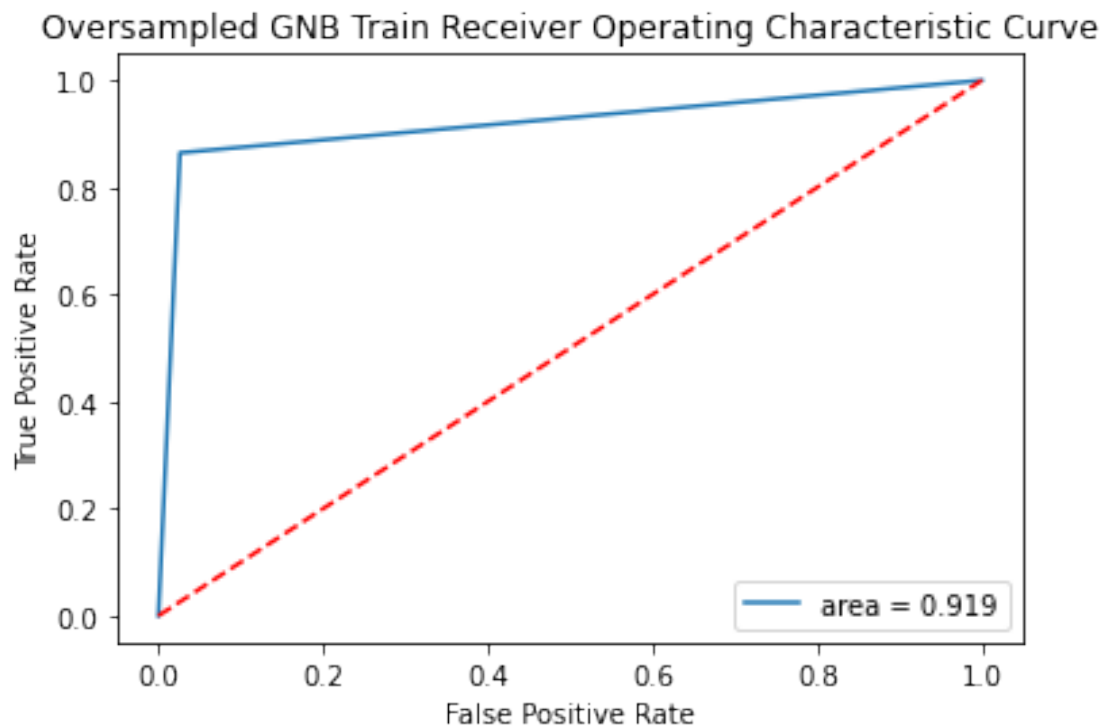
Train confusion matrix: Oversampled GNB



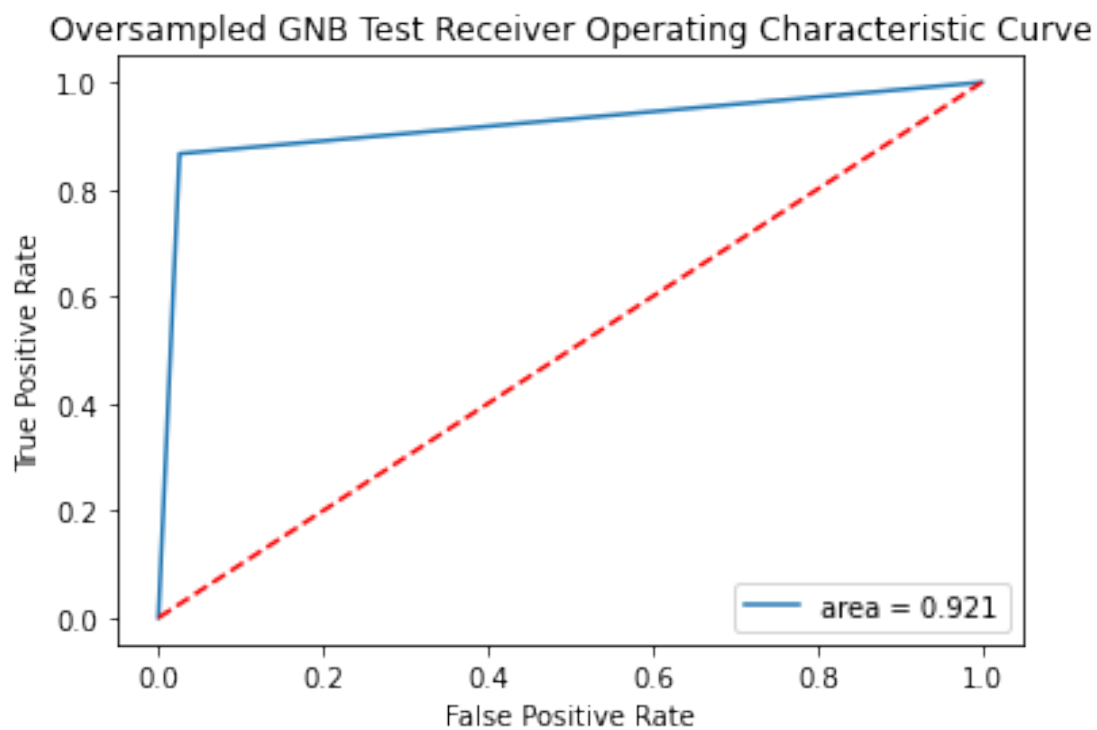
Test confusion matrix: Oversampled GNB



roc auc score train 0.919245396426169



roc auc score test 0.9205423187931663



Test accuracy score 0.9732628770057231

Classification report

	precision	recall	f1-score	support
0	1.00	0.97	0.99	56864
1	0.05	0.82	0.10	98
accuracy			0.97	56962
macro avg	0.53	0.89	0.54	56962
weighted avg	1.00	0.97	0.98	56962

Completed for Oversampled GNB
Saving model as Oversampled GNB.pkl

We are getting very good performance on the oversampled data and with the test data, it gave reasonable f1-score.

Naive Bayes with under sampled data

```
gnb_udr = GaussianNB()
```

```
gnb_params = {'var_smoothing': np.logspace(0, -9, num=100), 'priors':  
[[0.5, 0.5], [0.25, 0.75], [0.75, 0.25]]}
```

```
buildModel(gnb_udr, gnb_params, x_udr_train, y_udr_train, x_udr_test,  
y_udr_test, test_X, test_y, 'Undersampled GNB')
```

Building model Undersampled GNB.....

Best score 0.9200576725202432

Best param {'priors': [0.5, 0.5], 'var_smoothing':
0.004328761281083057}

Best model GaussianNB(priors=[0.5, 0.5],
var_smoothing=0.004328761281083057)

Model performance Undersampled GNB

accuracy score train 0.9303097345132744

accuracy score test 0.9383259911894273

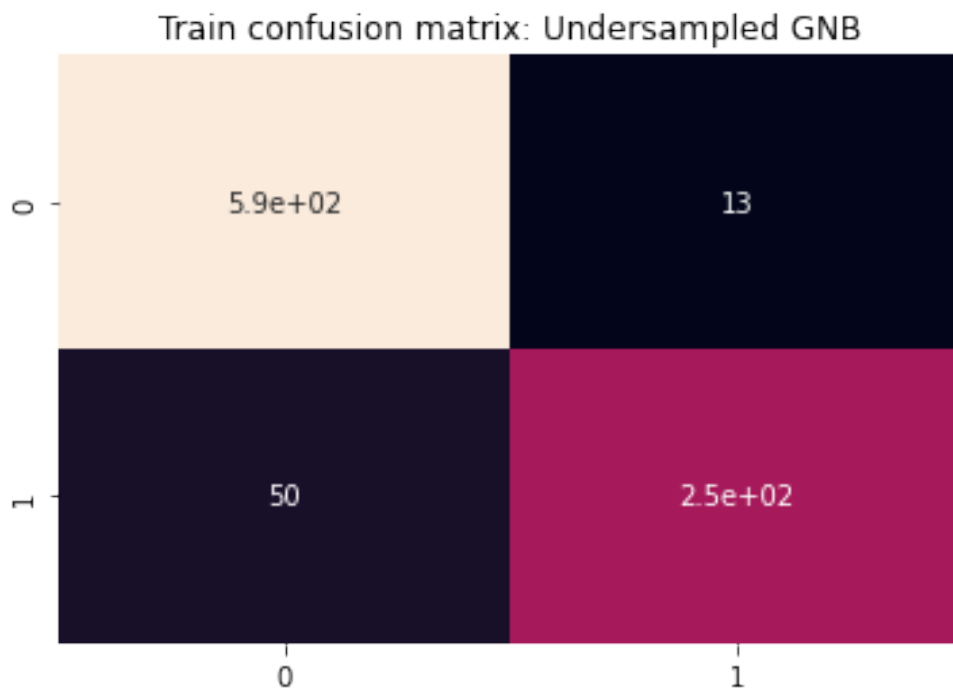
Train classification report: Undersampled GNB

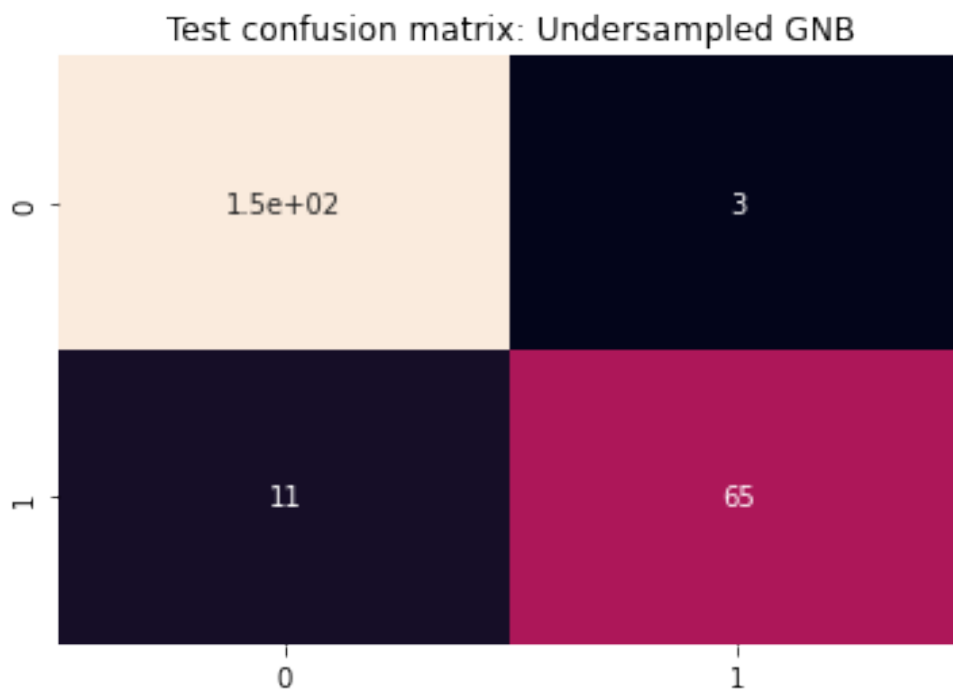
	precision	recall	f1-score	support
0	0.92	0.98	0.95	603
1	0.95	0.83	0.89	301
accuracy			0.93	904

macro avg	0.94	0.91	0.92	904
weighted avg	0.93	0.93	0.93	904

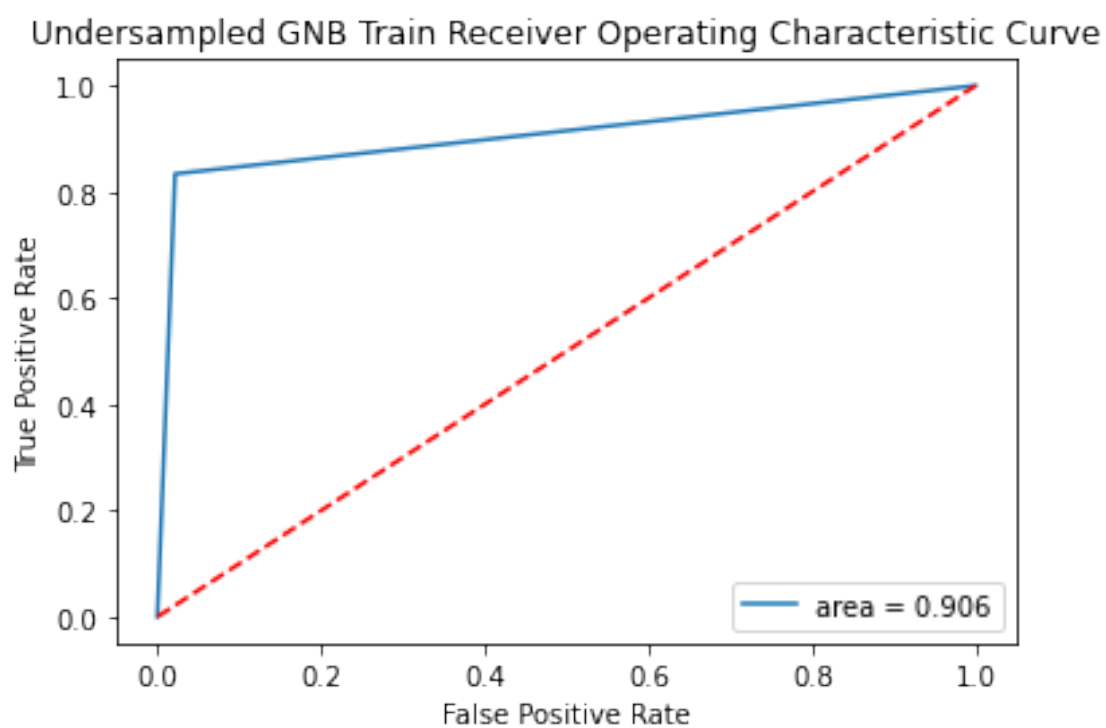
Test classification report: Undersampled GNB

	precision	recall	f1-score	support
0	0.93	0.98	0.95	151
1	0.96	0.86	0.90	76
accuracy			0.94	227
macro avg	0.94	0.92	0.93	227
weighted avg	0.94	0.94	0.94	227

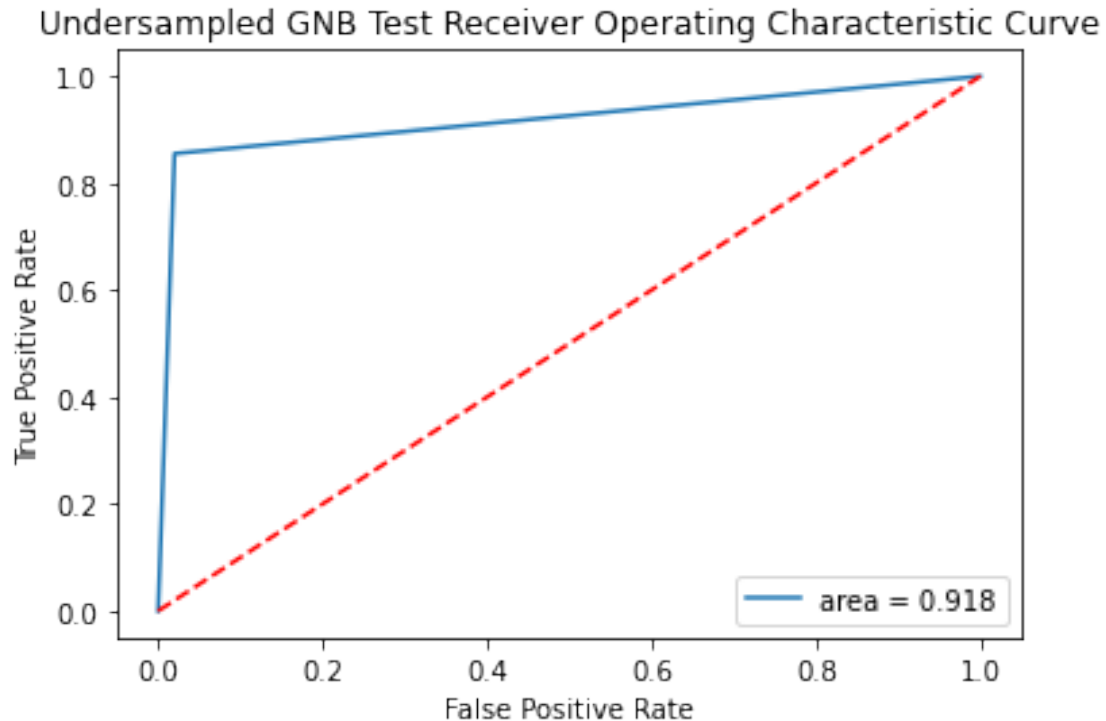




roc auc score train 0.9061640854421139



roc auc score test 0.9176978041129313



Test accuracy score 0.9698219865875496

Classification report

	precision	recall	f1-score	support
0	1.00	0.97	0.98	56864
1	0.04	0.82	0.09	98
accuracy			0.97	56962
macro avg	0.52	0.89	0.53	56962
weighted avg	1.00	0.97	0.98	56962

Completed for Undersampled GNB
Saving model as Undersampled GNB.pkl

Undersampled Gaussian Naive Bayes performed better than the oversampled model in terms of f1-score on training data. But for the test, both gave similar performance. We can choose oversampled naive bayes model.

[SVC](#)

[SVC with oversampled data](#)

```
svc_ovr = SGDClassifier(loss='hinge', class_weight='balanced')
```

```
svc_params = {'alpha' : [0.0001, 0.001, 0.01, 0.1], 'penalty' : ['l2',  
'l1', 'none']}
```

```
buildModel(svc_ovr, svc_params, x_ovr_train, y_ovr_train, x_ovr_test,  
y_ovr_test, test_X, test_y, 'Oversampled SVC')
```

Building model Oversampled SVC.....

Best score 0.9580153162855138

Best param {'alpha': 0.0001, 'penalty': 'l1'}

Best model SGDClassifier(class_weight='balanced', penalty='l1')

Model performance Oversampled SVC

accuracy score train 0.9531859701715427

accuracy score test 0.9534075950487273

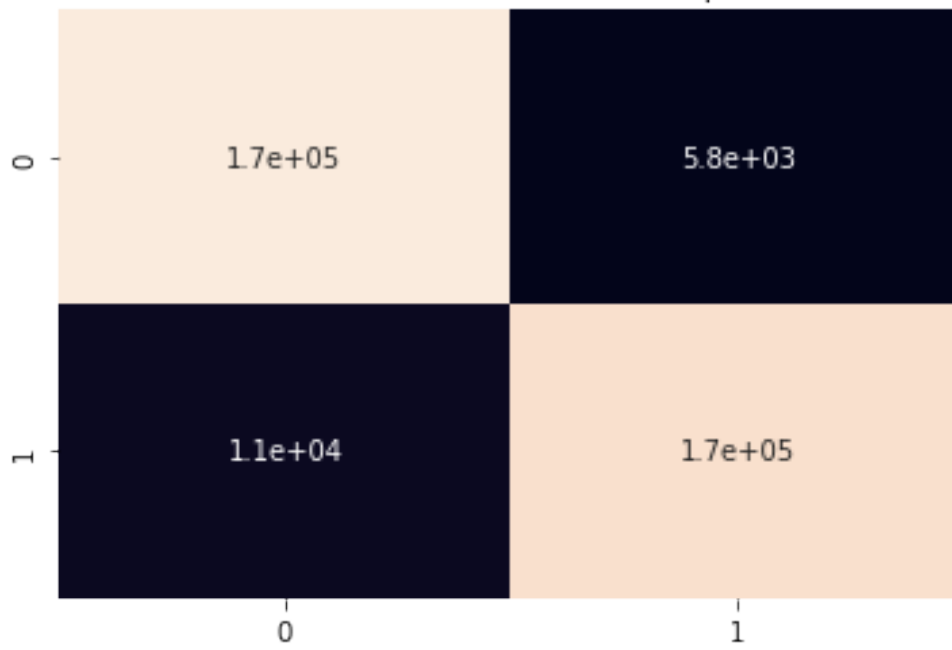
Train classification report: Oversampled SVC

	precision	recall	f1-score	support
0	0.94	0.97	0.95	180800
1	0.97	0.94	0.95	180801
accuracy			0.95	361601
macro avg	0.95	0.95	0.95	361601
weighted avg	0.95	0.95	0.95	361601

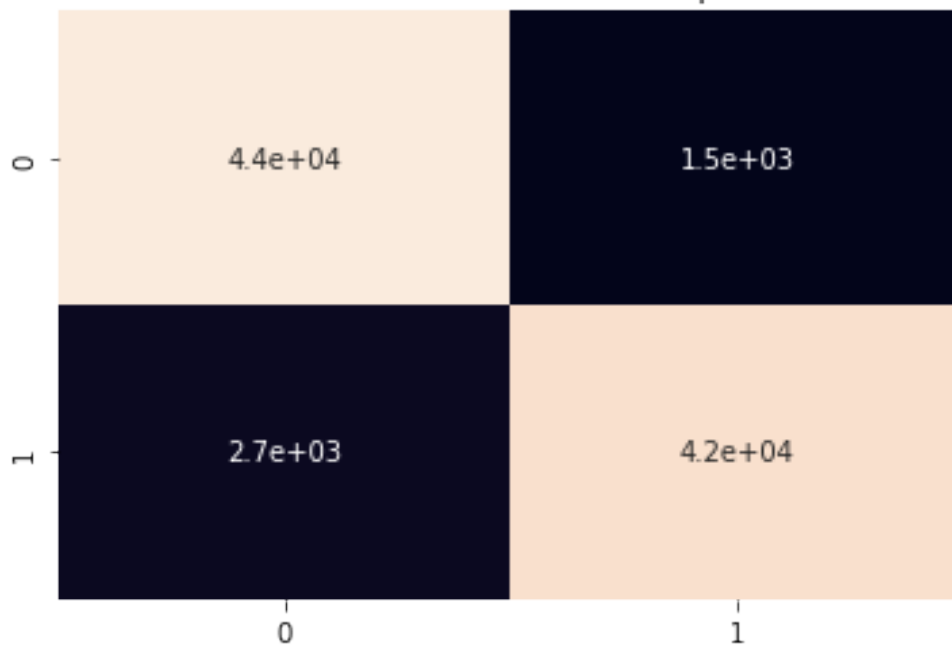
Test classification report: Oversampled SVC

	precision	recall	f1-score	support
0	0.94	0.97	0.95	45201
1	0.97	0.94	0.95	45200
accuracy			0.95	90401
macro avg	0.95	0.95	0.95	90401
weighted avg	0.95	0.95	0.95	90401

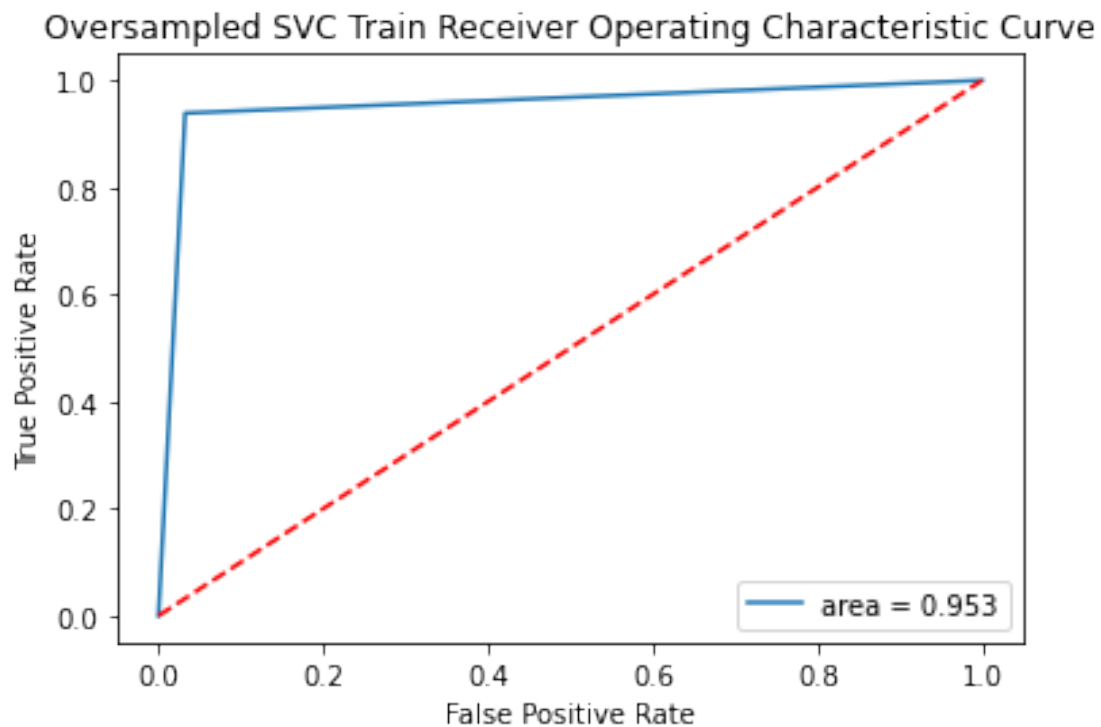
Train confusion matrix: Oversampled SVC



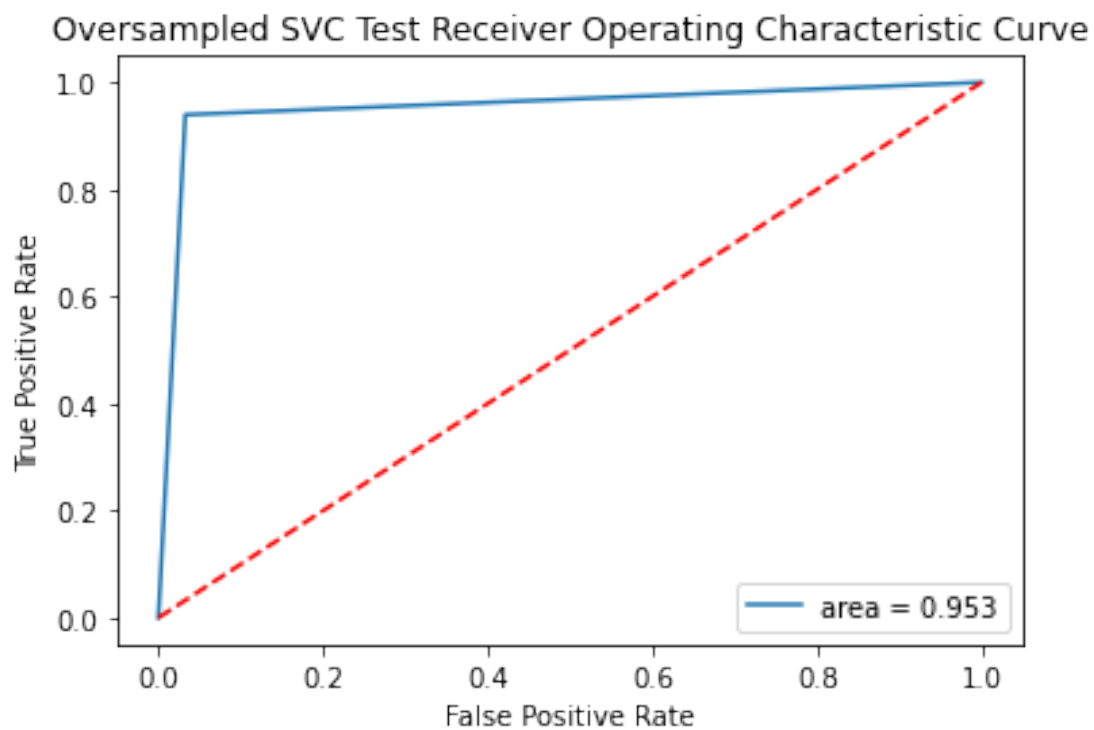
Test confusion matrix: Oversampled SVC



roc auc score train 0.95318601020016



roc auc score test 0.9534074411091616



Test accuracy score 0.966960429760191

Classification report

	precision	recall	f1-score	support
0	1.00	0.97	0.98	56864
1	0.04	0.89	0.08	98
accuracy			0.97	56962
macro avg	0.52	0.93	0.53	56962
weighted avg	1.00	0.97	0.98	56962

Completed for Oversampled SVC
Saving model as Oversampled SVC.pkl

SVC gave similar performance as undersampled the naive bayes model till now. Lets try out the undersampled svc.

Undersampled SVC

```
svc_uds = SGDClassifier(loss='hinge', class_weight='balanced')
```

```
svc_params = {'alpha' : [0.0001, 0.001, 0.01, 0.1], 'penalty' : ['l2',  
'l1', 'none']}
```

```
buildModel(svc_uds, svc_params, x_uds_train, y_uds_train, x_uds_test,  
y_uds_test, test_X, test_y, 'Undersampled SVC')
```

Building model Undersampled SVC.....

Best score 0.947805054083058

Best param {'alpha': 0.1, 'penalty': 'l2'}

Best model SGDClassifier(alpha=0.1, class_weight='balanced')

Model performance Undersampled SVC

accuracy score train 0.9612831858407079

accuracy score test 0.9515418502202643

Train classification report: Undersampled SVC

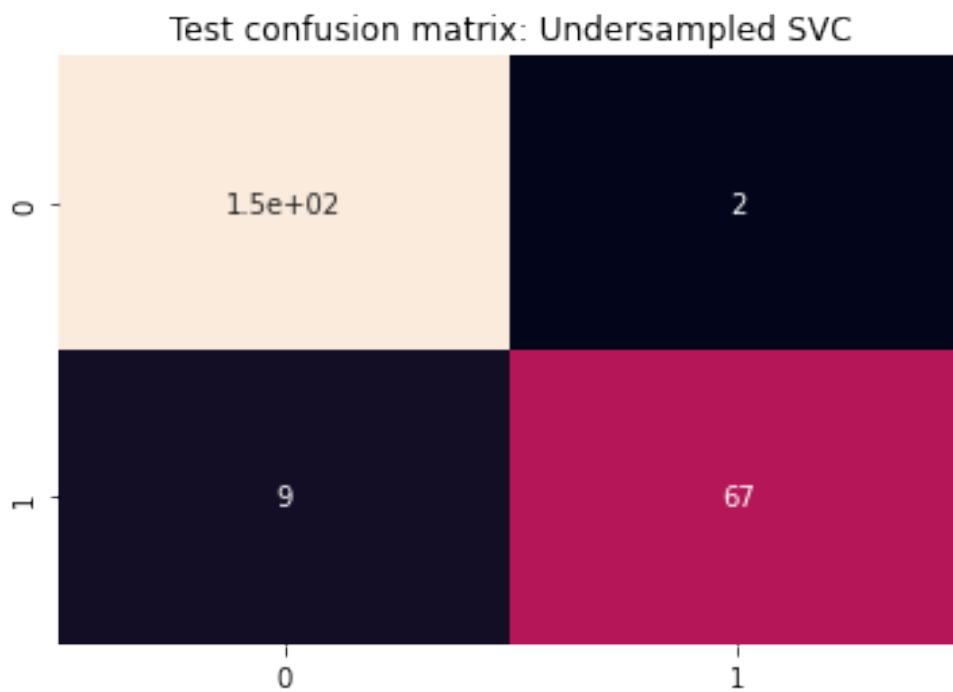
	precision	recall	f1-score	support
0	0.96	0.99	0.97	603
1	0.97	0.91	0.94	301
accuracy			0.96	904
macro avg	0.97	0.95	0.96	904
weighted avg	0.96	0.96	0.96	904

Test classification report: Undersampled SVC

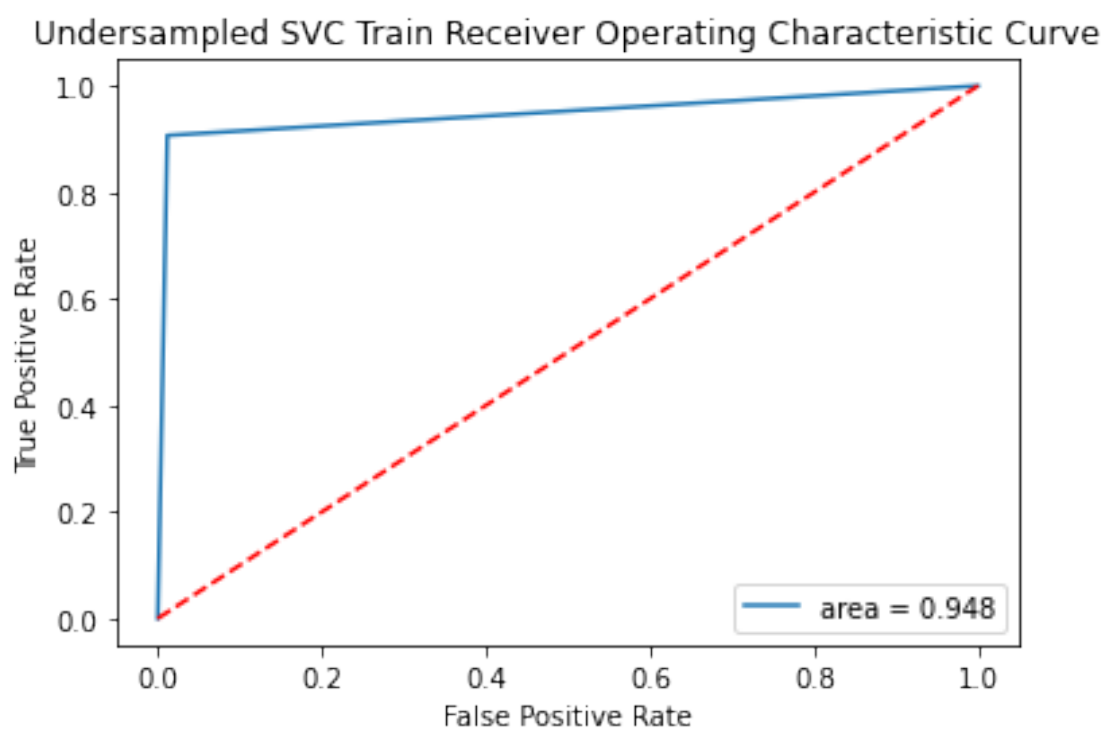
	precision	recall	f1-score	support
0	0.94	0.99	0.96	151
1	0.97	0.88	0.92	76
accuracy			0.95	227
macro avg	0.96	0.93	0.94	227
weighted avg	0.95	0.95	0.95	227

Train confusion matrix: Undersampled SVC

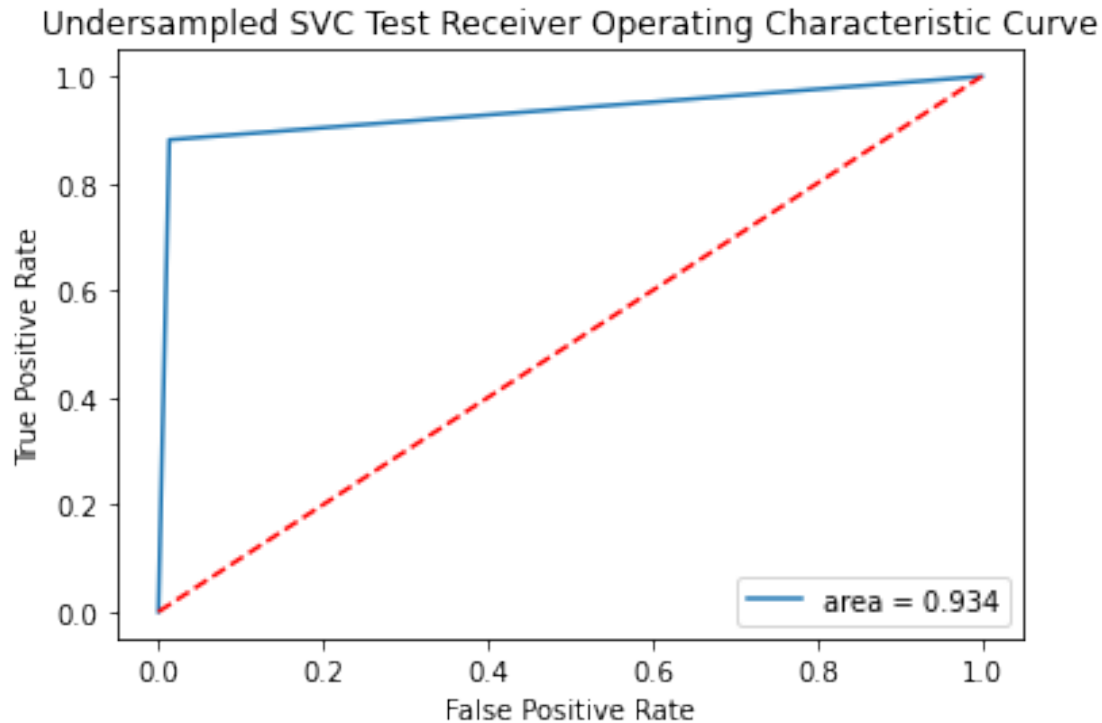




roc auc score train 0.9476840603185621



roc auc score test 0.9341669571279192



Test accuracy score 0.985604438046417

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	56864
1	0.10	0.87	0.17	98
accuracy			0.99	56962
macro avg	0.55	0.93	0.58	56962
weighted avg	1.00	0.99	0.99	56962

Completed for Undersampled SVC
Saving model as Undersampled SVC.pkl

SVC with unsampled data performed better than others.

Logistic Regression

Logistic Regression with oversampled data

```
lr_ovr = LogisticRegression(class_weight= 'balanced', solver=
'liblinear')
lr_params = {"C":np.logspace(-3,3,7), "penalty":["l1","l2", "none"]}
```

```
buildModel(lr_ovr, lr_params, x_ovr_train, y_ovr_train, x_ovr_test,
y_ovr_test, test_X, test_y, 'Oversampled LR')
```

Building model Oversampled LR.....

```
/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/
_validation.py:372: FitFailedWarning:
```

```
35 fits failed out of a total of 105.
```

```
The score on these train-test partitions for these parameters will be
set to nan.
```

```
If these failures are not expected, you can try to debug them by
setting error_score='raise'.
```

Below are more details about the failures:

```
-----
-----
```

```
35 fits failed with the following error:
```

```
Traceback (most recent call last):
```

```
File
```

```
"/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_valid
ation.py", line 680, in _fit_and_score
```

```
    estimator.fit(X_train, y_train, **fit_params)
```

```
File
```

```
"/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic
.py", line 1461, in fit
```

```
    solver = _check_solver(self.solver, self.penalty, self.dual)
```

```
File
```

```
"/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic
.py", line 464, in _check_solver
```

```
    raise ValueError("penalty='none' is not supported for the
liblinear solver")
```

```
ValueError: penalty='none' is not supported for the liblinear solver
```

```
    warnings.warn(some_fits_failed_message, FitFailedWarning)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_search
.py:972: UserWarning: One or more of the test scores are non-finite:
```

```
[0.94924394 0.94961435          nan 0.95194658 0.95191346          nan
 0.9516181  0.9516457          nan 0.95182911 0.9518374          nan
 0.95162638 0.9520594          nan 0.95157945 0.95206216          nan
 0.95183463 0.95206216          nan]
```

```
category=UserWarning,
```

```
Best score 0.9520621575772905
```

```
Best param {'C': 1000.0, 'penalty': 'l2'}
```

```
Best model LogisticRegression(C=1000.0, class_weight='balanced',
solver='liblinear')
```

Model performance Oversampled LR

accuracy score train 0.9516704876369257
accuracy score test 0.9521907943496201

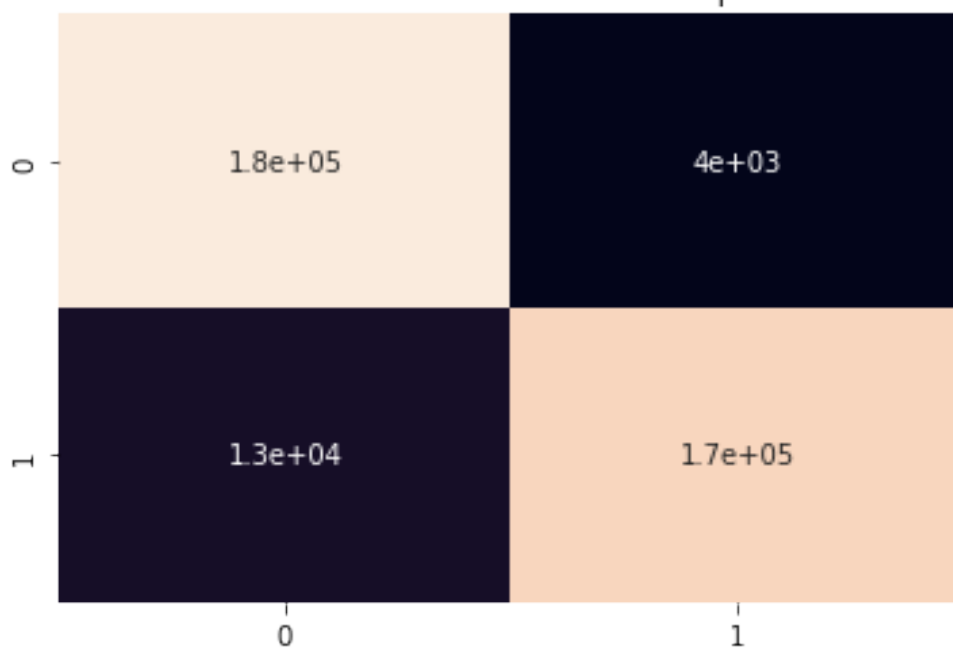
Train classification report: Oversampled LR

	precision	recall	f1-score	support
0	0.93	0.98	0.95	180800
1	0.98	0.93	0.95	180801
accuracy			0.95	361601
macro avg	0.95	0.95	0.95	361601
weighted avg	0.95	0.95	0.95	361601

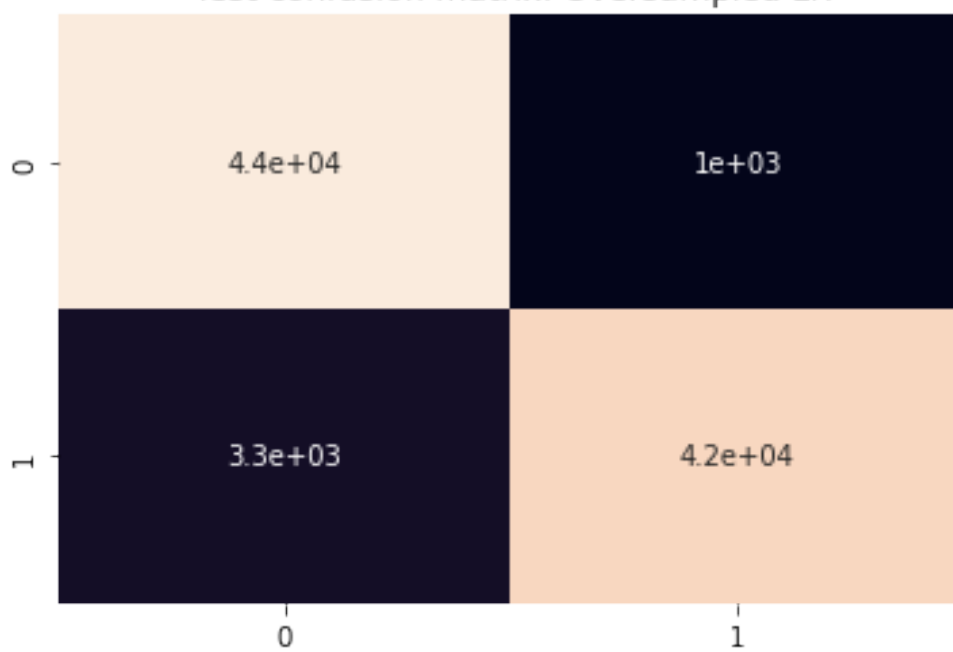
Test classification report: Oversampled LR

	precision	recall	f1-score	support
0	0.93	0.98	0.95	45201
1	0.98	0.93	0.95	45200
accuracy			0.95	90401
macro avg	0.95	0.95	0.95	90401
weighted avg	0.95	0.95	0.95	90401

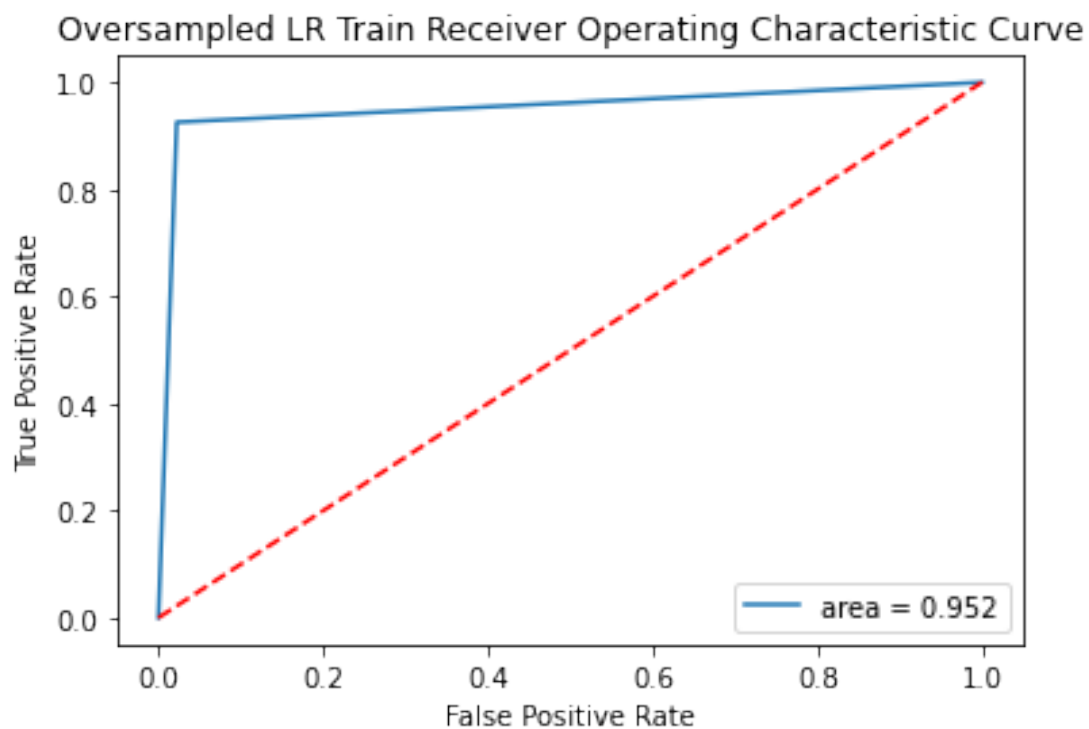
Train confusion matrix: Oversampled LR



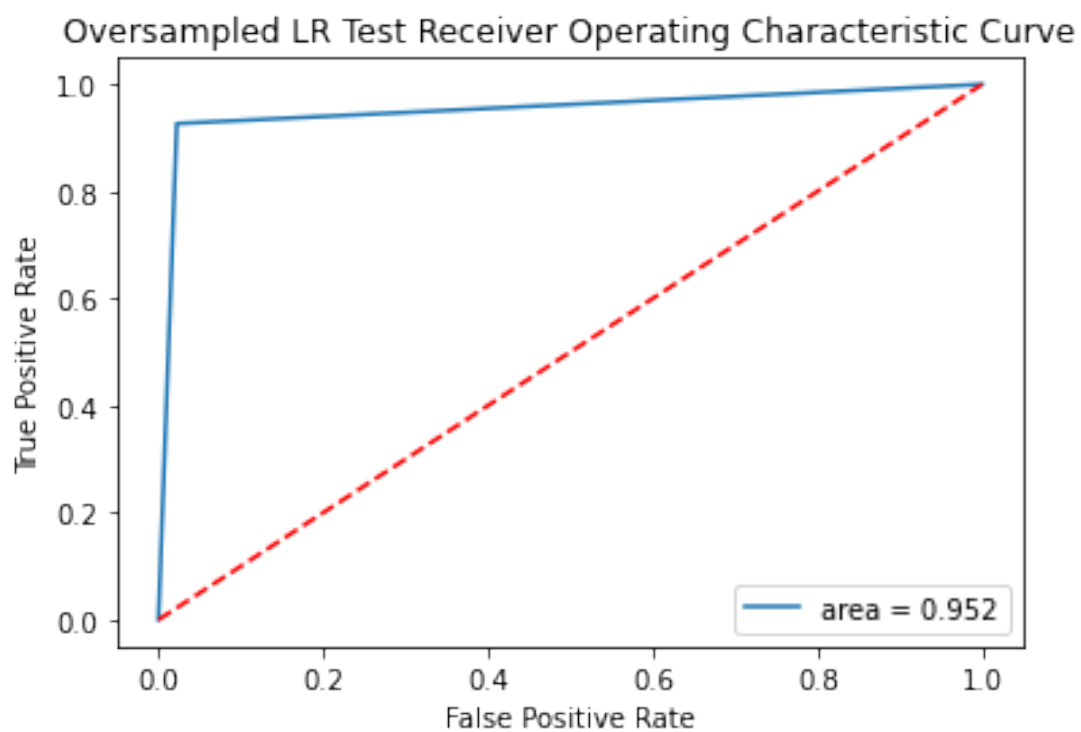
Test confusion matrix: Oversampled LR



roc auc score train 0.9516705599089704



roc auc score test 0.9521905119277454



Test accuracy score 0.9770373231276992

Classification report

	precision	recall	f1-score	support
0	1.00	0.98	0.99	56864
1	0.06	0.88	0.12	98
accuracy			0.98	56962
macro avg	0.53	0.93	0.55	56962
weighted avg	1.00	0.98	0.99	56962

Completed for Oversampled LR
Saving model as Oversampled LR.pkl

Oversampled logistic regression gave better performance than naive bayes, but not svc.

Logistic Regression with undersampled data

```
lr_uds = LogisticRegression(class_weight= 'balanced', solver=  
'liblinear')  
lr_params = {"C":np.logspace(-3,3,7), "penalty":["l1","l2", "none"]}
```

```
buildModel(lr_uds, lr_params, x_uds_train, y_uds_train, x_uds_test,  
y_uds_test, test_X, test_y, 'Undersampled LR')
```

Building model Undersampled LR.....

```
/usr/local/lib/python3.7/dist-packages/sklearn/svm/_base.py:1208:  
ConvergenceWarning: Liblinear failed to converge, increase the number  
of iterations.
```

```
ConvergenceWarning,  
/usr/local/lib/python3.7/dist-packages/sklearn/svm/_base.py:1208:  
ConvergenceWarning: Liblinear failed to converge, increase the number  
of iterations.
```

```
ConvergenceWarning,
```

```
Best score 0.9471951318150978  
Best param {'C': 0.1, 'penalty': 'l2'}  
Best model LogisticRegression(C=0.1, class_weight='balanced',  
solver='liblinear')
```

Model performance Undersampled LR

```
accuracy score train 0.9579646017699115  
accuracy score test 0.9515418502202643
```

Train classification report: Undersampled LR

	precision	recall	f1-score	support
0	0.96	0.98	0.97	603
1	0.95	0.92	0.94	301
accuracy			0.96	904
macro avg	0.96	0.95	0.95	904
weighted avg	0.96	0.96	0.96	904

Test classification report: Undersampled LR

	precision	recall	f1-score	support
0	0.95	0.97	0.96	151
1	0.95	0.91	0.93	76
accuracy			0.95	227
macro avg	0.95	0.94	0.95	227
weighted avg	0.95	0.95	0.95	227

```

/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/
_validation.py:372: FitFailedWarning:
35 fits failed out of a total of 105.
The score on these train-test partitions for these parameters will be
set to nan.
If these failures are not expected, you can try to debug them by
setting error_score='raise'.

```

Below are more details about the failures:

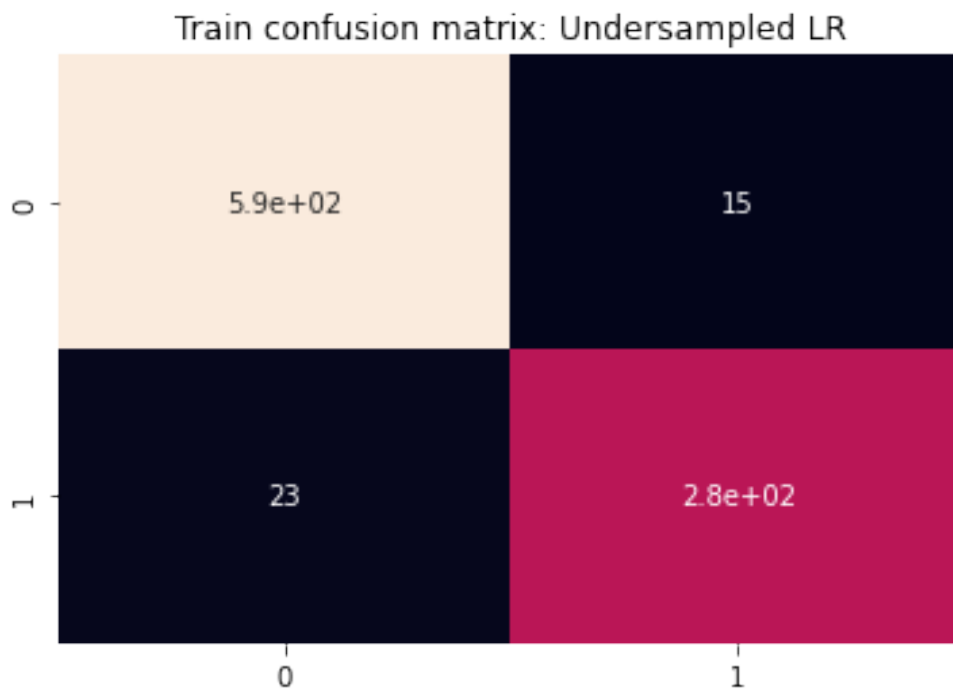
```

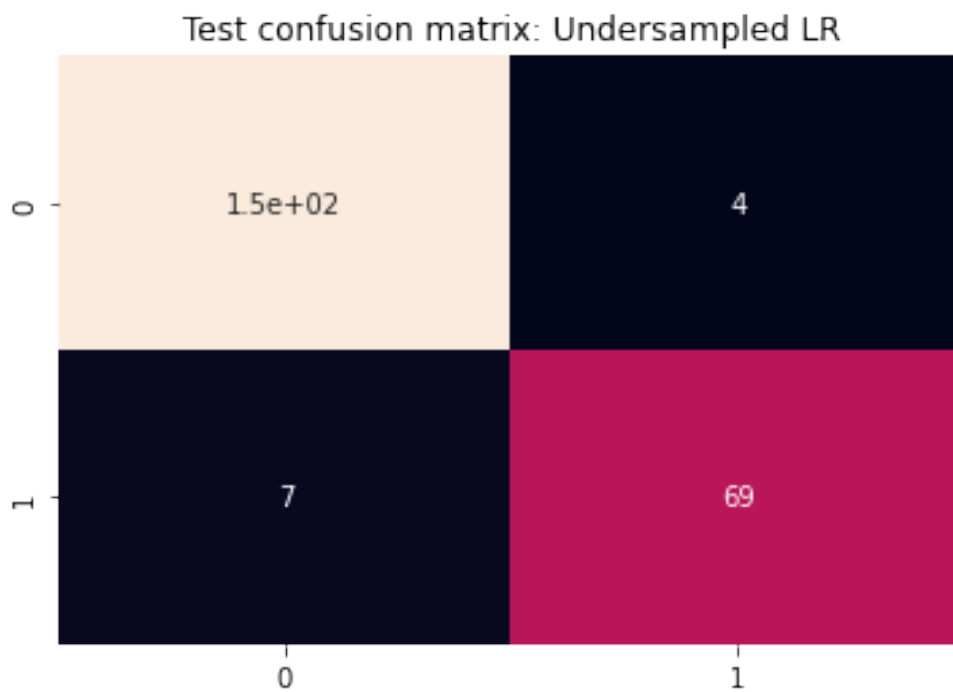
-----
-----
35 fits failed with the following error:
Traceback (most recent call last):
  File
"/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_valid
ation.py", line 680, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File
"/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic
.py", line 1461, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
  File
"/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic
.py", line 464, in _check_solver
    raise ValueError("penalty='none' is not supported for the

```

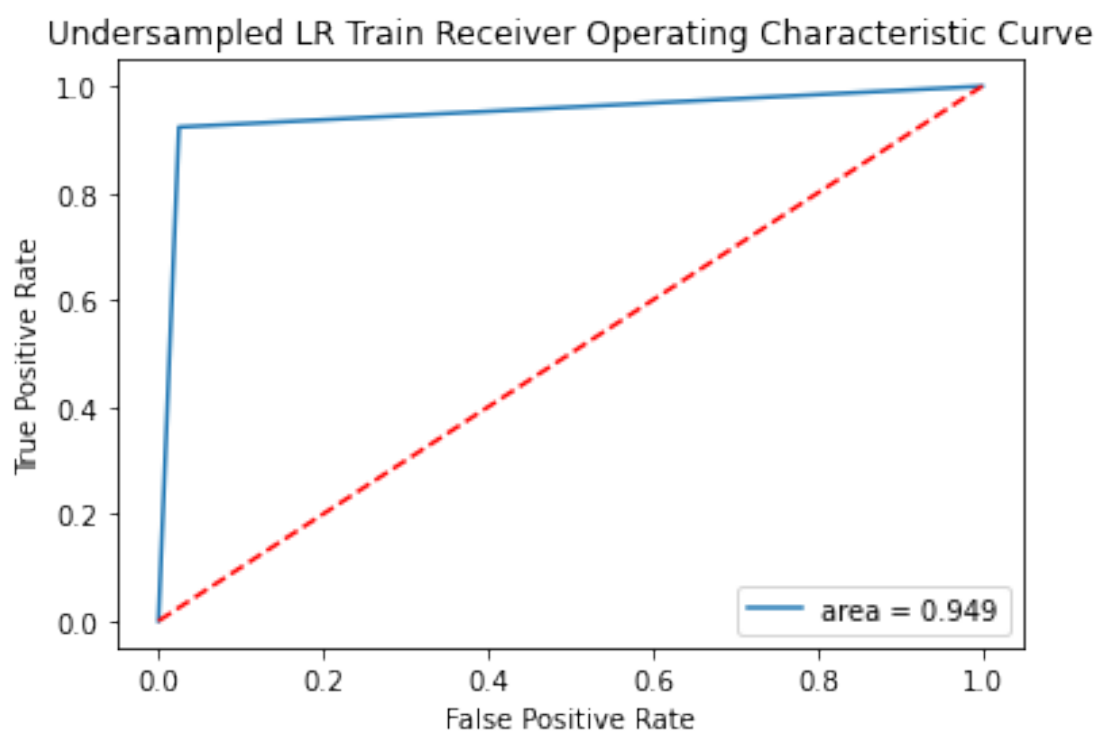
```
liblinear solver")
ValueError: penalty='none' is not supported for the liblinear solver
```

```
warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_search
.py:972: UserWarning: One or more of the test scores are non-finite:
[0.61243345 0.90812638          nan 0.89353767 0.9436896          nan
 0.94279731 0.94719513          nan 0.94123003 0.9450495          nan
 0.94023415 0.94270683          nan 0.94023415 0.93892794          nan
 0.94017528 0.94144928          nan]
  category=UserWarning,
```

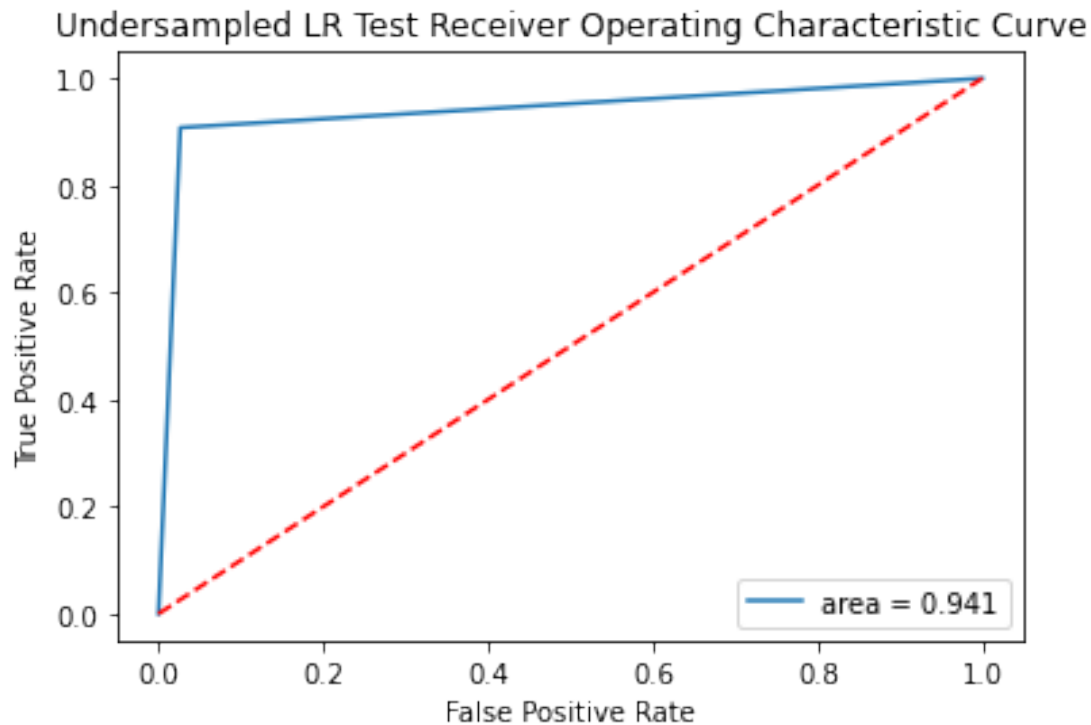




roc auc score train 0.9493562089882812



roc auc score test 0.9407023353084699



Test accuracy score 0.9765808784803904

Classification report

	precision	recall	f1-score	support
0	1.00	0.98	0.99	56864
1	0.06	0.87	0.11	98
accuracy			0.98	56962
macro avg	0.53	0.92	0.55	56962
weighted avg	1.00	0.98	0.99	56962

Completed for Undersampled LR
Saving model as Undersampled LR.pkl

Undersampled logistic regression same similar performance as oversampled data.

RandomForest Classifier

RandomForest Classifier with oversampled data

```
rf_ovr = RandomForestClassifier(class_weight='balanced')
rf_params = {'n_estimators': [100, 150], 'max_depth': [10, 15],
             'min_samples_split': [2, 4]}
```

```
buildModel(rf_ovr, rf_params, x_ovr_train, y_ovr_train, x_ovr_test,
y_ovr_test, test_X, test_y, 'Oversampled RF')
```

Building model Oversampled RF.....

Best score 0.9999225664854812

Best param {'max_depth': 15, 'min_samples_split': 2, 'n_estimators': 100}

Best model RandomForestClassifier(class_weight='balanced', max_depth=15)

Model performance Oversampled RF

accuracy score train 0.9999502213766002

accuracy score test 0.9998672581055519

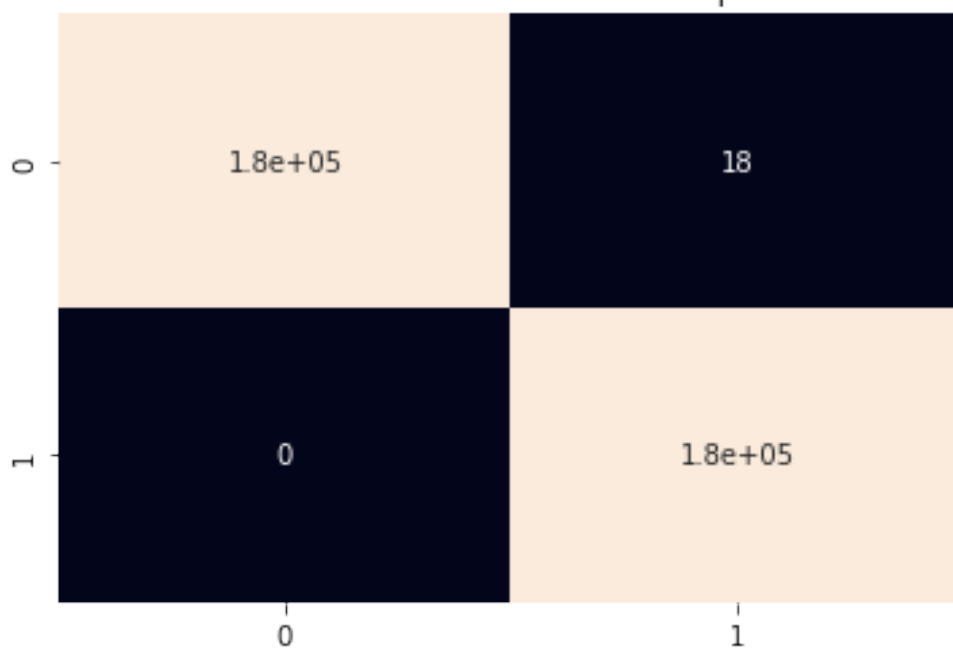
Train classification report: Oversampled RF

	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	1.00	1.00	1.00	180801
accuracy			1.00	361601
macro avg	1.00	1.00	1.00	361601
weighted avg	1.00	1.00	1.00	361601

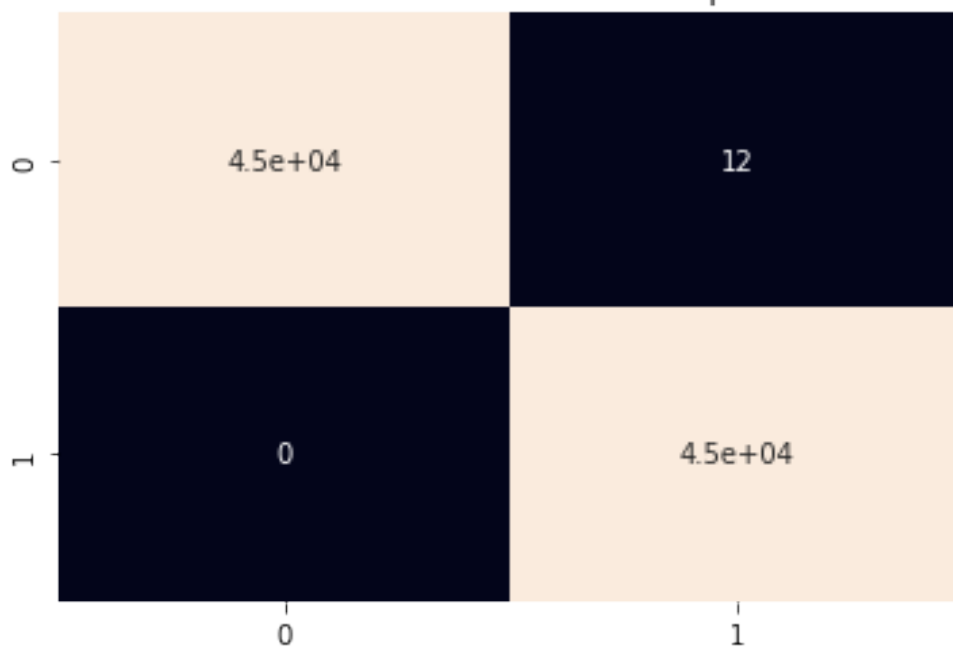
Test classification report: Oversampled RF

	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	1.00	1.00	1.00	45200
accuracy			1.00	90401
macro avg	1.00	1.00	1.00	90401
weighted avg	1.00	1.00	1.00	90401

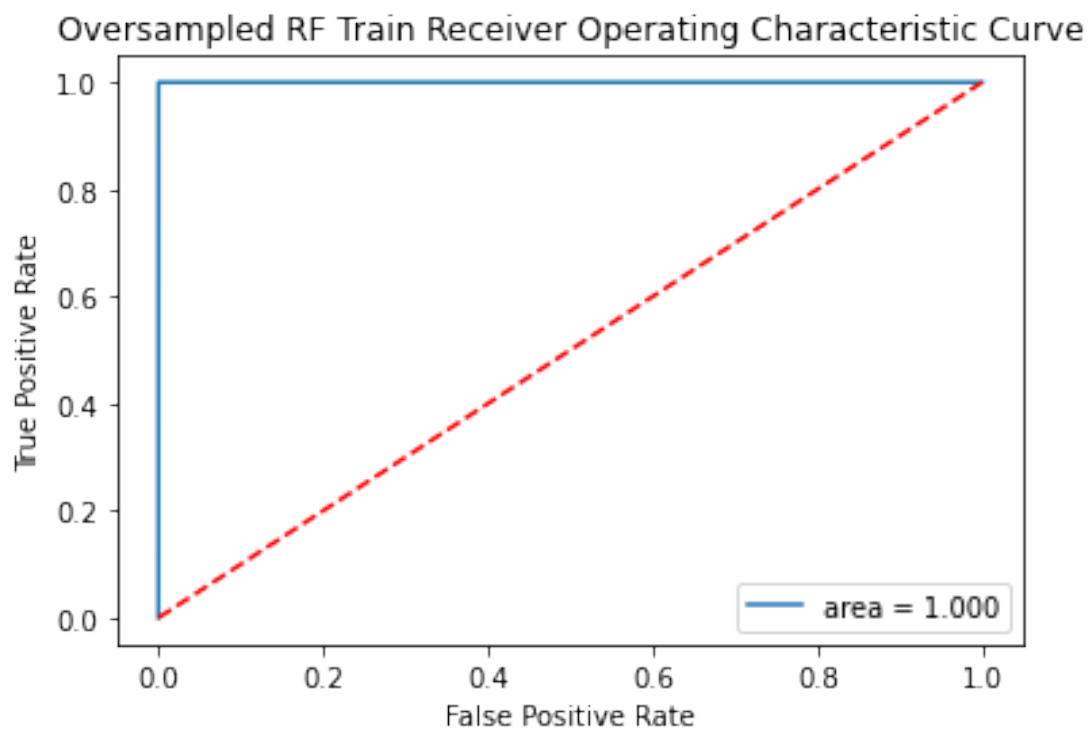
Train confusion matrix: Oversampled RF



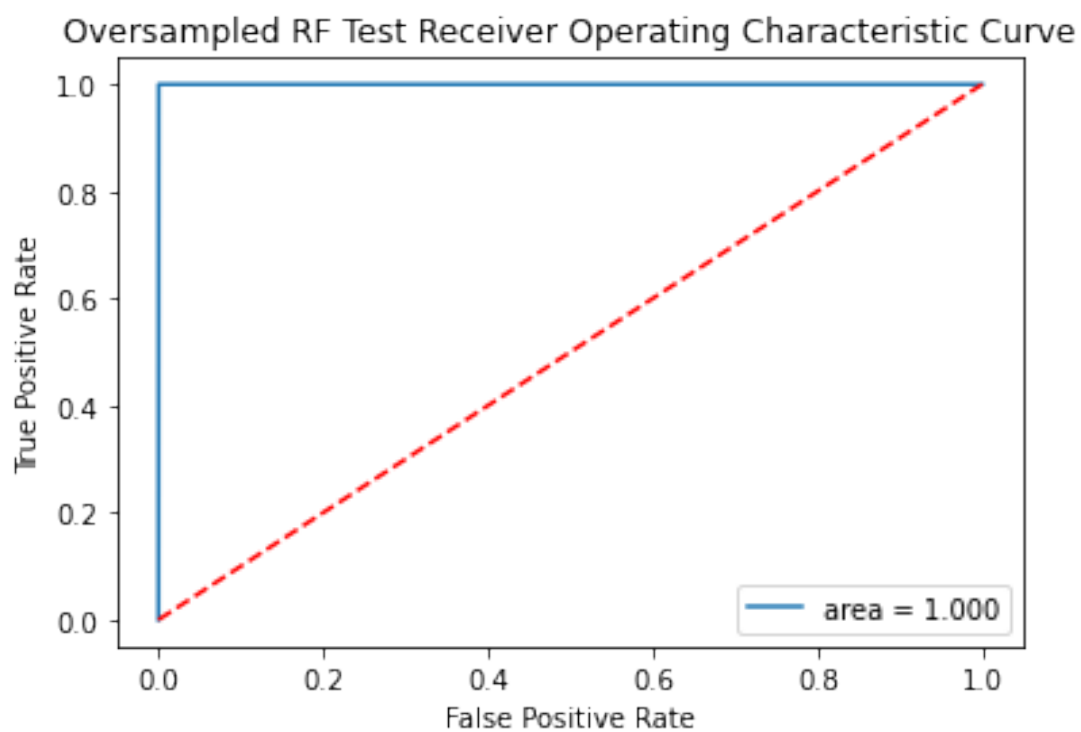
Test confusion matrix: Oversampled RF



roc auc score train 0.9999502212389381



roc auc score test 0.9998672595739032



Test accuracy score 0.9994557775359011

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.89	0.79	0.83	98
accuracy			1.00	56962
macro avg	0.94	0.89	0.92	56962
weighted avg	1.00	1.00	1.00	56962

Completed for Oversampled RF
Saving model as Oversampled RF.pkl

RandomForest classifier with oversampled data gave the performance among all the models with significant difference.

RandomForest Classifier with undersampled data

```
rf_udr = RandomForestClassifier(class_weight='balanced')
rf_params = {'n_estimators': [100, 150], 'max_depth': [10, 15],
             'min_samples_split': [2, 4]}

buildModel(rf_udr, rf_params, x_udr_train, y_udr_train, x_udr_test,
           y_udr_test, test_X, test_y, 'Undersampled RF')
```

Building model Undersampled RF.....

```
Best score 0.9500027939245086
Best param {'max_depth': 10, 'min_samples_split': 4, 'n_estimators': 100}
Best model RandomForestClassifier(class_weight='balanced',
                                  max_depth=10,
                                  min_samples_split=4)
```

Model performance Undersampled RF

```
accuracy score train 0.9944690265486725
accuracy score test 0.9515418502202643
```

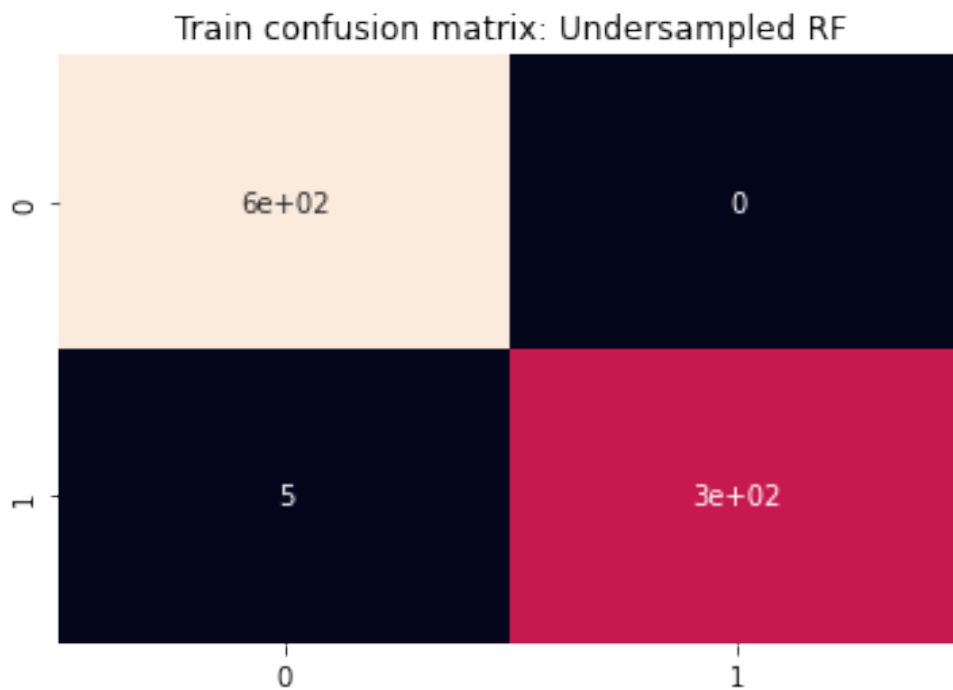
Train classification report: Undersampled RF

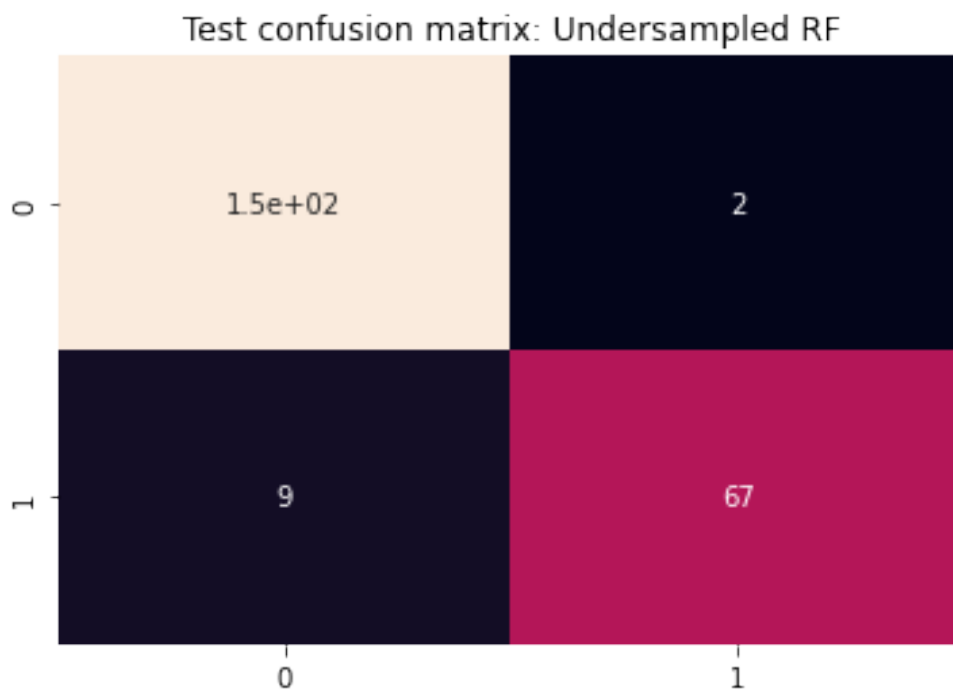
	precision	recall	f1-score	support
0	0.99	1.00	1.00	603
1	1.00	0.98	0.99	301
accuracy			0.99	904

macro avg	1.00	0.99	0.99	904
weighted avg	0.99	0.99	0.99	904

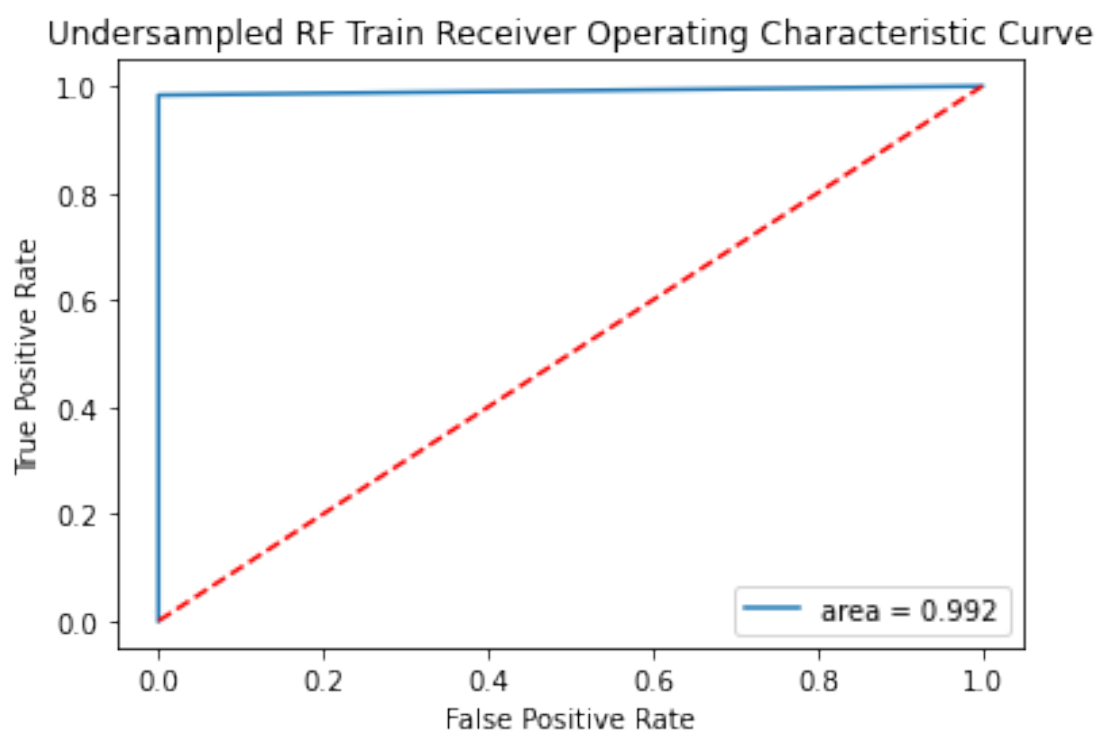
Test classification report: Undersampled RF

	precision	recall	f1-score	support
0	0.94	0.99	0.96	151
1	0.97	0.88	0.92	76
accuracy			0.95	227
macro avg	0.96	0.93	0.94	227
weighted avg	0.95	0.95	0.95	227

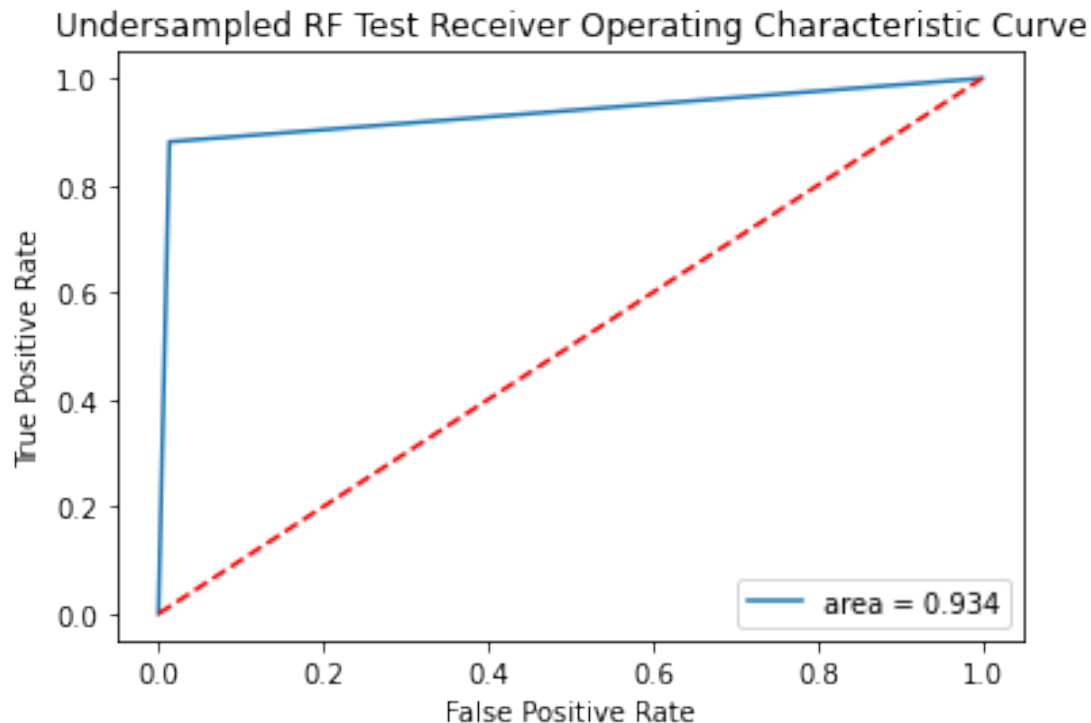




roc auc score train 0.9916943521594684



roc auc score test 0.9341669571279192



Test accuracy score 0.9913275517011341

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	1.00	56864
1	0.15	0.86	0.25	98
accuracy			0.99	56962
macro avg	0.57	0.92	0.62	56962
weighted avg	1.00	0.99	0.99	56962

Completed for Undersampled RF
Saving model as Undersampled RF.pkl

Random forest with undersampled data gave better performance than the other models. but its less as compared to the same with oversampled data. Thats why its always good to try an ensamble technique.

XGBoost Classifier

XGBClassifier with oversampled data

```
xgbc_ovr = XGBClassifier(objective='binary:logistic')
xgbc_params = {
```

```
"gamma": [0.05, 0.1], "max_depth": [10, 15],  
"n_estimators": [120, 150]  
}
```

```
buildModel(xgbc_ovr, xgbc_params, x_ovr_train, y_ovr_train,  
x_ovr_test, y_ovr_test, test_X, test_y, 'Oversampled XGBC')
```

Building model Oversampled XGBC.....

Best score 0.9999087390899989

Best param {'gamma': 0.05, 'max_depth': 10, 'n_estimators': 150}

Best model XGBClassifier(gamma=0.05, max_depth=10, n_estimators=150)

Model performance Oversampled XGBC

accuracy score train 1.0

accuracy score test 0.9999225672282386

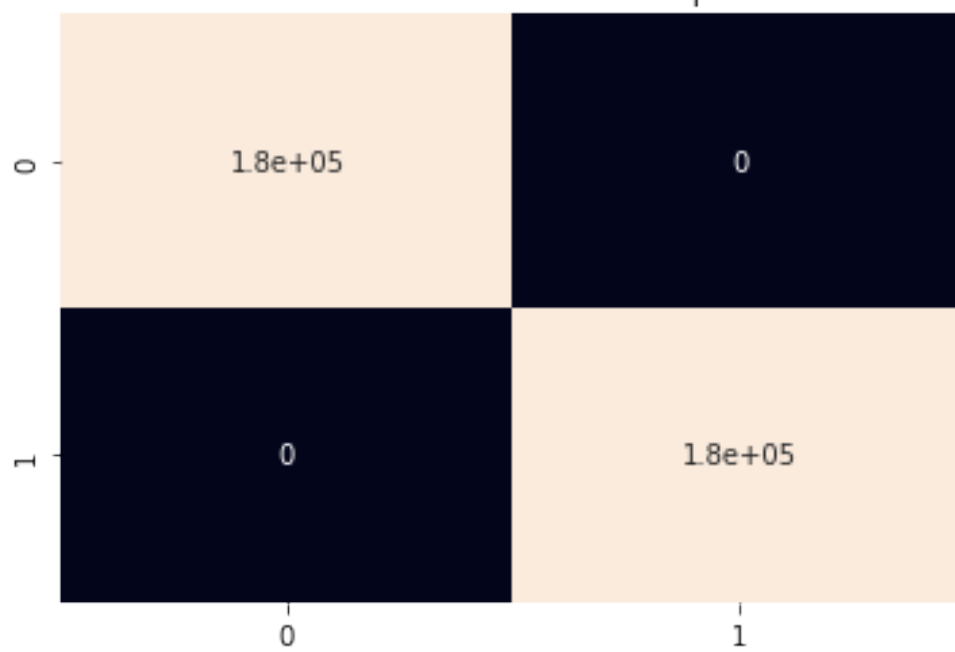
Train classification report: Oversampled XGBC

	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	1.00	1.00	1.00	180801
accuracy			1.00	361601
macro avg	1.00	1.00	1.00	361601
weighted avg	1.00	1.00	1.00	361601

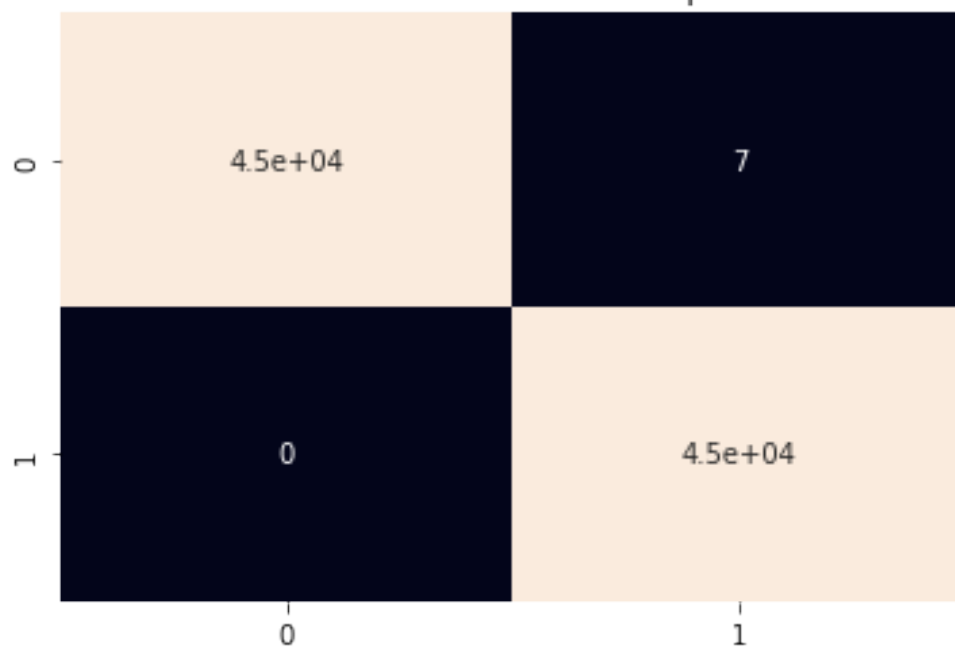
Test classification report: Oversampled XGBC

	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	1.00	1.00	1.00	45200
accuracy			1.00	90401
macro avg	1.00	1.00	1.00	90401
weighted avg	1.00	1.00	1.00	90401

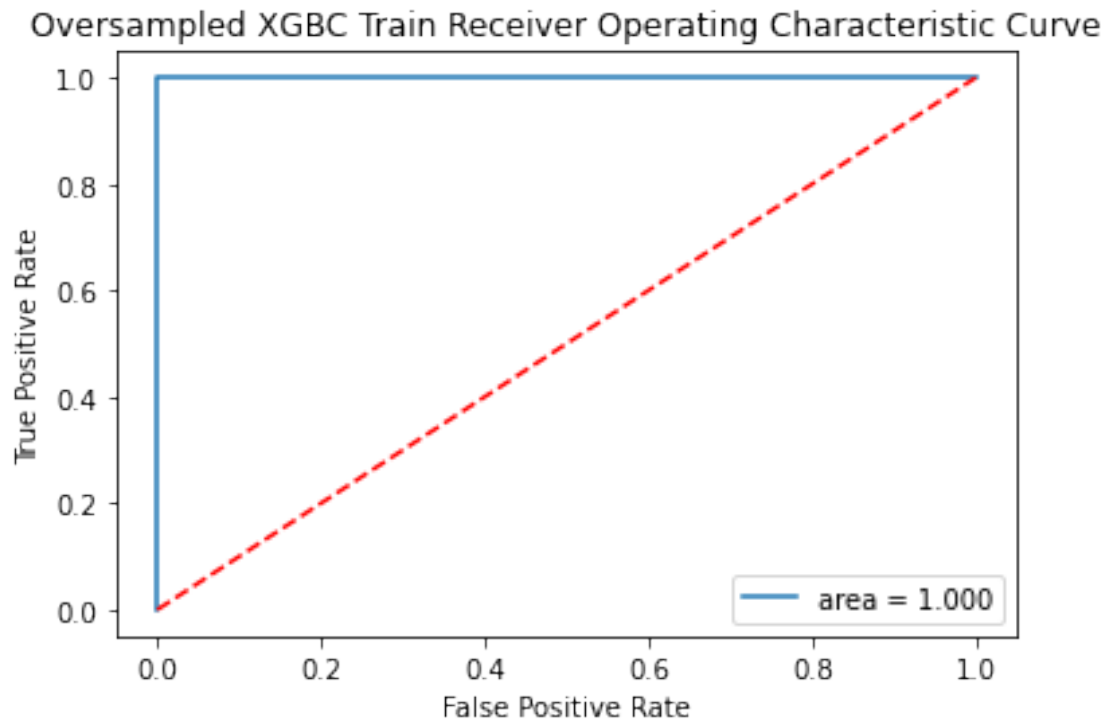
Train confusion matrix: Oversampled XGBC



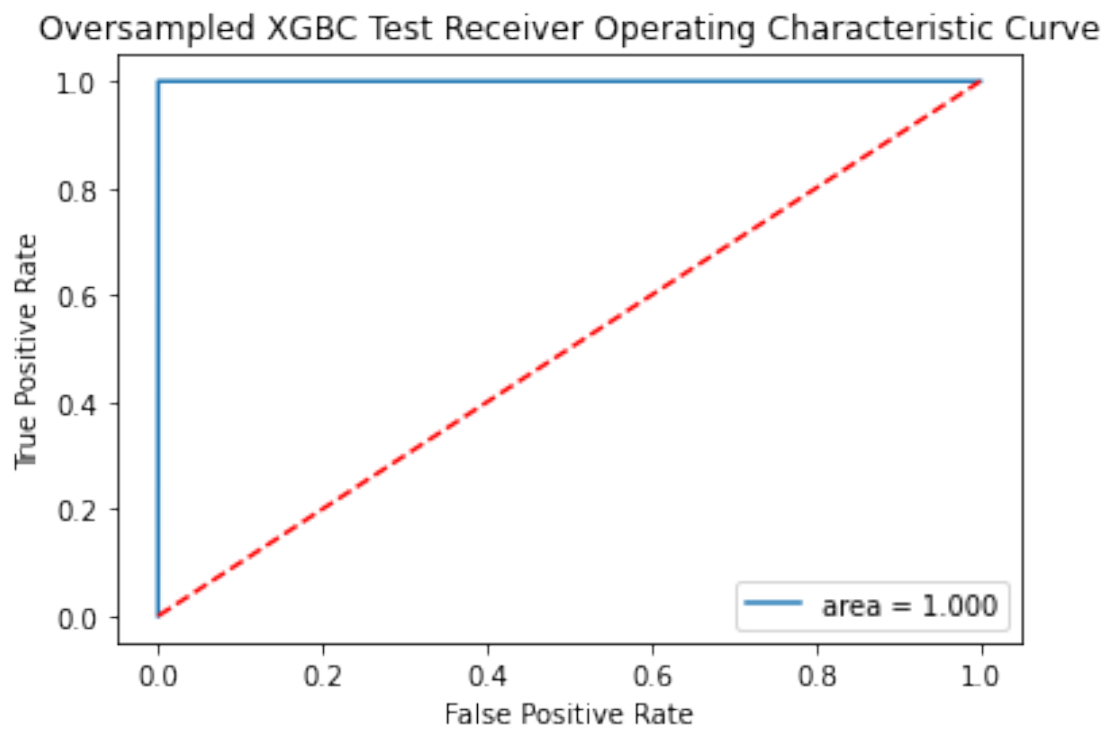
Test confusion matrix: Oversampled XGBC



roc auc score train 1.0



roc auc score test 0.9999225680847769



Test accuracy score 0.999403110845827

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.86	0.79	0.82	98
accuracy			1.00	56962
macro avg	0.93	0.89	0.91	56962
weighted avg	1.00	1.00	1.00	56962

Completed for Oversampled XGBC
Saving model as Oversampled XGBC.pkl

XGBClassifier with oversampled data performed so well that its similar to random forest.

With all there performances, we can see how ensable techniques with proper data can give significant better performance than the other models.

XGBClassifier with undersampled data

```
xgbc_udr = XGBClassifier(objective='binary:logistic')
xgbc_params = {
    "gamma": [0.01, 0.05, 0.1], "max_depth": [5, 10, 15],
    "n_estimators": [100, 120, 150]
}
```

```
buildModel(xgbc_udr, xgbc_params, x_udr_train, y_udr_train,
x_udr_test, y_udr_test, test_X, test_y, 'Undersampled XGBC')
```

Building model Undersampled XGBC.....

Best score 0.9517150786855014

Best param {'gamma': 0.01, 'max_depth': 10, 'n_estimators': 150}

Best model XGBClassifier(gamma=0.01, max_depth=10, n_estimators=150)

Model performance Undersampled XGBC

accuracy score train 1.0

accuracy score test 0.9559471365638766

Train classification report: Undersampled XGBC

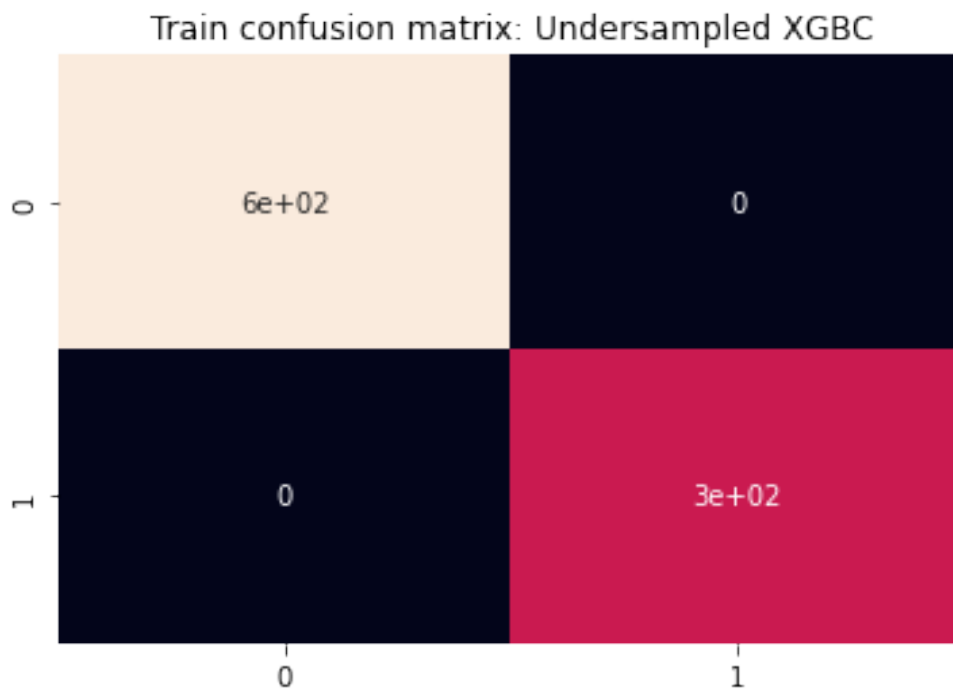
	precision	recall	f1-score	support
0	1.00	1.00	1.00	603
1	1.00	1.00	1.00	301

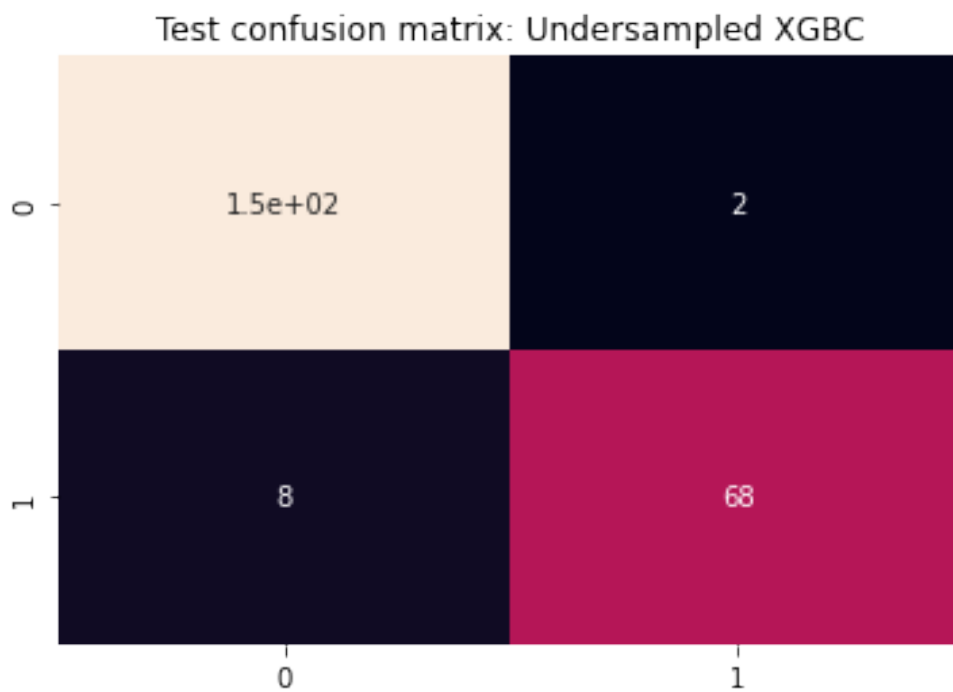
accuracy			1.00	904
macro avg	1.00	1.00	1.00	904
weighted avg	1.00	1.00	1.00	904

Test classification report: Undersampled XGBC

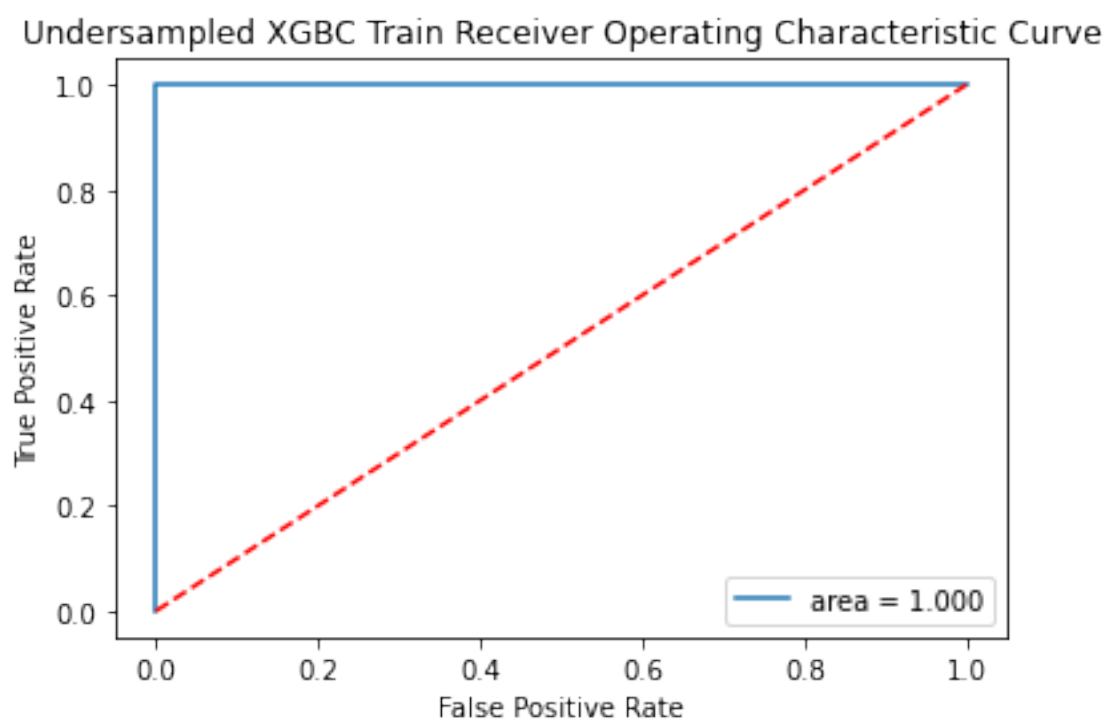
	precision	recall	f1-score	support
0	0.95	0.99	0.97	151
1	0.97	0.89	0.93	76

accuracy			0.96	227
macro avg	0.96	0.94	0.95	227
weighted avg	0.96	0.96	0.96	227

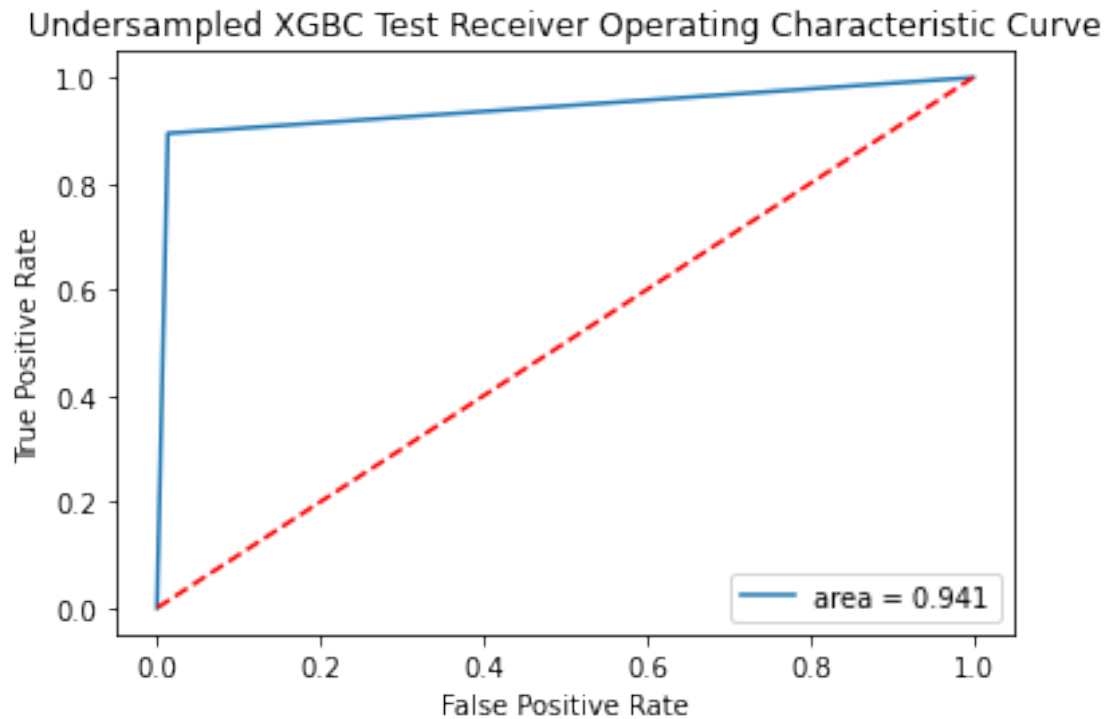




roc auc score train 1.0



roc auc score test 0.9407459044963403



Test accuracy score 0.9878515501562445

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	56864
1	0.11	0.86	0.20	98
accuracy			0.99	56962
macro avg	0.55	0.92	0.59	56962
weighted avg	1.00	0.99	0.99	56962

Completed for Undersampled XGBC
Saving model as Undersampled XGBC.pkl

XGBClassifier with undersampled data performed better than other models, but its less than random forest classifier and its oversampled version.

For models like Logistic regression, random forest and xgboost, performed better wwith the oversampled data.

SVC model gave better performance with undersampled data, where as naive bayes gave almost similar performance.

So we have random forest with oversampled data gave the highest performance in terms of f1-score (0.92) on test data.

SVC with undersampled data gave the lowest performance.

Other models with different combination of data, gave moderate performance.

So we can consider Random forest with oversampled data as our final ML model.

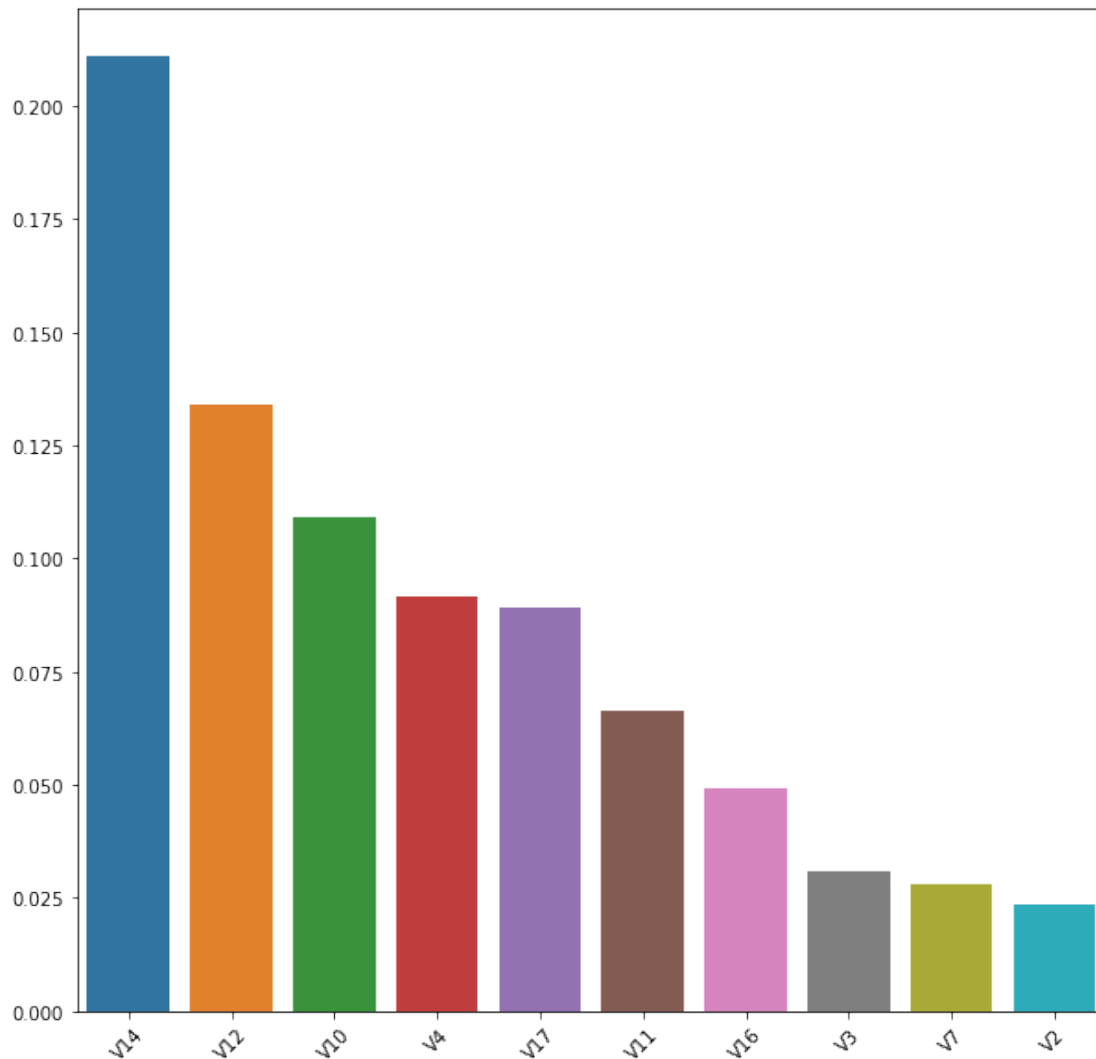
Final ML Model (Random Forest with Oversampled data)

Lets upload the random forest model from the pickle file and try to get top 10 important features from it.

```
train_udr_df = pd.read_pickle('finance_udr_train.pkl')
rf_ovr = pickle.load(open('Oversampled RF.pkl', 'rb'))
train_udr_df.columns
Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9',
      'V10',
      'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19',
      'V20',
      'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28',
      'Amount',
      'Class'],
      dtype='object')

feature_names = train_udr_df.columns[:-1]
importances = rf_ovr.feature_importances_
important_features = np.argsort(importances)[::-1][:10]
names = feature_names[important_features]
values = importances[important_features]
plt.figure(figsize=(10,10))
sns.barplot(names, values)
plt.xticks(rotation=45)
plt.show()

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variables as keyword args: x, y.
From version 0.12, the only valid positional argument will be `data`,
and passing other arguments without an explicit keyword will result in
an error or misinterpretation.
FutureWarning
```



Out of all the PCA transformed features, above are the most important features as per random forest model.

Unfortunately, we don't see amount and time here. So it's possible that time and amount don't have a close relationship with the class labels.

Project Task: Week 2

Applying ANN

For this binary classification problem, we can try out different ANN models where we can experiment with the number of layers, number of neurons, activation function, kernel initializers, regularizers, batch size, number of epochs, optimizers etc.

So, we can randomly experiment by selecting different combinations and can build 6 models and finally we can pick the best model.

```

def buildANN(num_layer, num_neuron, activation_fn, initializer,
regularizers, optimizerName, batch_size, epochs, name, dropOut= None):
    input = Input(x_train.shape[-1],)
    x = input
    nu_num = num_neuron
    for i in range(num_layer):
        x = Dense(units = nu_num, activation = activation_fn,
                    kernel_initializer = initializer, kernel_regularizer =
regularizers)(x)
        nu_num //= 2
    if dropOut is not None:
        x = Dropout(dropOut)(x)
        x = BatchNormalization()(x)

    x = Dense(units = 10, activation = activation_fn,
                kernel_initializer = initializer, kernel_regularizer =
regularizers)(x)
    output = Dense(2, activation = 'softmax')(x)

    model = Model(input, output)
    print(model.summary())
    model.compile(loss='categorical_crossentropy', optimizer=
optimizerName, metrics=[F1Score(num_classes= 2, average= 'macro')])
    callback = EarlyStopping(monitor='val_loss', patience=3)
    model.fit(x_train, y_train,
                validation_data=(x_test, y_test), batch_size=
batch_size, epochs=epochs, callbacks=[callback])

    y_train_pred = model.predict(x_train)
    y_test_pred = model.predict(x_test)
    y_train_label = np.argmax(y_train, axis= 1)
    y_train_pred = np.argmax(y_train_pred, axis= 1)
    y_test_label = np.argmax(y_test, axis= 1)
    y_test_pred = np.argmax(y_test_pred, axis= 1)

    getPerformance(y_train_label, y_train_pred, y_test_label,
y_test_pred, name)

    test_y_pred = model.predict(test_X)
    test_y_label = np.argmax(test_y, axis= 1)
    test_y_pred = np.argmax(test_y_pred, axis= 1)

    print('\nTest accuracy score {} \
n'.format(accuracy_score(test_y_label, test_y_pred)))
    print('Classification report\n')
    print(classification_report(test_y_label, test_y_pred))
    print('\nCompleted and saved for model ' + name)
    model.save(name)

```

Oversampled data

```
finance_ovr_train = pd.read_pickle('finance_ovr_train.pkl')
finance_test = pd.read_pickle('finance_test.pkl')

train_ovr_X = finance_ovr_train.drop(['Class'], axis=1)
train_ovr_y = finance_ovr_train[['Class']]

test_X = finance_test.drop(['Class'], axis=1)
test_y = finance_test[['Class']]

x_train, x_test, y_train, y_test = train_test_split(train_ovr_X,
train_ovr_y,

stratify= train_ovr_y,

test_size= 0.2, random_state= 0)

y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
test_y = to_categorical(test_y)

print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
print(test_X.shape)
print(test_y.shape)

(361601, 30)
(361601, 2)
(90401, 30)
(90401, 2)
(56962, 30)
(56962, 2)
```

ANN with oversampled data

```
buildANN(1, 32, 'relu', 'he_normal', 'l2', 'sgd', 30, 5, 'Ovr_ANN1')
```

Model: "model_22"

Layer (type)	Output Shape	Param #
input_30 (InputLayer)	[(None, 30)]	0
dense_130 (Dense)	(None, 32)	992
dense_131 (Dense)	(None, 10)	330
dense_132 (Dense)	(None, 2)	22

Total params: 1,344
Trainable params: 1,344
Non-trainable params: 0

None

Epoch 1/5

12054/12054 [=====] - 26s 2ms/step - loss: 0.3099 - f1_score: 0.9580 - val_loss: 0.1203 - val_f1_score: 0.9738

Epoch 2/5

12054/12054 [=====] - 25s 2ms/step - loss: 0.1037 - f1_score: 0.9789 - val_loss: 0.0953 - val_f1_score: 0.9853

Epoch 3/5

12054/12054 [=====] - 25s 2ms/step - loss: 0.0884 - f1_score: 0.9857 - val_loss: 0.0848 - val_f1_score: 0.9870

Epoch 4/5

12054/12054 [=====] - 26s 2ms/step - loss: 0.0812 - f1_score: 0.9890 - val_loss: 0.0804 - val_f1_score: 0.9870

Epoch 5/5

12054/12054 [=====] - 27s 2ms/step - loss: 0.0770 - f1_score: 0.9905 - val_loss: 0.0759 - val_f1_score: 0.9913

11301/11301 [=====] - 16s 1ms/step

2826/2826 [=====] - 4s 1ms/step

Model performance Ovr_ANN1

accuracy score train 0.9911919491373088

accuracy score test 0.9912832822645767

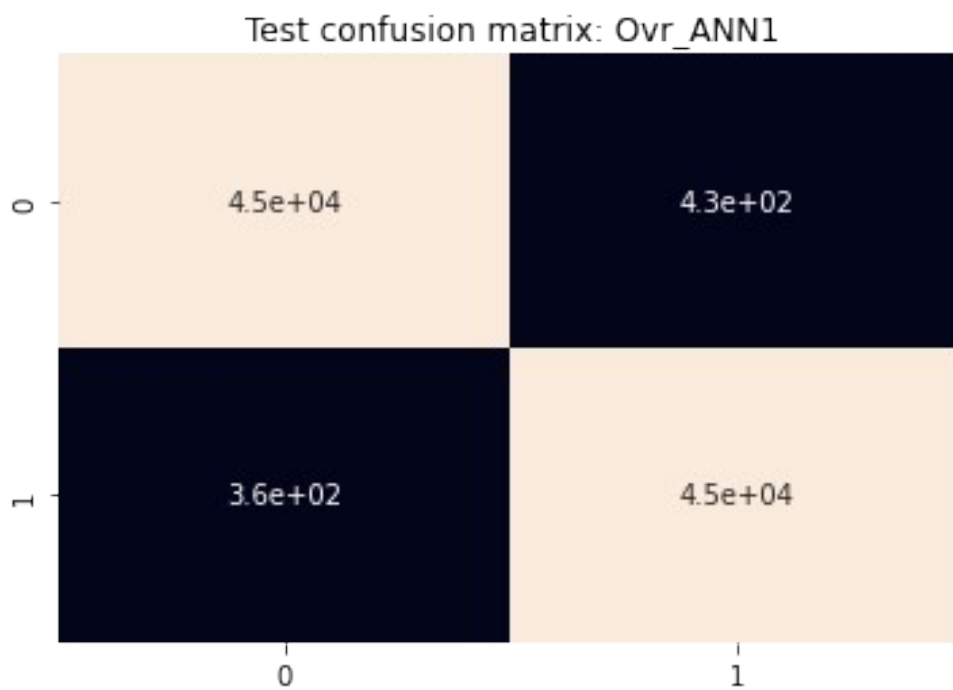
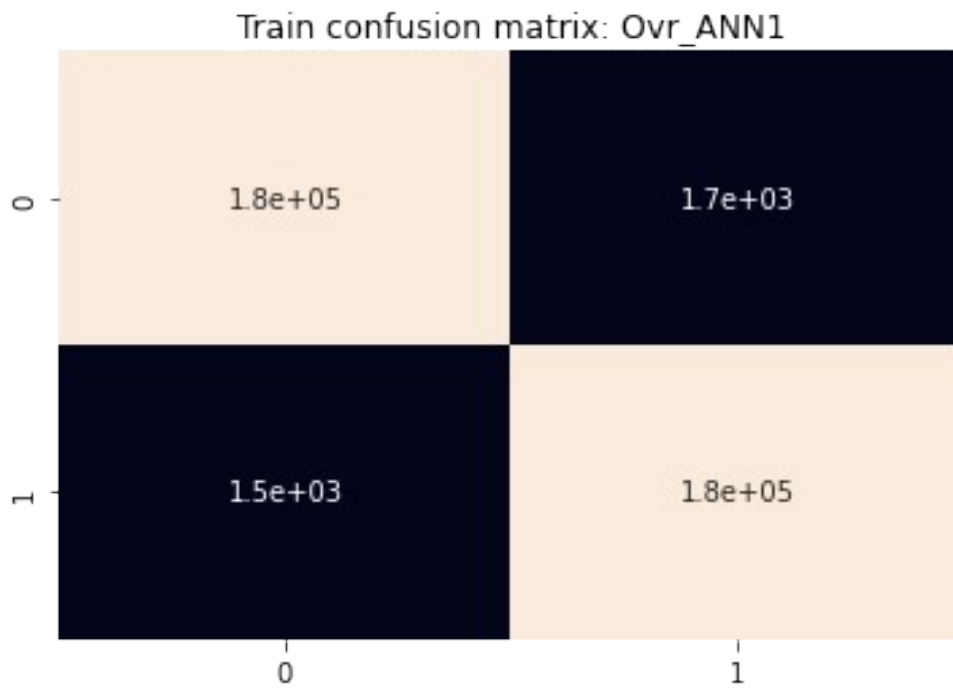
Train classification report: Ovr_ANN1

	precision	recall	f1-score	support
0	0.99	0.99	0.99	180800
1	0.99	0.99	0.99	180801
accuracy			0.99	361601
macro avg	0.99	0.99	0.99	361601
weighted avg	0.99	0.99	0.99	361601

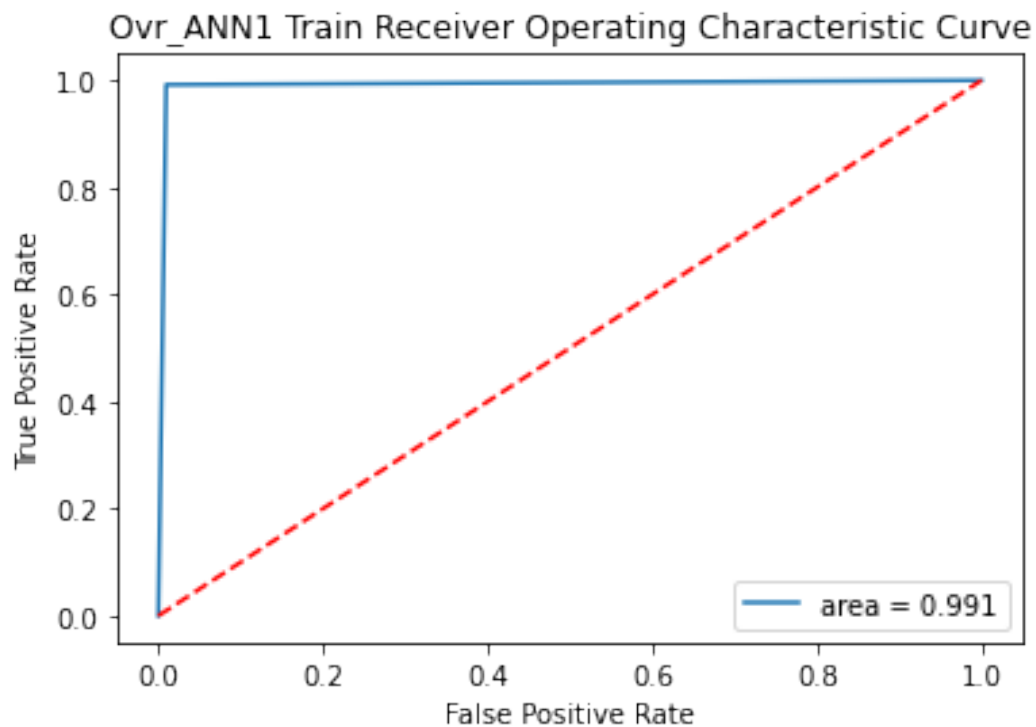
Test classification report: Ovr_ANN1

	precision	recall	f1-score	support
0	0.99	0.99	0.99	45201
1	0.99	0.99	0.99	45200
accuracy			0.99	90401
macro avg	0.99	0.99	0.99	90401

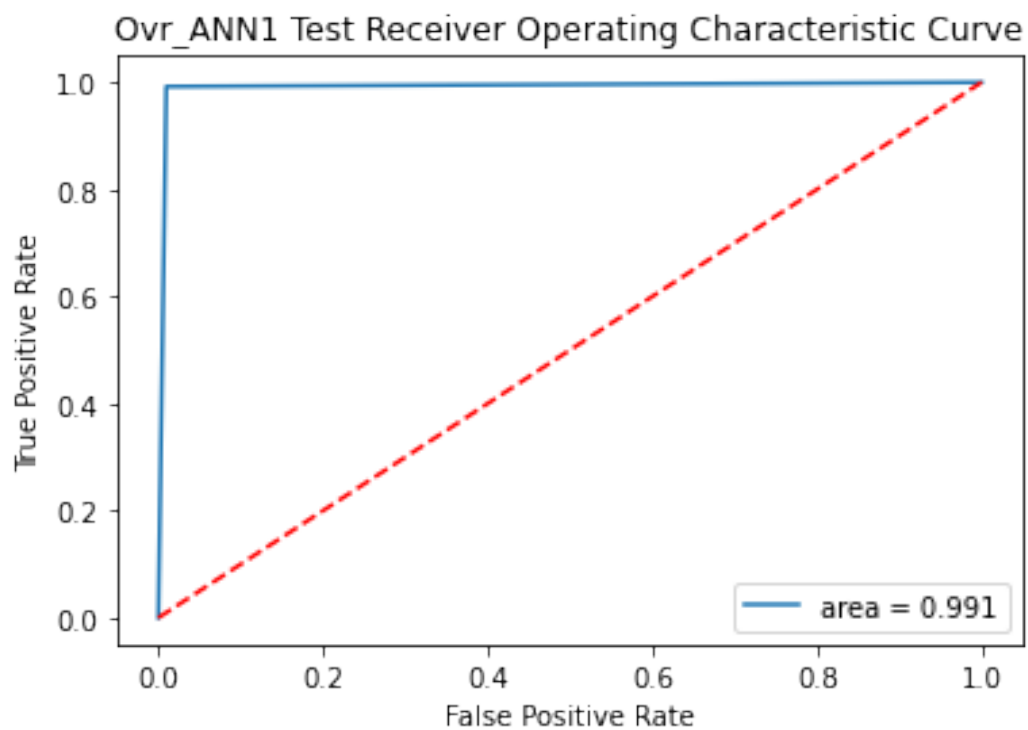
weighted avg 0.99 0.99 0.99 90401



roc auc score train 0.9911919473093994



roc auc score test 0.9912832918078991



1781/1781 [=====] - 2s 1ms/step

Test accuracy score 0.9896773287454794

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	56864
1	0.13	0.89	0.23	98
accuracy			0.99	56962
macro avg	0.57	0.94	0.61	56962
weighted avg	1.00	0.99	0.99	56962

Completed and saved for model Ovr_ANN1

buildANN(2, 32, 'relu', 'he_normal', 'l2', 'sgd', 30, 5, 'Ovr_ANN2')

Model: "model_23"

Layer (type)	Output Shape	Param #
input_31 (InputLayer)	[(None, 30)]	0
dense_133 (Dense)	(None, 32)	992
dense_134 (Dense)	(None, 16)	528
dense_135 (Dense)	(None, 10)	170
dense_136 (Dense)	(None, 2)	22

=====
Total params: 1,712

Trainable params: 1,712

Non-trainable params: 0

None

Epoch 1/5

12054/12054 [=====] - 29s 2ms/step - loss: 0.3813 - f1_score: 0.9644 - val_loss: 0.1275 - val_f1_score: 0.9821

Epoch 2/5

12054/12054 [=====] - 27s 2ms/step - loss: 0.1084 - f1_score: 0.9864 - val_loss: 0.0989 - val_f1_score: 0.9910

Epoch 3/5

12054/12054 [=====] - 27s 2ms/step - loss: 0.0940 - f1_score: 0.9906 - val_loss: 0.0919 - val_f1_score: 0.9917

Epoch 4/5

12054/12054 [=====] - 27s 2ms/step - loss: 0.0881 - f1_score: 0.9919 - val_loss: 0.0873 - val_f1_score: 0.9914

Epoch 5/5
12054/12054 [=====] - 26s 2ms/step - loss:
0.0842 - f1_score: 0.9926 - val_loss: 0.0847 - val_f1_score: 0.9920
11301/11301 [=====] - 16s 1ms/step
2826/2826 [=====] - 4s 1ms/step

Model performance Ovr_ANN2

accuracy score train 0.9921958180425386
accuracy score test 0.9919801772104291

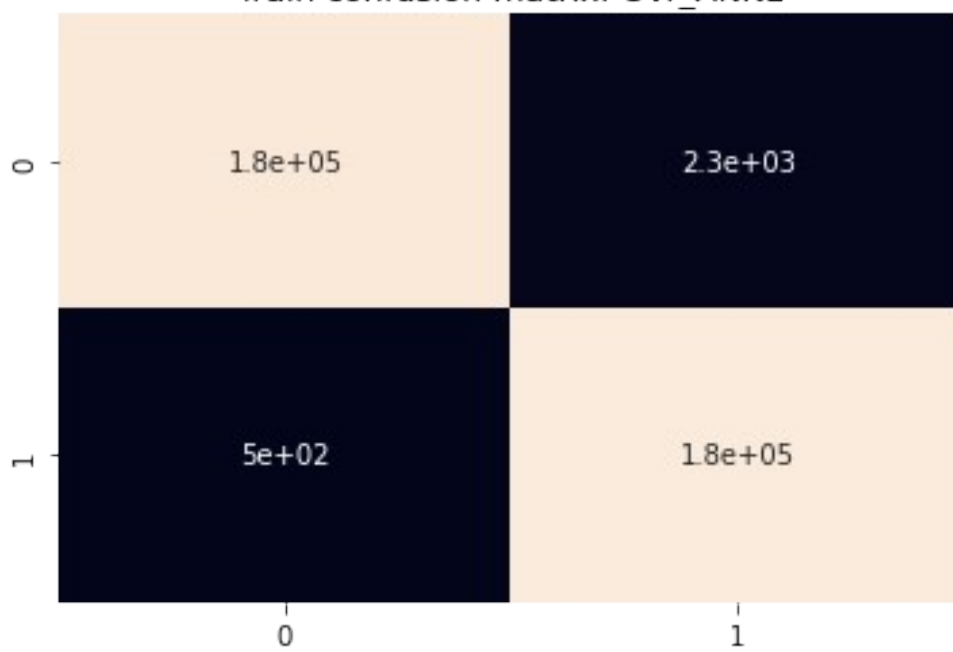
Train classification report: Ovr_ANN2

	precision	recall	f1-score	support
0	1.00	0.99	0.99	180800
1	0.99	1.00	0.99	180801
accuracy			0.99	361601
macro avg	0.99	0.99	0.99	361601
weighted avg	0.99	0.99	0.99	361601

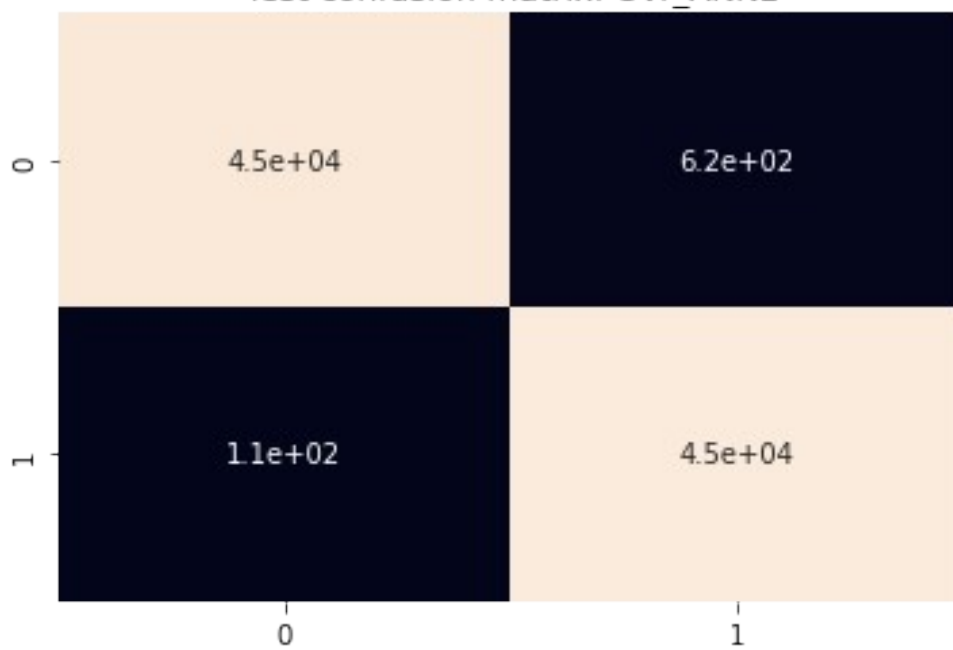
Test classification report: Ovr_ANN2

	precision	recall	f1-score	support
0	1.00	0.99	0.99	45201
1	0.99	1.00	0.99	45200
accuracy			0.99	90401
macro avg	0.99	0.99	0.99	90401
weighted avg	0.99	0.99	0.99	90401

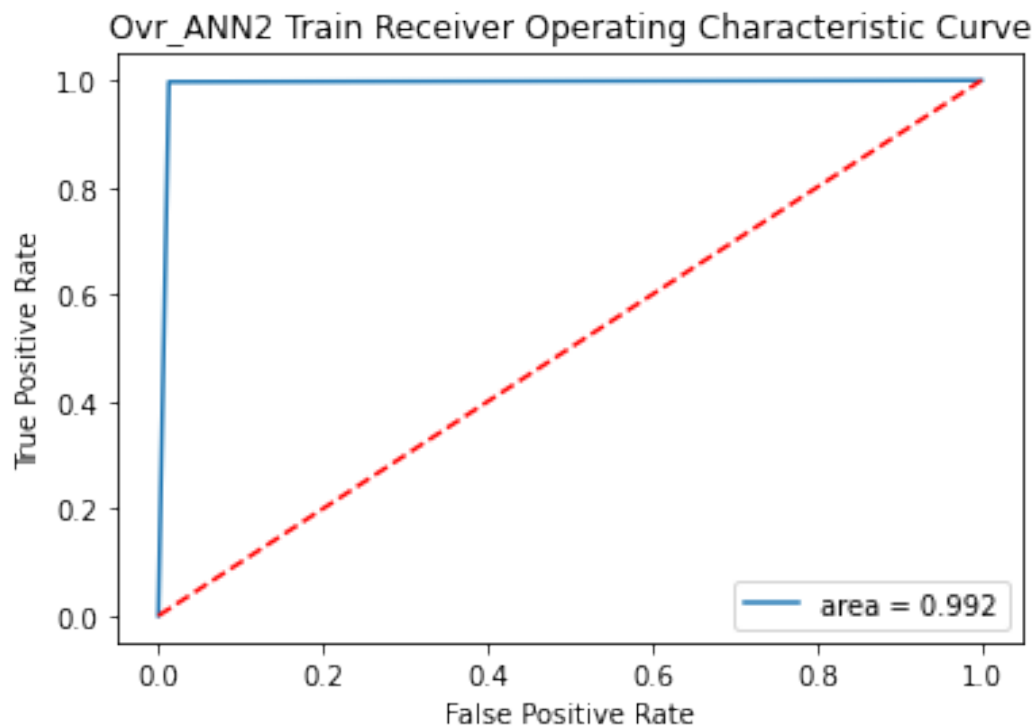
Train confusion matrix: Ovr_ANN2



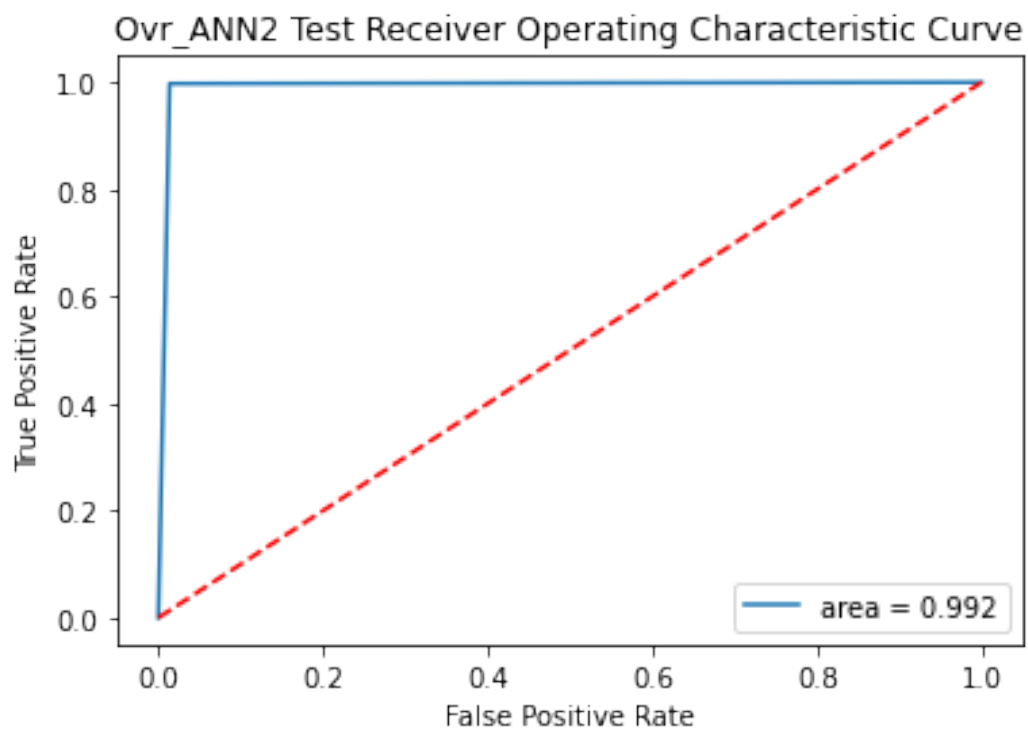
Test confusion matrix: Ovr_ANN2



roc auc score train 0.9921958041386431



roc auc score test 0.9919802399821603



1781/1781 [=====] - 3s 1ms/step

Test accuracy score 0.9861311049471577

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	56864
1	0.10	0.91	0.18	98
accuracy			0.99	56962
macro avg	0.55	0.95	0.59	56962
weighted avg	1.00	0.99	0.99	56962

Completed and saved for model Ovr_ANN2

buildANN(2, 128, 'relu', 'he_normal', 'l1', 'sgd', 30, 10, 'Ovr_ANN3')

Model: "model_24"

Layer (type)	Output Shape	Param #
input_32 (InputLayer)	[(None, 30)]	0
dense_137 (Dense)	(None, 128)	3968
dense_138 (Dense)	(None, 64)	8256
dense_139 (Dense)	(None, 10)	650
dense_140 (Dense)	(None, 2)	22

Total params: 12,896

Trainable params: 12,896

Non-trainable params: 0

None

Epoch 1/10

12054/12054 [=====] - 30s 2ms/step - loss: 1.9296 - f1_score: 0.9461 - val_loss: 0.1912 - val_f1_score: 0.9496

Epoch 2/10

12054/12054 [=====] - 29s 2ms/step - loss: 0.1863 - f1_score: 0.9490 - val_loss: 0.1811 - val_f1_score: 0.9483

Epoch 3/10

12054/12054 [=====] - 28s 2ms/step - loss: 0.1783 - f1_score: 0.9491 - val_loss: 0.1767 - val_f1_score: 0.9507

Epoch 4/10

12054/12054 [=====] - 28s 2ms/step - loss: 0.1775 - f1_score: 0.9486 - val_loss: 0.1764 - val_f1_score: 0.9483

Epoch 5/10
 12054/12054 [=====] - 28s 2ms/step - loss:
 0.1767 - f1_score: 0.9489 - val_loss: 0.1760 - val_f1_score: 0.9480
 Epoch 6/10
 12054/12054 [=====] - 29s 2ms/step - loss:
 0.1763 - f1_score: 0.9489 - val_loss: 0.2042 - val_f1_score: 0.9394
 Epoch 7/10
 12054/12054 [=====] - 28s 2ms/step - loss:
 0.1760 - f1_score: 0.9487 - val_loss: 0.1826 - val_f1_score: 0.9445
 Epoch 8/10
 12054/12054 [=====] - 29s 2ms/step - loss:
 0.1756 - f1_score: 0.9486 - val_loss: 0.1837 - val_f1_score: 0.9489
 11301/11301 [=====] - 16s 1ms/step
 2826/2826 [=====] - 4s 1ms/step

Model performance Ovr_ANN3

accuracy score train 0.9486865357120141

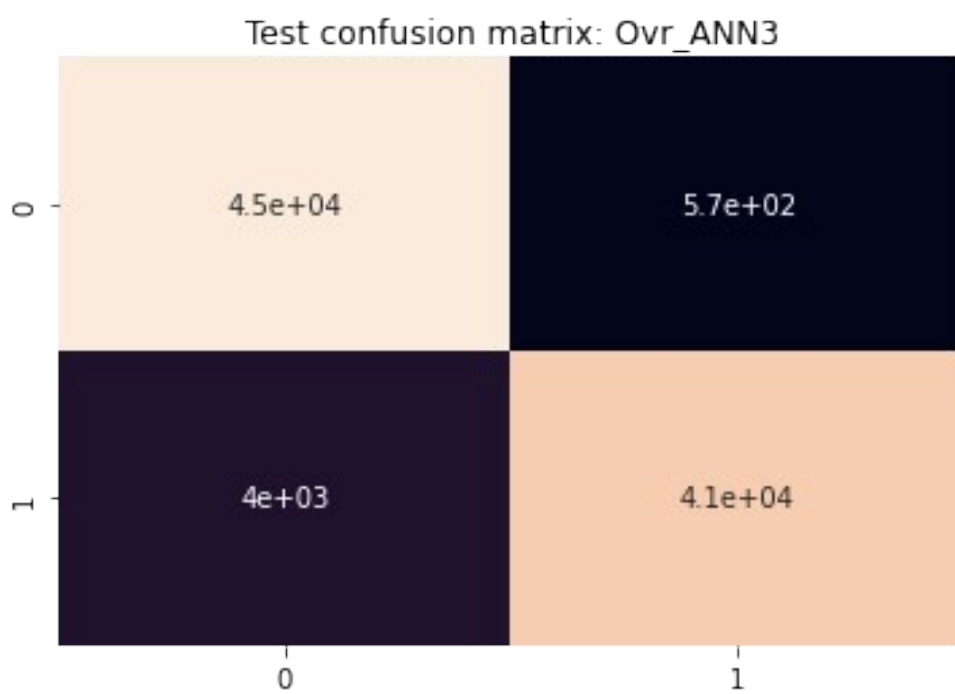
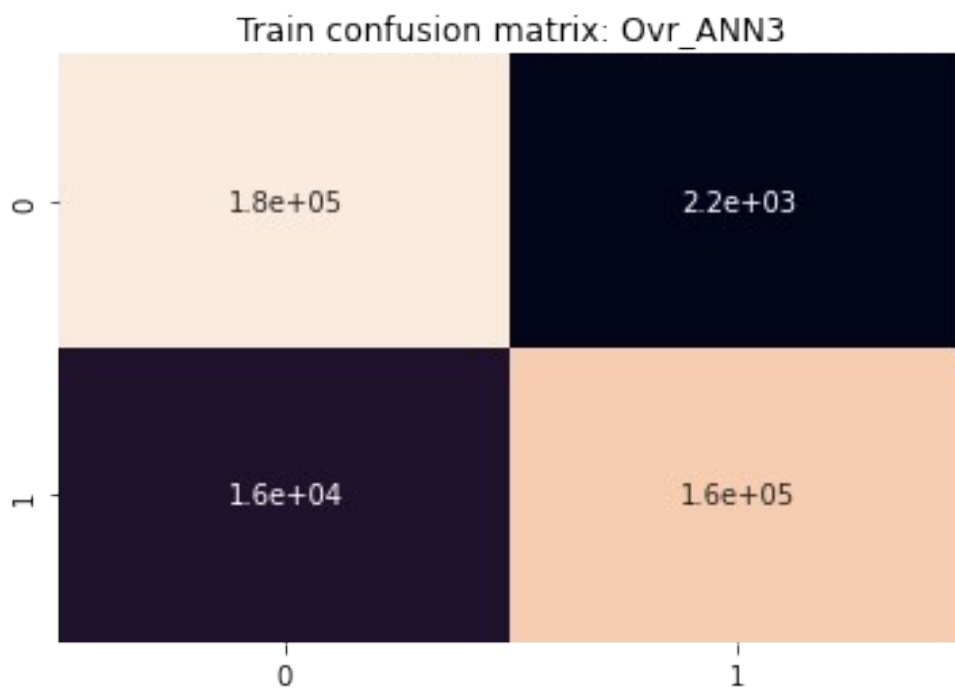
accuracy score test 0.948927556111105

Train classification report: Ovr_ANN3

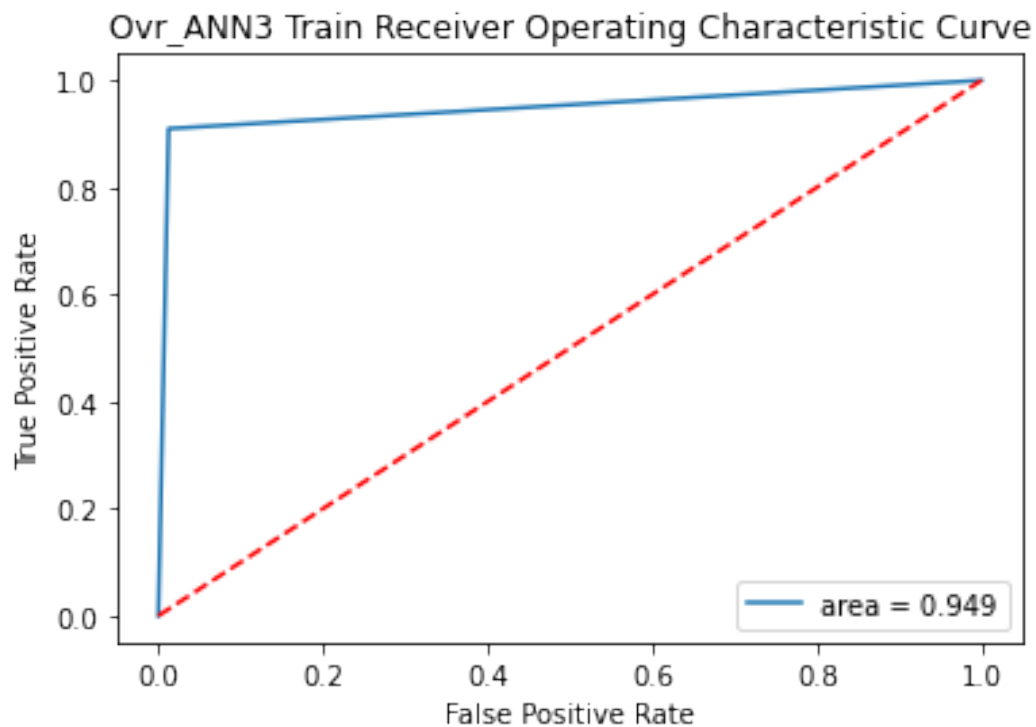
	precision	recall	f1-score	support
0	0.92	0.99	0.95	180800
1	0.99	0.91	0.95	180801
accuracy			0.95	361601
macro avg	0.95	0.95	0.95	361601
weighted avg	0.95	0.95	0.95	361601

Test classification report: Ovr_ANN3

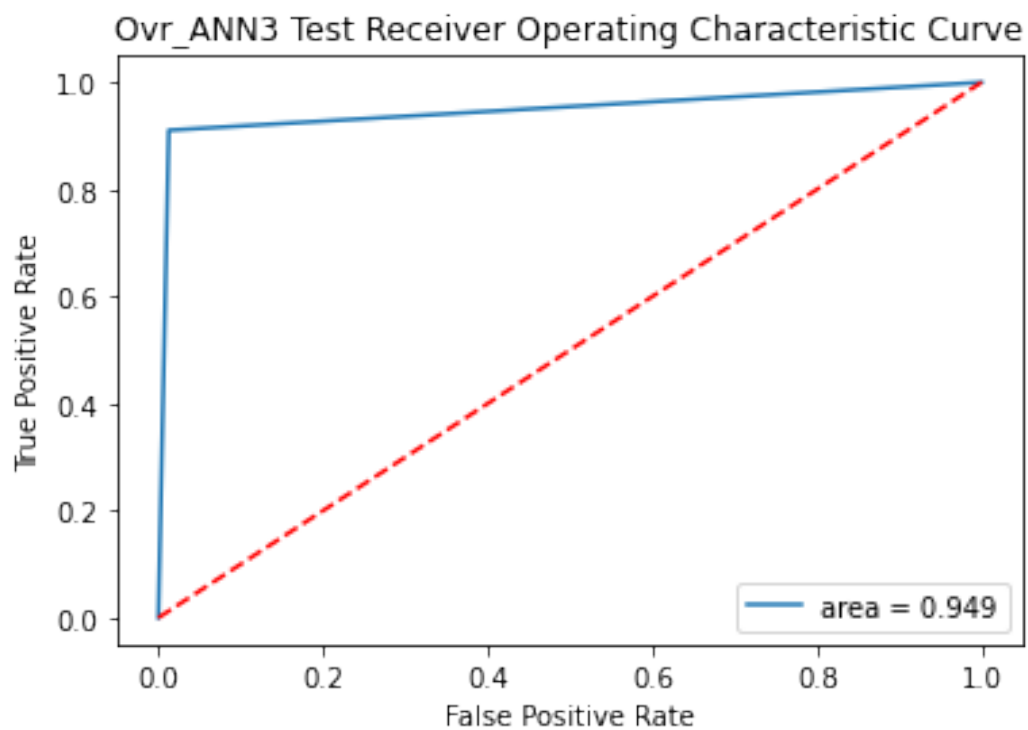
	precision	recall	f1-score	support
0	0.92	0.99	0.95	45201
1	0.99	0.91	0.95	45200
accuracy			0.95	90401
macro avg	0.95	0.95	0.95	90401
weighted avg	0.95	0.95	0.95	90401



roc auc score train 0.9486866432789769



roc auc score test 0.9489271311348152



1781/1781 [=====] - 3s 1ms/step

Test accuracy score 0.9870088831150592

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	56864
1	0.10	0.87	0.19	98
accuracy			0.99	56962
macro avg	0.55	0.93	0.59	56962
weighted avg	1.00	0.99	0.99	56962

Completed and saved for model Ovr_ANN3

```
buildANN(3, 128, 'relu', 'he_normal', 'l1', 'sgd', 30, 10, 'Ovr_ANN4', 0.2)
```

Model: "model_25"

Layer (type)	Output Shape	Param #
input_33 (InputLayer)	[(None, 30)]	0
dense_141 (Dense)	(None, 128)	3968
dense_142 (Dense)	(None, 64)	8256
dense_143 (Dense)	(None, 32)	2080
dropout_9 (Dropout)	(None, 32)	0
batch_normalization_9 (Batch Normalization)	(None, 32)	128
dense_144 (Dense)	(None, 10)	330
dense_145 (Dense)	(None, 2)	22

=====
Total params: 14,784

Trainable params: 14,720

Non-trainable params: 64

None

Epoch 1/10

12054/12054 [=====] - 33s 3ms/step - loss:

2.2359 - f1_score: 0.9478 - val_loss: 0.2221 - val_f1_score: 0.9484

Epoch 2/10

```

12054/12054 [=====] - 32s 3ms/step - loss:
0.2220 - f1_score: 0.9552 - val_loss: 0.2121 - val_f1_score: 0.9524
Epoch 3/10
12054/12054 [=====] - 32s 3ms/step - loss:
0.2183 - f1_score: 0.9551 - val_loss: 0.2086 - val_f1_score: 0.9531
Epoch 4/10
12054/12054 [=====] - 32s 3ms/step - loss:
0.2173 - f1_score: 0.9536 - val_loss: 0.1895 - val_f1_score: 0.9632
Epoch 5/10
12054/12054 [=====] - 32s 3ms/step - loss:
0.2141 - f1_score: 0.9538 - val_loss: 0.2417 - val_f1_score: 0.9373
Epoch 6/10
12054/12054 [=====] - 32s 3ms/step - loss:
0.2150 - f1_score: 0.9535 - val_loss: 0.2896 - val_f1_score: 0.9372
Epoch 7/10
12054/12054 [=====] - 32s 3ms/step - loss:
0.2166 - f1_score: 0.9525 - val_loss: 0.2202 - val_f1_score: 0.9485
11301/11301 [=====] - 18s 2ms/step
2826/2826 [=====] - 5s 2ms/step

```

Model performance Ovr_ANN4

```

accuracy score train 0.948603571339681
accuracy score test 0.9485735777259101

```

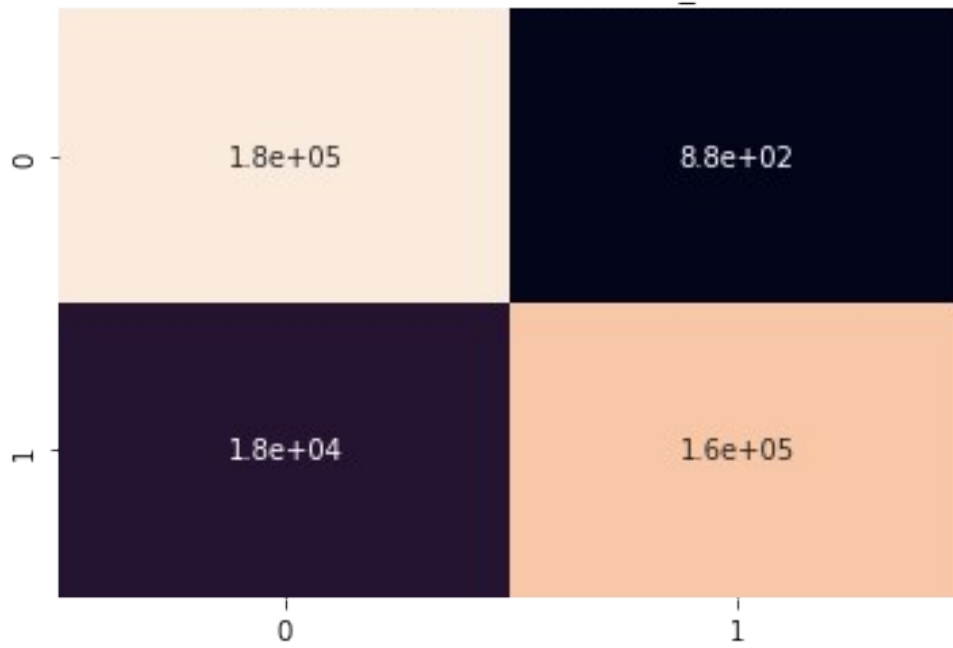
Train classification report: Ovr_ANN4

	precision	recall	f1-score	support
0	0.91	1.00	0.95	180800
1	0.99	0.90	0.95	180801
accuracy			0.95	361601
macro avg	0.95	0.95	0.95	361601
weighted avg	0.95	0.95	0.95	361601

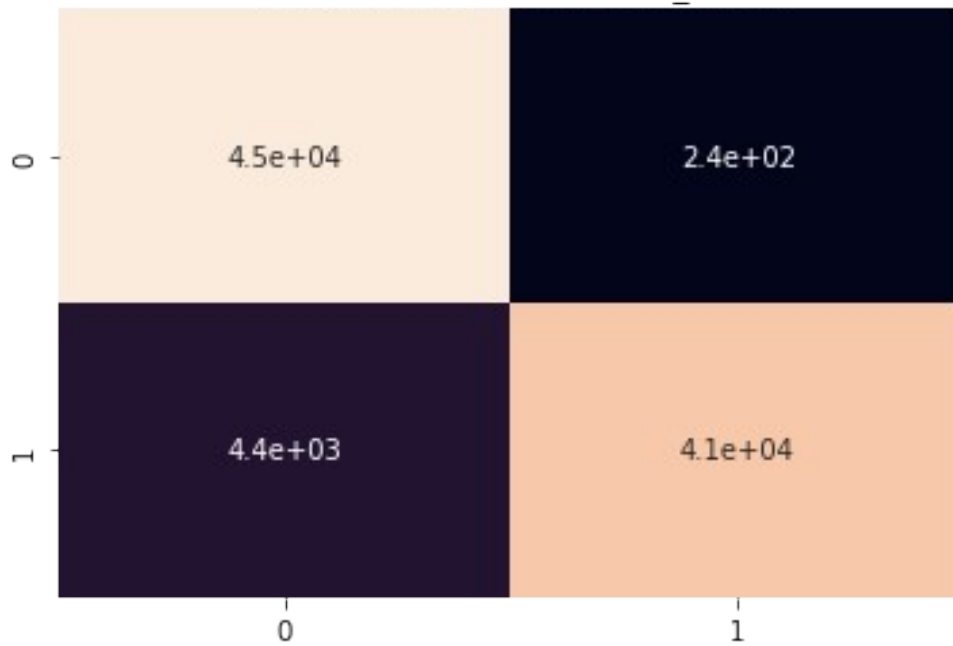
Test classification report: Ovr_ANN4

	precision	recall	f1-score	support
0	0.91	0.99	0.95	45201
1	0.99	0.90	0.95	45200
accuracy			0.95	90401
macro avg	0.95	0.95	0.95	90401
weighted avg	0.95	0.95	0.95	90401

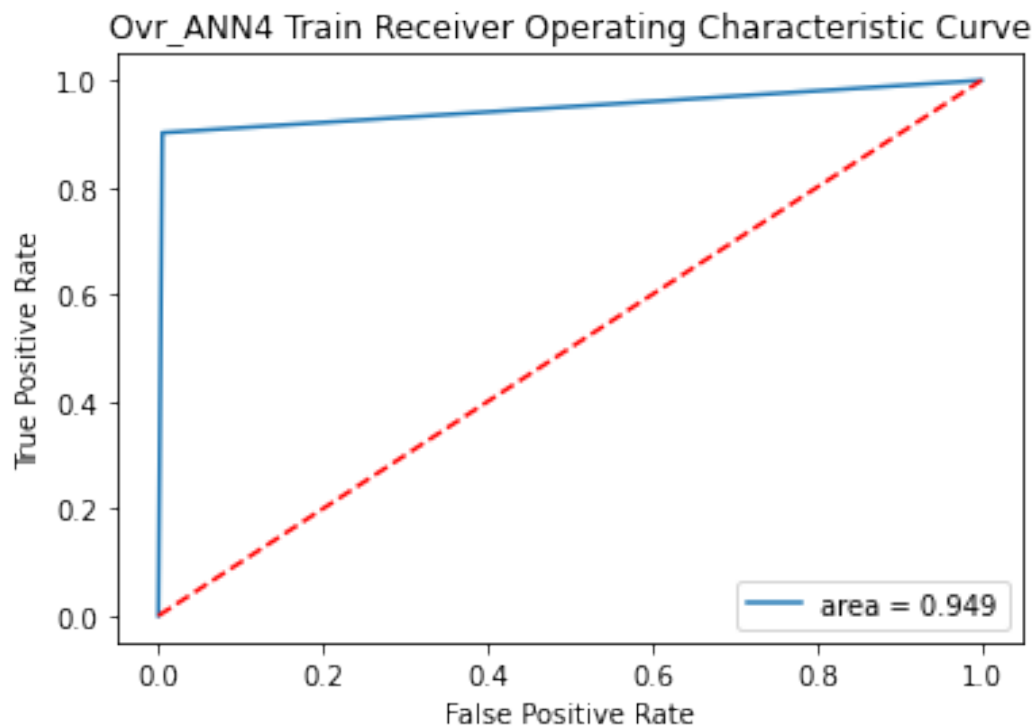
Train confusion matrix: Ovr_ANN4



Test confusion matrix: Ovr_ANN4



roc auc score train 0.9486037000147769



roc auc score test 0.9485730683184431



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9945928864857273

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	1.00	56864
1	0.22	0.86	0.35	98
accuracy			0.99	56962
macro avg	0.61	0.93	0.68	56962
weighted avg	1.00	0.99	1.00	56962

Completed and saved for model Ovr_ANN4

```
buildANN(3, 128, 'relu', 'he_normal', 'l2', 'rmsprop', 30, 10, 'Ovr_ANN5')
```

Model: "model_26"

Layer (type)	Output Shape	Param #
input_34 (InputLayer)	[(None, 30)]	0
dense_146 (Dense)	(None, 128)	3968
dense_147 (Dense)	(None, 64)	8256
dense_148 (Dense)	(None, 32)	2080
dense_149 (Dense)	(None, 10)	330
dense_150 (Dense)	(None, 2)	22

Total params: 14,656

Trainable params: 14,656

Non-trainable params: 0

None

Epoch 1/10

12054/12054 [=====] - 33s 3ms/step - loss: 0.1897 - f1_score: 0.9829 - val_loss: 0.0841 - val_f1_score: 0.9927

Epoch 2/10

12054/12054 [=====] - 31s 3ms/step - loss: 0.0816 - f1_score: 0.9903 - val_loss: 0.0749 - val_f1_score: 0.9931

Epoch 3/10

12054/12054 [=====] - 31s 3ms/step - loss: 0.0746 - f1_score: 0.9913 - val_loss: 0.0927 - val_f1_score: 0.9720


```

Epoch 4/10
12054/12054 [=====] - 31s 3ms/step - loss:
0.0705 - f1_score: 0.9919 - val_loss: 0.0656 - val_f1_score: 0.9944
Epoch 5/10
12054/12054 [=====] - 31s 3ms/step - loss:
0.0676 - f1_score: 0.9923 - val_loss: 0.0710 - val_f1_score: 0.9918
Epoch 6/10
12054/12054 [=====] - 32s 3ms/step - loss:
0.0663 - f1_score: 0.9922 - val_loss: 0.0801 - val_f1_score: 0.9799
Epoch 7/10
12054/12054 [=====] - 31s 3ms/step - loss:
0.0648 - f1_score: 0.9923 - val_loss: 0.0598 - val_f1_score: 0.9971
Epoch 8/10
12054/12054 [=====] - 32s 3ms/step - loss:
0.0635 - f1_score: 0.9926 - val_loss: 0.0663 - val_f1_score: 0.9928
Epoch 9/10
12054/12054 [=====] - 32s 3ms/step - loss:
0.0623 - f1_score: 0.9928 - val_loss: 0.0694 - val_f1_score: 0.9890
Epoch 10/10
12054/12054 [=====] - 31s 3ms/step - loss:
0.0615 - f1_score: 0.9930 - val_loss: 0.0613 - val_f1_score: 0.9940
11301/11301 [=====] - 17s 1ms/step
2826/2826 [=====] - 4s 1ms/step

```

Model performance Ovr_ANN5

```

accuracy score train 0.9940569854618765
accuracy score test 0.9940044911007622

```

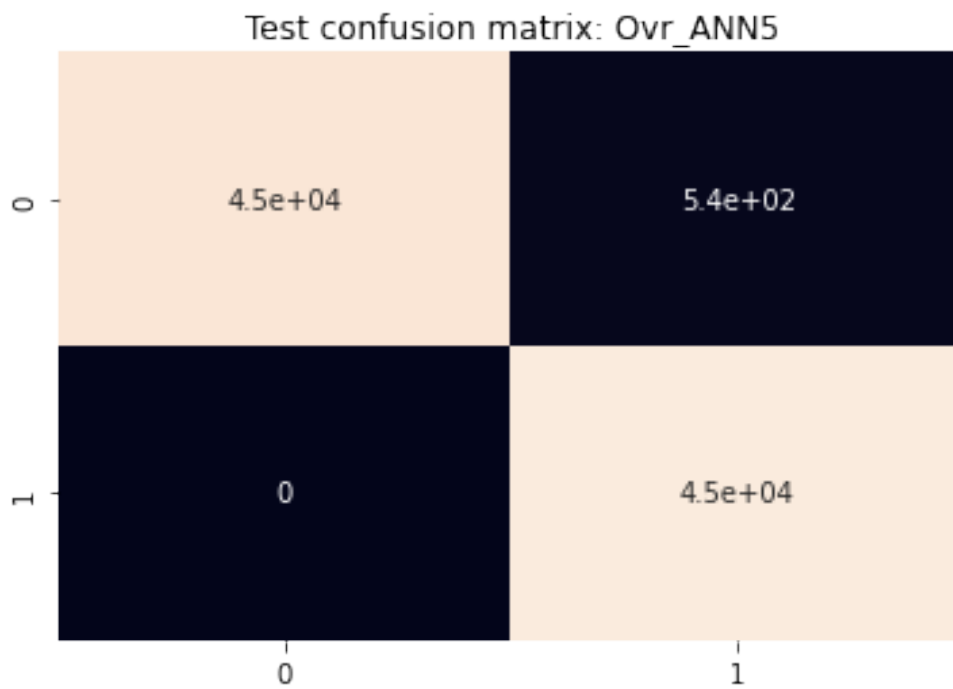
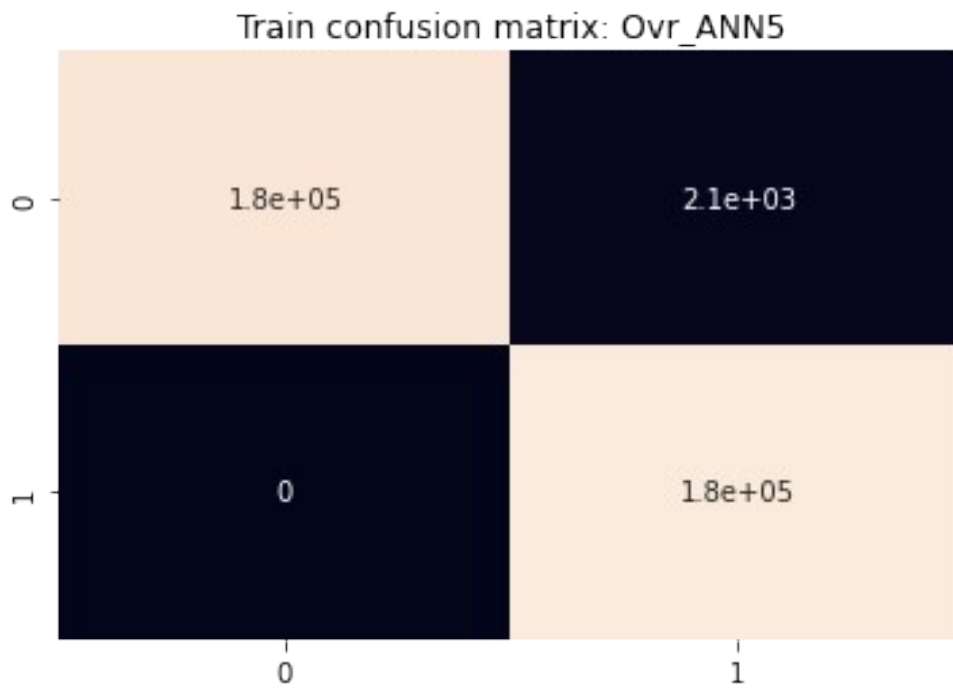
Train classification report: Ovr_ANN5

	precision	recall	f1-score	support
0	1.00	0.99	0.99	180800
1	0.99	1.00	0.99	180801
accuracy			0.99	361601
macro avg	0.99	0.99	0.99	361601
weighted avg	0.99	0.99	0.99	361601

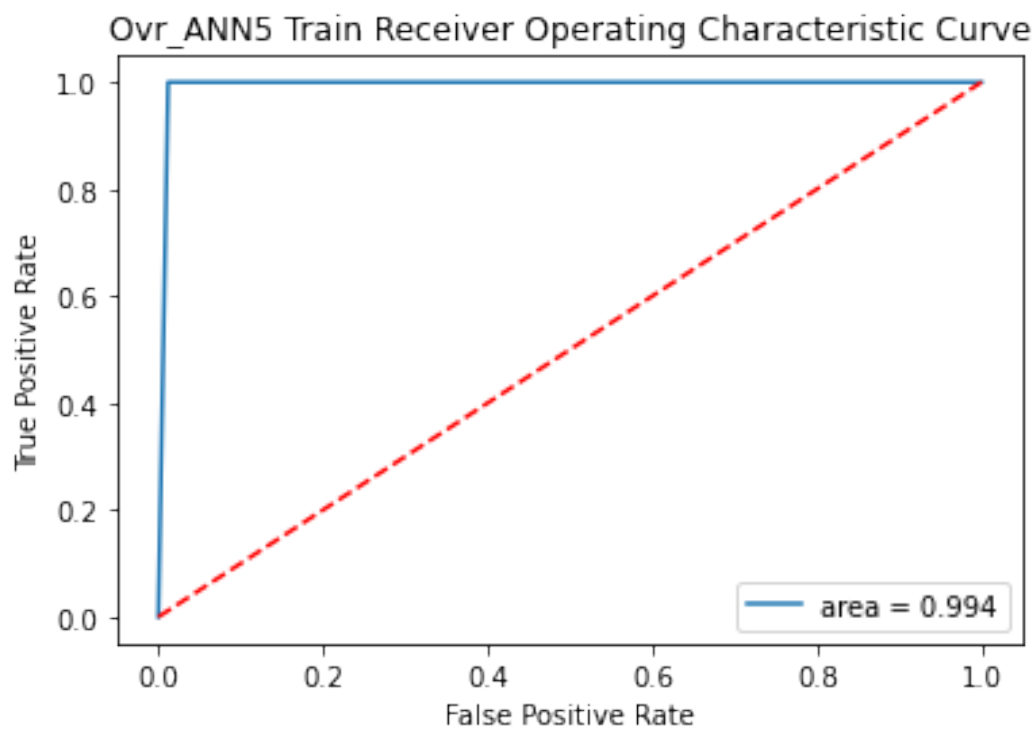
Test classification report: Ovr_ANN5

	precision	recall	f1-score	support
0	1.00	0.99	0.99	45201
1	0.99	1.00	0.99	45200
accuracy			0.99	90401

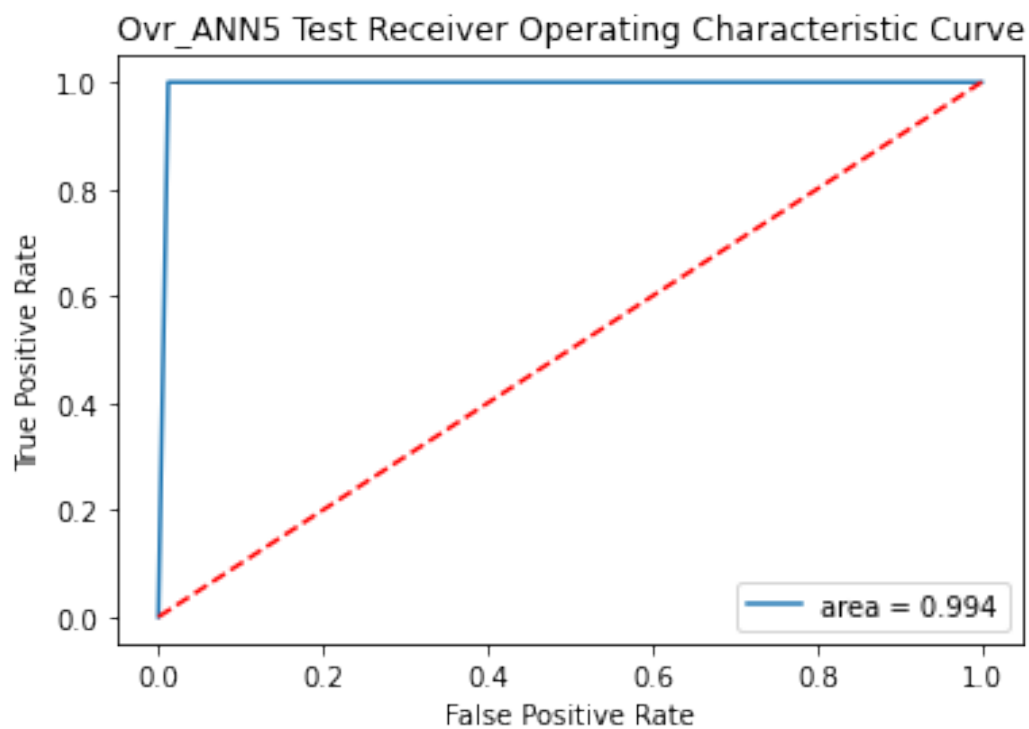
macro avg	0.99	0.99	0.99	90401
weighted avg	0.99	0.99	0.99	90401



roc auc score train 0.9940569690265486



roc auc score test 0.994004557421296



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9876057722692321

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	56864
1	0.11	0.87	0.19	98
accuracy			0.99	56962
macro avg	0.55	0.93	0.59	56962
weighted avg	1.00	0.99	0.99	56962

Completed and saved for model Ovr_ANN5

```
buildANN(3, 128, 'relu', 'he_uniform', 'l1', 'adadelata', 30, 10,  
'Ovr_ANN6', 0.2)
```

Model: "model_27"

Layer (type)	Output Shape	Param #
input_35 (InputLayer)	[(None, 30)]	0
dense_151 (Dense)	(None, 128)	3968
dense_152 (Dense)	(None, 64)	8256
dense_153 (Dense)	(None, 32)	2080
dropout_10 (Dropout)	(None, 32)	0
batch_normalization_10 (Batch Normalization)	(None, 32)	128
dense_154 (Dense)	(None, 10)	330
dense_155 (Dense)	(None, 2)	22

=====
Total params: 14,784

Trainable params: 14,720

Non-trainable params: 64

None

Epoch 1/10

12054/12054 [=====] - 35s 3ms/step - loss:

```

21.4032 - f1_score: 0.6867 - val_loss: 20.7938 - val_f1_score: 0.8490
Epoch 2/10
12054/12054 [=====] - 35s 3ms/step - loss:
20.2433 - f1_score: 0.8410 - val_loss: 19.6695 - val_f1_score: 0.8955
Epoch 3/10
12054/12054 [=====] - 34s 3ms/step - loss:
19.1308 - f1_score: 0.8831 - val_loss: 18.5701 - val_f1_score: 0.9126
Epoch 4/10
12054/12054 [=====] - 34s 3ms/step - loss:
18.0212 - f1_score: 0.9036 - val_loss: 17.4477 - val_f1_score: 0.9273
Epoch 5/10
12054/12054 [=====] - 35s 3ms/step - loss:
16.9231 - f1_score: 0.9163 - val_loss: 16.3920 - val_f1_score: 0.9330
Epoch 6/10
12054/12054 [=====] - 35s 3ms/step - loss:
15.9089 - f1_score: 0.9250 - val_loss: 15.4093 - val_f1_score: 0.9349
Epoch 7/10
12054/12054 [=====] - 35s 3ms/step - loss:
14.9457 - f1_score: 0.9303 - val_loss: 14.4624 - val_f1_score: 0.9415
Epoch 8/10
12054/12054 [=====] - 35s 3ms/step - loss:
14.0237 - f1_score: 0.9341 - val_loss: 13.5619 - val_f1_score: 0.9444
Epoch 9/10
12054/12054 [=====] - 35s 3ms/step - loss:
13.1404 - f1_score: 0.9373 - val_loss: 12.6942 - val_f1_score: 0.9452
Epoch 10/10
12054/12054 [=====] - 35s 3ms/step - loss:
12.3093 - f1_score: 0.9389 - val_loss: 11.8949 - val_f1_score: 0.9470
11301/11301 [=====] - 18s 2ms/step
2826/2826 [=====] - 4s 2ms/step

```

Model performance Ovr_ANN6

```

accuracy score train 0.946601364487377
accuracy score test 0.9470359841152199

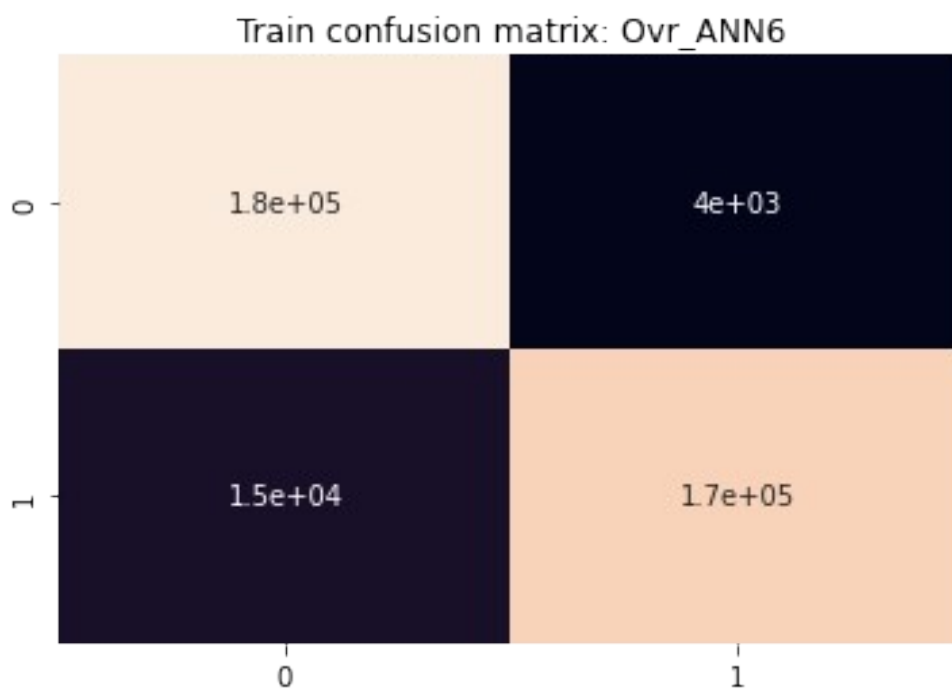
```

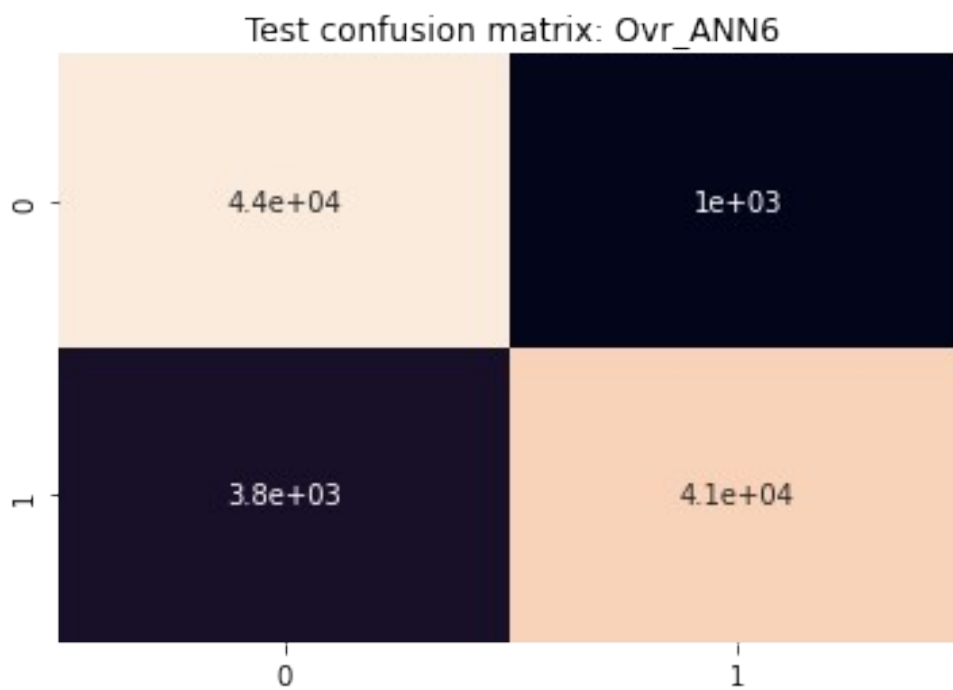
Train classification report: Ovr_ANN6

	precision	recall	f1-score	support
0	0.92	0.98	0.95	180800
1	0.98	0.92	0.94	180801
accuracy			0.95	361601
macro avg	0.95	0.95	0.95	361601
weighted avg	0.95	0.95	0.95	361601

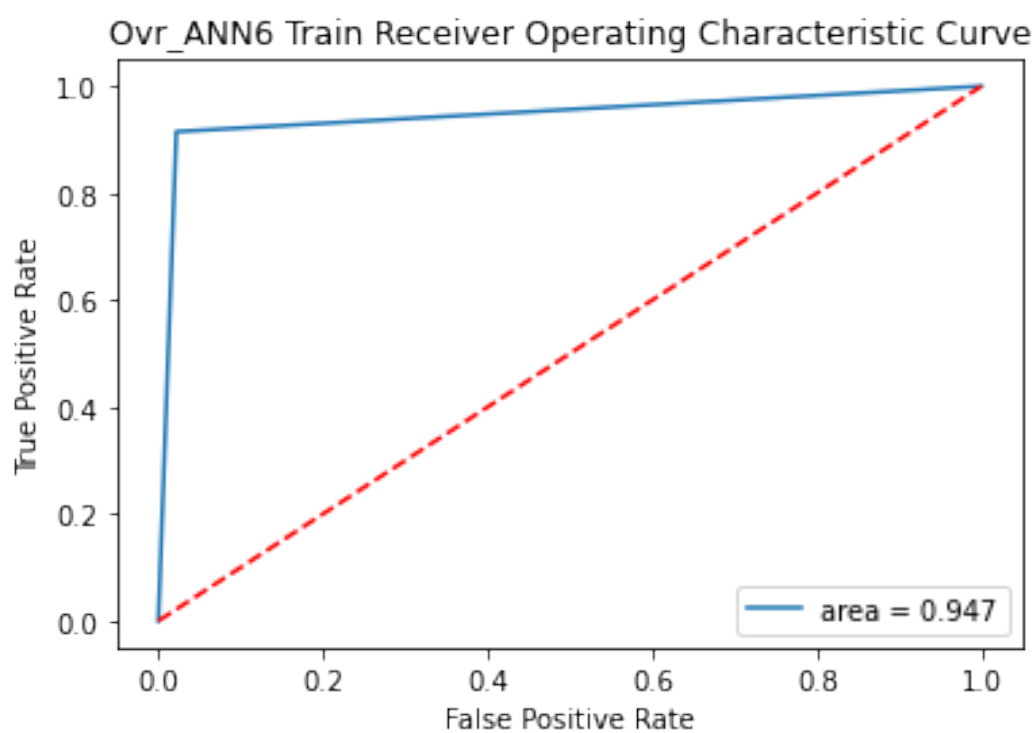
Test classification report: Ovr_ANN6

	precision	recall	f1-score	support
0	0.92	0.98	0.95	45201
1	0.98	0.92	0.95	45200
accuracy			0.95	90401
macro avg	0.95	0.95	0.95	90401
weighted avg	0.95	0.95	0.95	90401

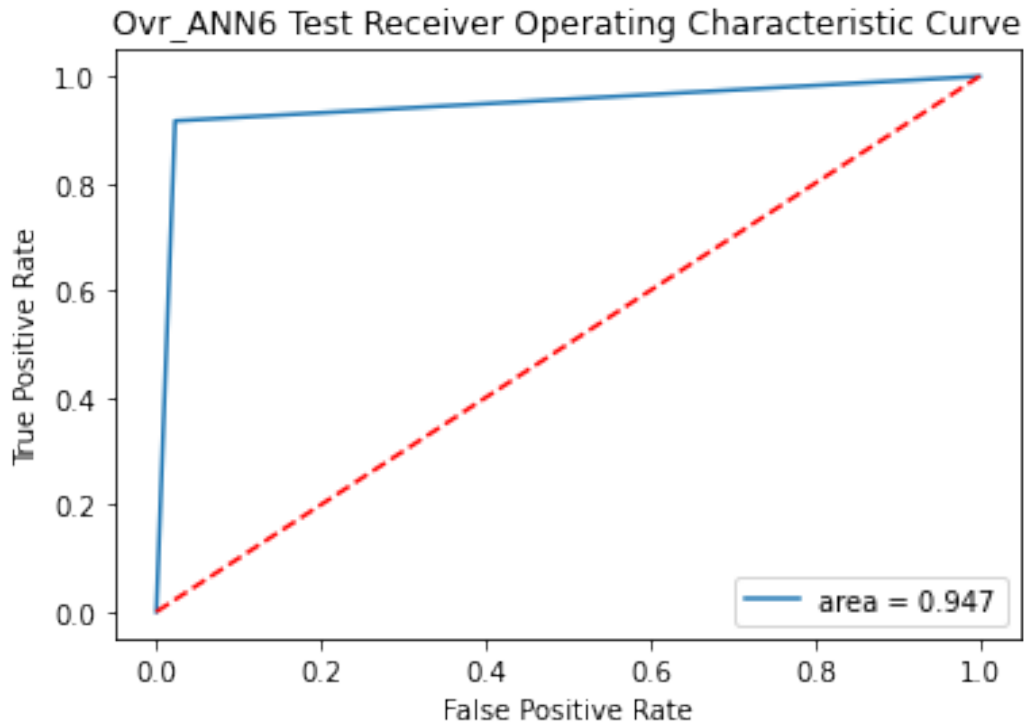




roc auc score train 0.9466014517262733



roc auc score test 0.9470356493209388



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9779853235490327

Classification report

	precision	recall	f1-score	support
0	1.00	0.98	0.99	56864
1	0.06	0.87	0.12	98
accuracy			0.98	56962
macro avg	0.53	0.92	0.55	56962
weighted avg	1.00	0.98	0.99	56962

Completed and saved for model Ovr_ANN6

buildANN(4, 128, 'tanh', 'he_uniform', 'l2', 'adagrad', 20, 10, 'Ovr_ANN7')

Model: "model_28"

Layer (type)	Output Shape	Param #
input_36 (InputLayer)	[(None, 30)]	0

dense_156 (Dense)	(None, 128)	3968
dense_157 (Dense)	(None, 64)	8256
dense_158 (Dense)	(None, 32)	2080
dense_159 (Dense)	(None, 16)	528
dense_160 (Dense)	(None, 10)	170
dense_161 (Dense)	(None, 2)	22

```

=====
Total params: 15,024
Trainable params: 15,024
Non-trainable params: 0

```

None

Epoch 1/10

18081/18081 [=====] - 51s 3ms/step - loss: 3.0693 - f1_score: 0.9534 - val_loss: 1.9878 - val_f1_score: 0.9627

Epoch 2/10

18081/18081 [=====] - 50s 3ms/step - loss: 1.5443 - f1_score: 0.9620 - val_loss: 1.2180 - val_f1_score: 0.9625

Epoch 3/10

18081/18081 [=====] - 45s 2ms/step - loss: 1.0217 - f1_score: 0.9615 - val_loss: 0.8654 - val_f1_score: 0.9620

Epoch 4/10

18081/18081 [=====] - 49s 3ms/step - loss: 0.7582 - f1_score: 0.9615 - val_loss: 0.6698 - val_f1_score: 0.9614

Epoch 5/10

18081/18081 [=====] - 49s 3ms/step - loss: 0.6040 - f1_score: 0.9611 - val_loss: 0.5487 - val_f1_score: 0.9618

Epoch 6/10

18081/18081 [=====] - 49s 3ms/step - loss: 0.5049 - f1_score: 0.9603 - val_loss: 0.4679 - val_f1_score: 0.9607

Epoch 7/10

18081/18081 [=====] - 47s 3ms/step - loss: 0.4372 - f1_score: 0.9596 - val_loss: 0.4113 - val_f1_score: 0.9601

Epoch 8/10

18081/18081 [=====] - 49s 3ms/step - loss: 0.3887 - f1_score: 0.9587 - val_loss: 0.3697 - val_f1_score: 0.9589

Epoch 9/10

18081/18081 [=====] - 45s 3ms/step - loss: 0.3526 - f1_score: 0.9577 - val_loss: 0.3384 - val_f1_score: 0.9603

Epoch 10/10

18081/18081 [=====] - 49s 3ms/step - loss: 0.3250 - f1_score: 0.9576 - val_loss: 0.3141 - val_f1_score: 0.9577

11301/11301 [=====] - 17s 2ms/step

2826/2826 [=====] - 4s 2ms/step

Model performance Ovr_ANN7

accuracy score train 0.9574973520537831

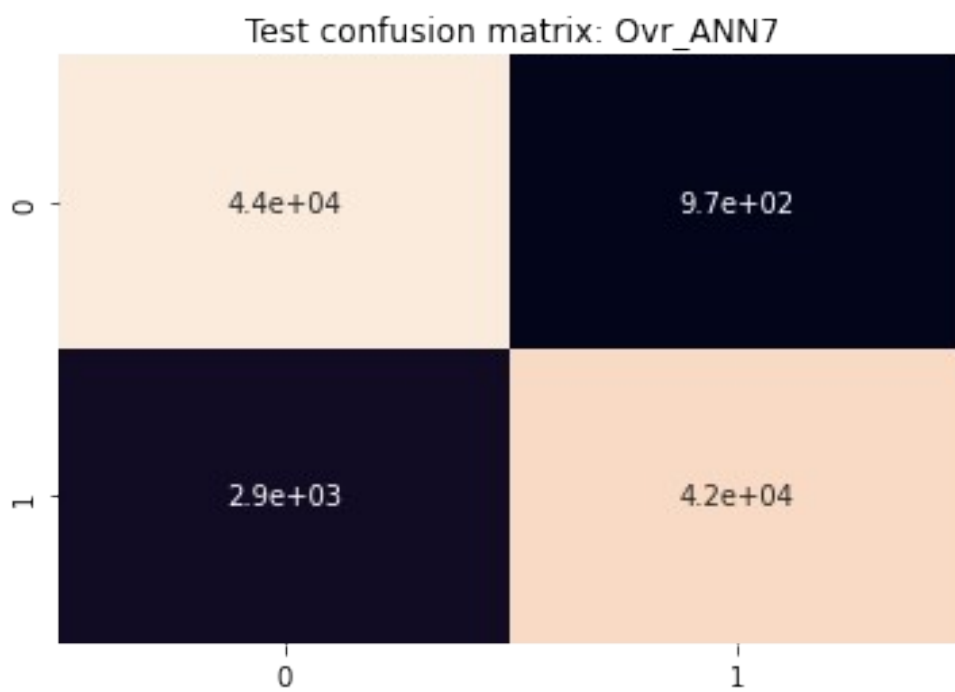
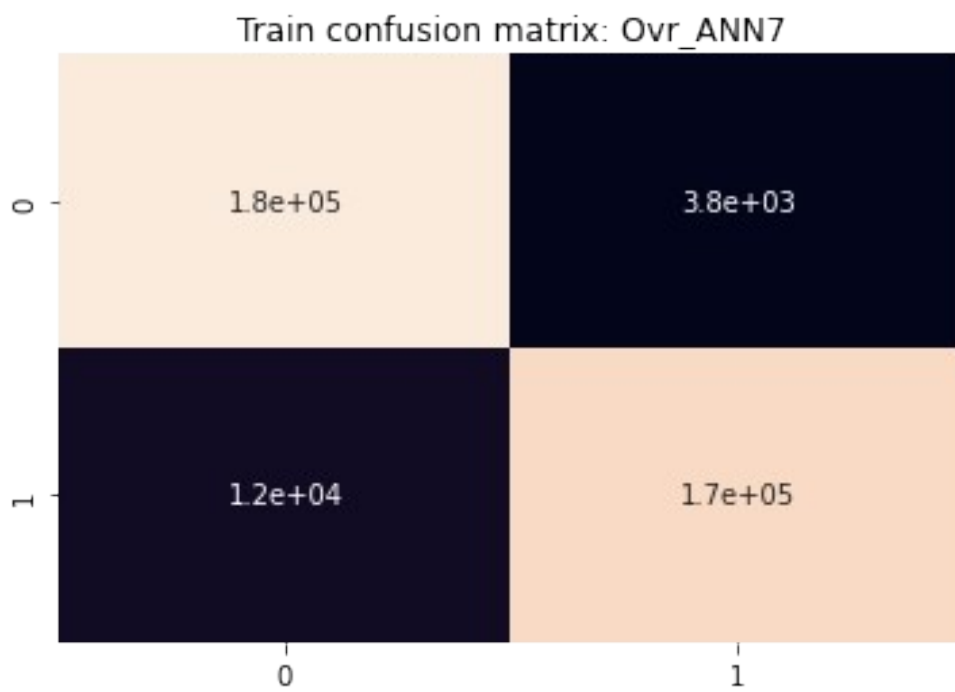
accuracy score test 0.9576885211446776

Train classification report: Ovr_ANN7

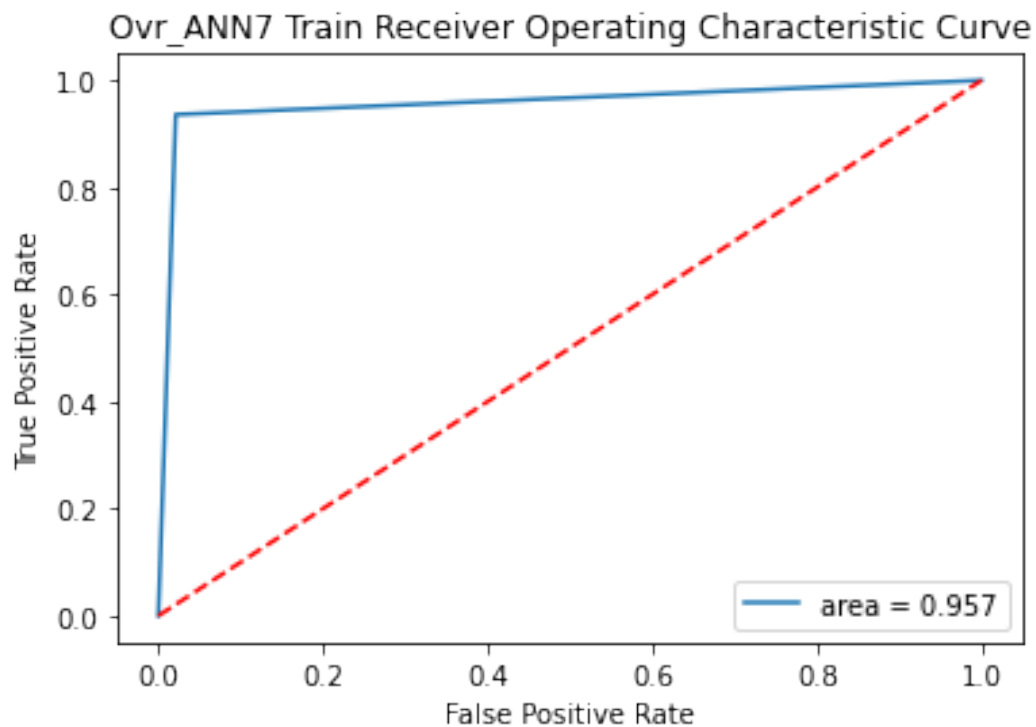
	precision	recall	f1-score	support
0	0.94	0.98	0.96	180800
1	0.98	0.94	0.96	180801
accuracy			0.96	361601
macro avg	0.96	0.96	0.96	361601
weighted avg	0.96	0.96	0.96	361601

Test classification report: Ovr_ANN7

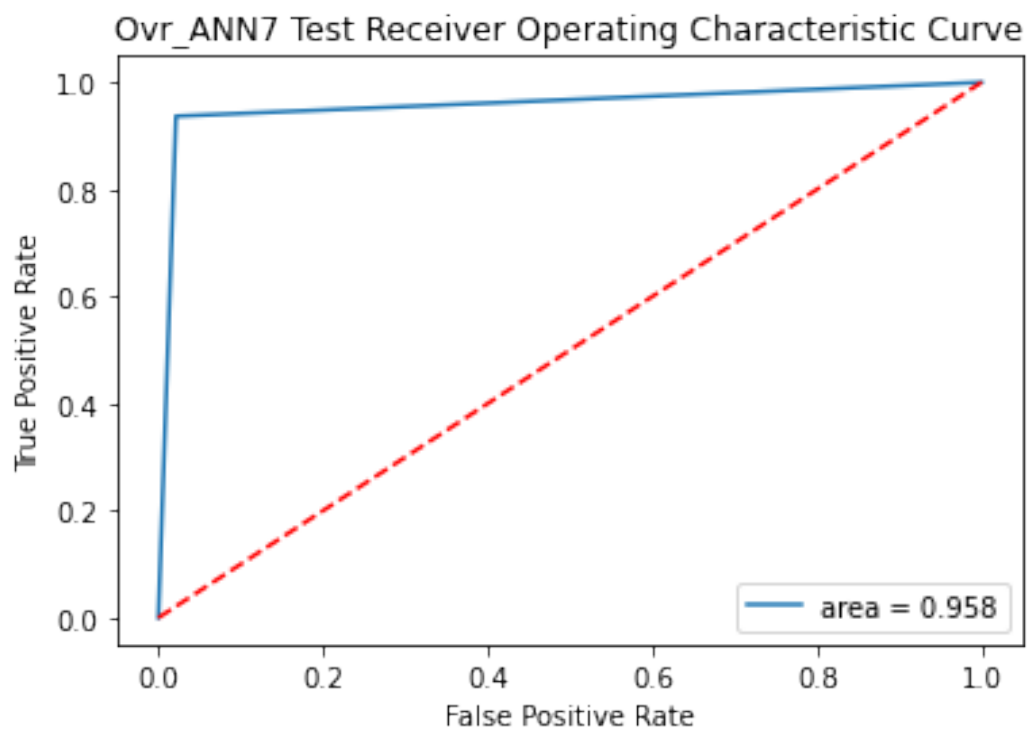
	precision	recall	f1-score	support
0	0.94	0.98	0.96	45201
1	0.98	0.94	0.96	45200
accuracy			0.96	90401
macro avg	0.96	0.96	0.96	90401
weighted avg	0.96	0.96	0.96	90401



roc auc score train 0.9574974113015419



roc auc score test 0.9576882895045199



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9782486569994031

Classification report

	precision	recall	f1-score	support
0	1.00	0.98	0.99	56864
1	0.07	0.89	0.12	98
accuracy			0.98	56962
macro avg	0.53	0.93	0.56	56962
weighted avg	1.00	0.98	0.99	56962

Completed and saved for model Ovr_ANN7

```
buildANN(4, 128, 'relu', 'he_normal', 'l1', 'adam', 40, 10, 'Ovr_ANN8')
```

Model: "model_29"

Layer (type)	Output Shape	Param #
input_37 (InputLayer)	[(None, 30)]	0
dense_162 (Dense)	(None, 128)	3968
dense_163 (Dense)	(None, 64)	8256
dense_164 (Dense)	(None, 32)	2080
dense_165 (Dense)	(None, 16)	528
dense_166 (Dense)	(None, 10)	170
dense_167 (Dense)	(None, 2)	22

=====
Total params: 15,024

Trainable params: 15,024

Non-trainable params: 0

None

Epoch 1/10

9041/9041 [=====] - 33s 4ms/step - loss: 0.6429 - f1_score: 0.9459 - val_loss: 0.2139 - val_f1_score: 0.9493

Epoch 2/10

9041/9041 [=====] - 28s 3ms/step - loss: 0.2104 - f1_score: 0.9498 - val_loss: 0.2090 - val_f1_score: 0.9525

Epoch 3/10

```

9041/9041 [=====] - 30s 3ms/step - loss:
0.2054 - f1_score: 0.9500 - val_loss: 0.2001 - val_f1_score: 0.9521
Epoch 4/10
9041/9041 [=====] - 29s 3ms/step - loss:
0.1990 - f1_score: 0.9500 - val_loss: 0.1992 - val_f1_score: 0.9497
Epoch 5/10
9041/9041 [=====] - 30s 3ms/step - loss:
0.1974 - f1_score: 0.9503 - val_loss: 0.1987 - val_f1_score: 0.9481
Epoch 6/10
9041/9041 [=====] - 30s 3ms/step - loss:
0.1964 - f1_score: 0.9503 - val_loss: 0.1966 - val_f1_score: 0.9489
Epoch 7/10
9041/9041 [=====] - 30s 3ms/step - loss:
0.1957 - f1_score: 0.9504 - val_loss: 0.1951 - val_f1_score: 0.9496
Epoch 8/10
9041/9041 [=====] - 28s 3ms/step - loss:
0.1950 - f1_score: 0.9502 - val_loss: 0.1951 - val_f1_score: 0.9491
Epoch 9/10
9041/9041 [=====] - 28s 3ms/step - loss:
0.1944 - f1_score: 0.9502 - val_loss: 0.1954 - val_f1_score: 0.9527
Epoch 10/10
9041/9041 [=====] - 28s 3ms/step - loss:
0.1938 - f1_score: 0.9502 - val_loss: 0.1938 - val_f1_score: 0.9487
11301/11301 [=====] - 17s 2ms/step
2826/2826 [=====] - 4s 2ms/step

```

Model performance Ovr_ANN8

```

accuracy score train 0.9483380853482153
accuracy score test 0.9487616287430449

```

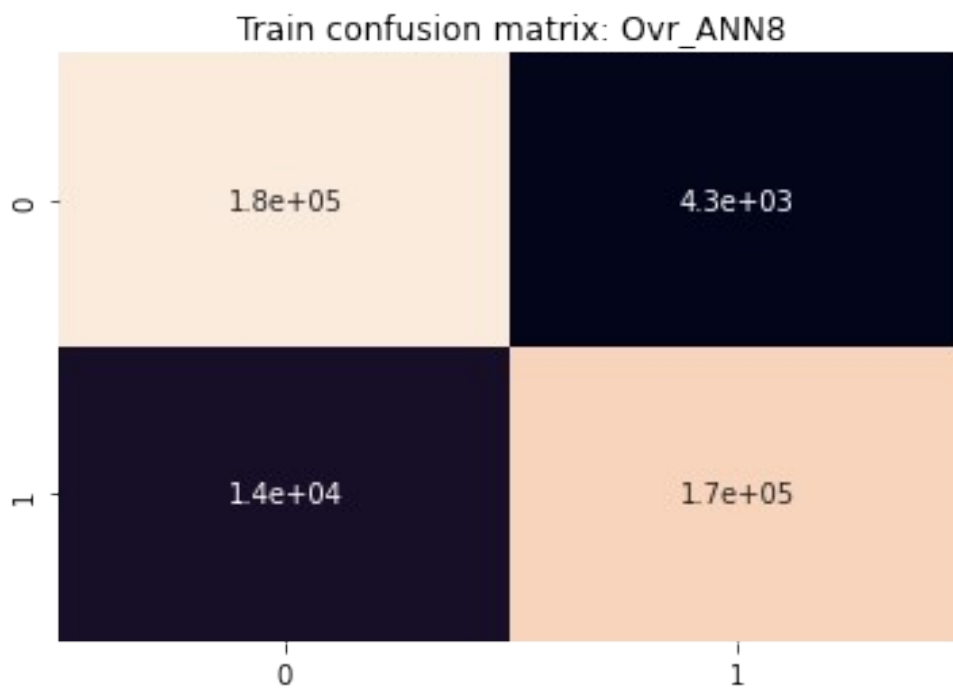
Train classification report: Ovr_ANN8

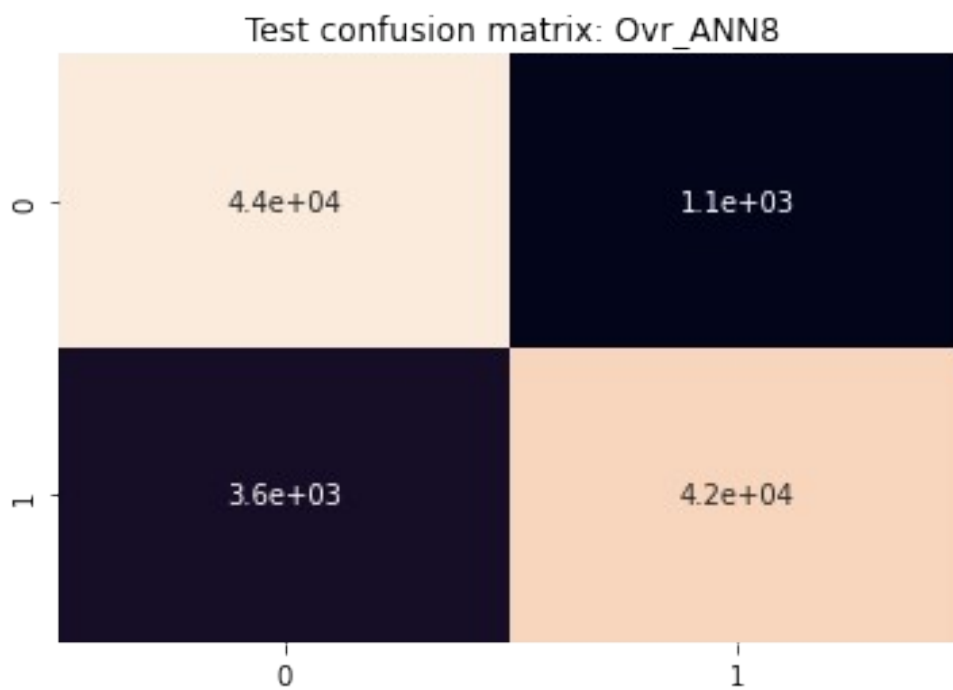
	precision	recall	f1-score	support
0	0.92	0.98	0.95	180800
1	0.97	0.92	0.95	180801
accuracy			0.95	361601
macro avg	0.95	0.95	0.95	361601
weighted avg	0.95	0.95	0.95	361601

Test classification report: Ovr_ANN8

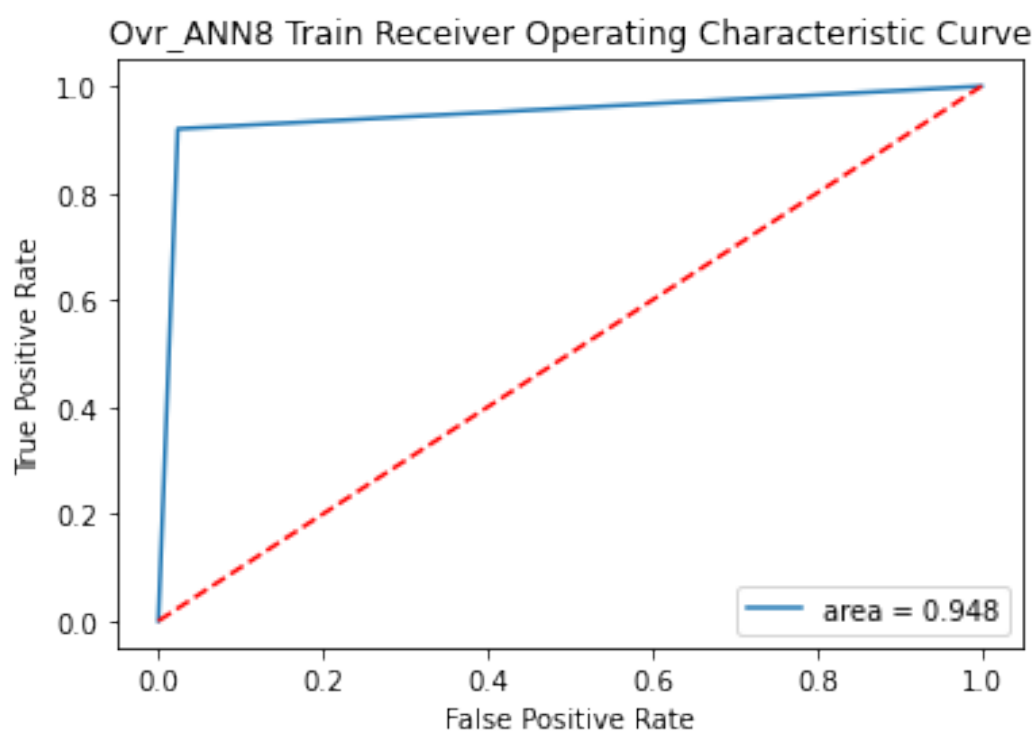
	precision	recall	f1-score	support
0	0.93	0.98	0.95	45201
1	0.98	0.92	0.95	45200

accuracy			0.95	90401
macro avg	0.95	0.95	0.95	90401
weighted avg	0.95	0.95	0.95	90401

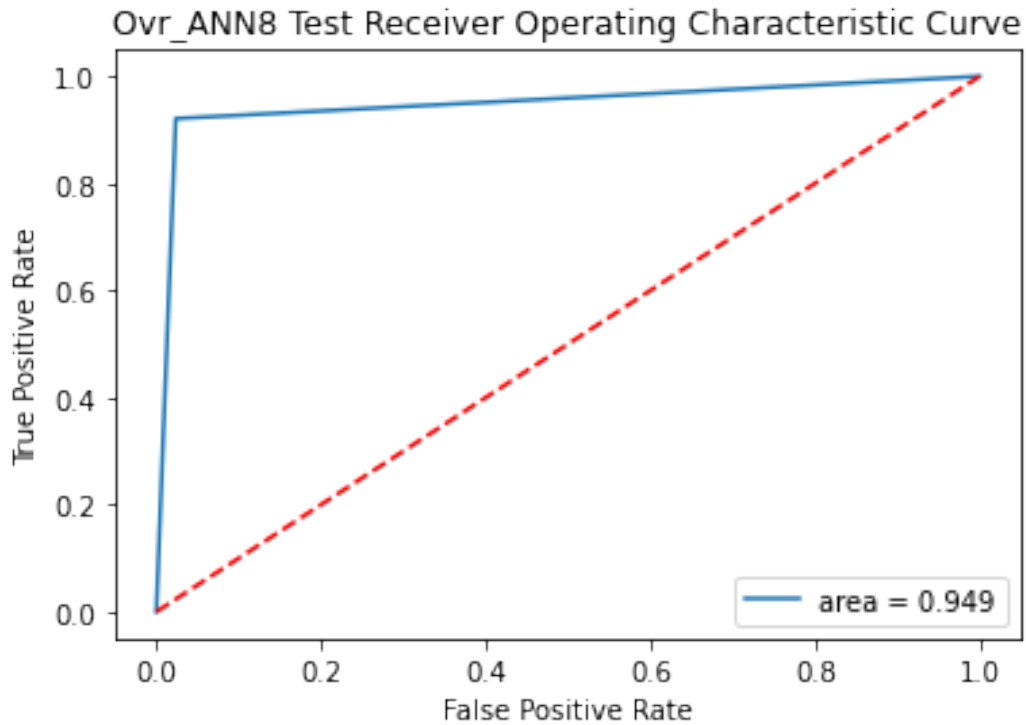




roc auc score train 0.9483381629049158



roc auc score test 0.948761322582142



1781/1781 [=====] - 3s 1ms/step

Test accuracy score 0.9761771005231558

Classification report

	precision	recall	f1-score	support
0	1.00	0.98	0.99	56864
1	0.06	0.88	0.11	98
accuracy			0.98	56962
macro avg	0.53	0.93	0.55	56962
weighted avg	1.00	0.98	0.99	56962

Completed and saved for model Ovr_ANN8

buildANN(4, 256, 'relu', 'he_normal', 'l2', 'adam', 30, 10, 'Ovr_ANN9')

Model: "model_30"

Layer (type)	Output Shape	Param #
input_38 (InputLayer)	[(None, 30)]	0

dense_168 (Dense)	(None, 256)	7936
dense_169 (Dense)	(None, 128)	32896
dense_170 (Dense)	(None, 64)	8256
dense_171 (Dense)	(None, 32)	2080
dense_172 (Dense)	(None, 10)	330
dense_173 (Dense)	(None, 2)	22

```
=====
Total params: 51,520
Trainable params: 51,520
Non-trainable params: 0
```

None

Epoch 1/10

12054/12054 [=====] - 44s 4ms/step - loss: 0.2647 - f1_score: 0.9812 - val_loss: 0.1043 - val_f1_score: 0.9915

Epoch 2/10

12054/12054 [=====] - 43s 4ms/step - loss: 0.0972 - f1_score: 0.9916 - val_loss: 0.1099 - val_f1_score: 0.9858

Epoch 3/10

12054/12054 [=====] - 42s 3ms/step - loss: 0.0887 - f1_score: 0.9928 - val_loss: 0.0858 - val_f1_score: 0.9938

Epoch 4/10

12054/12054 [=====] - 42s 3ms/step - loss: 0.0839 - f1_score: 0.9934 - val_loss: 0.0834 - val_f1_score: 0.9932

Epoch 5/10

12054/12054 [=====] - 42s 4ms/step - loss: 0.0808 - f1_score: 0.9938 - val_loss: 0.0893 - val_f1_score: 0.9928

Epoch 6/10

12054/12054 [=====] - 43s 4ms/step - loss: 0.0790 - f1_score: 0.9937 - val_loss: 0.0794 - val_f1_score: 0.9942

Epoch 7/10

12054/12054 [=====] - 44s 4ms/step - loss: 0.0770 - f1_score: 0.9940 - val_loss: 0.0756 - val_f1_score: 0.9959

Epoch 8/10

12054/12054 [=====] - 43s 4ms/step - loss: 0.0757 - f1_score: 0.9940 - val_loss: 0.0799 - val_f1_score: 0.9923

Epoch 9/10

12054/12054 [=====] - 42s 3ms/step - loss: 0.0748 - f1_score: 0.9940 - val_loss: 0.0739 - val_f1_score: 0.9973

Epoch 10/10

12054/12054 [=====] - 42s 4ms/step - loss: 0.0739 - f1_score: 0.9942 - val_loss: 0.0708 - val_f1_score: 0.9946

11301/11301 [=====] - 19s 2ms/step

2826/2826 [=====] - 5s 2ms/step

Model performance Ovr_ANN9

accuracy score train 0.9951299913440504

accuracy score test 0.9945797059767038

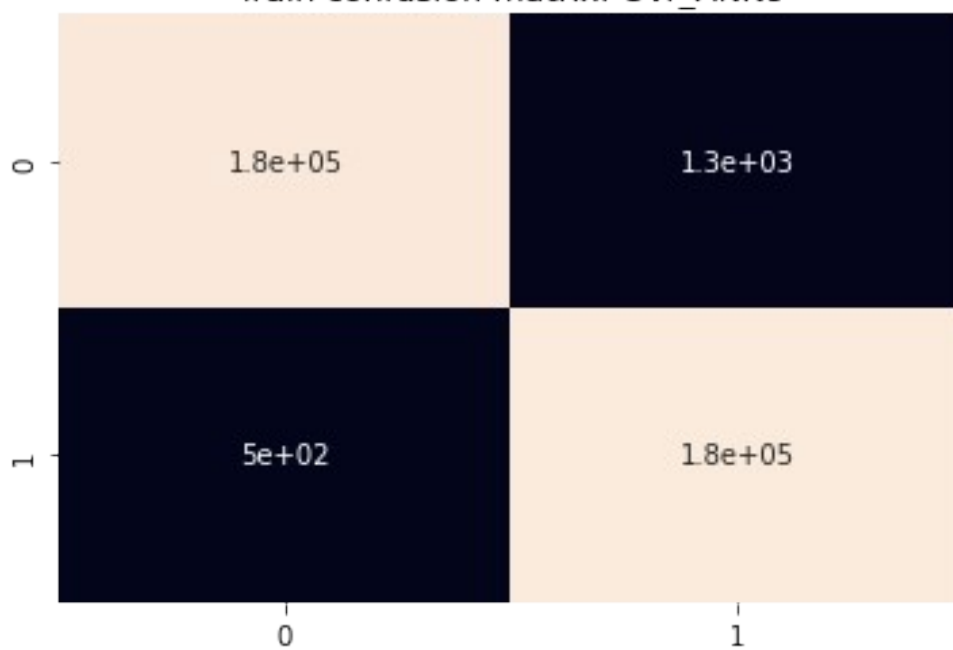
Train classification report: Ovr_ANN9

	precision	recall	f1-score	support
0	1.00	0.99	1.00	180800
1	0.99	1.00	1.00	180801
accuracy			1.00	361601
macro avg	1.00	1.00	1.00	361601
weighted avg	1.00	1.00	1.00	361601

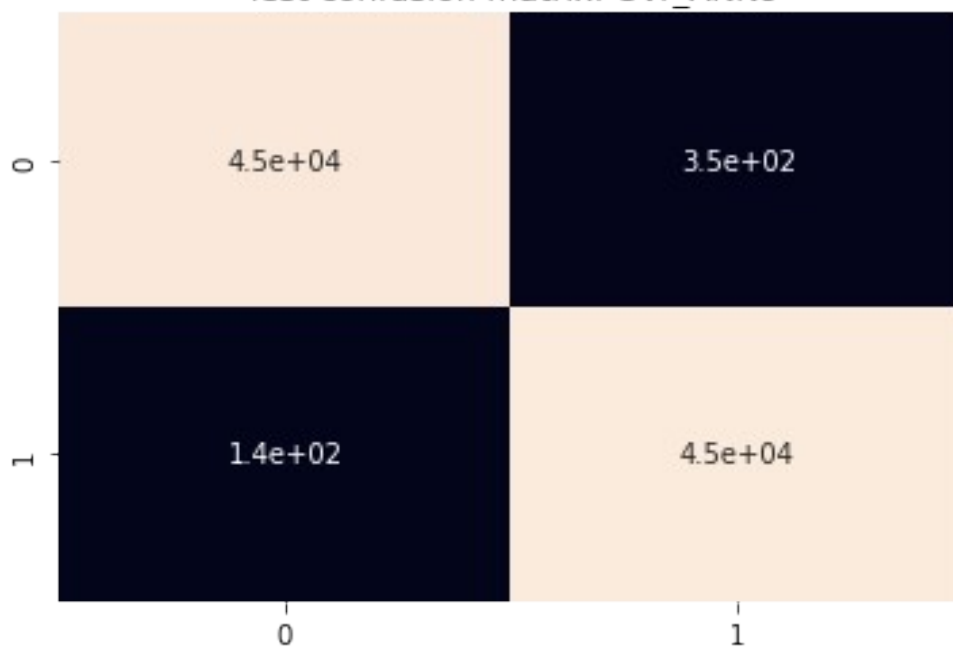
Test classification report: Ovr_ANN9

	precision	recall	f1-score	support
0	1.00	0.99	0.99	45201
1	0.99	1.00	0.99	45200
accuracy			0.99	90401
macro avg	0.99	0.99	0.99	90401
weighted avg	0.99	0.99	0.99	90401

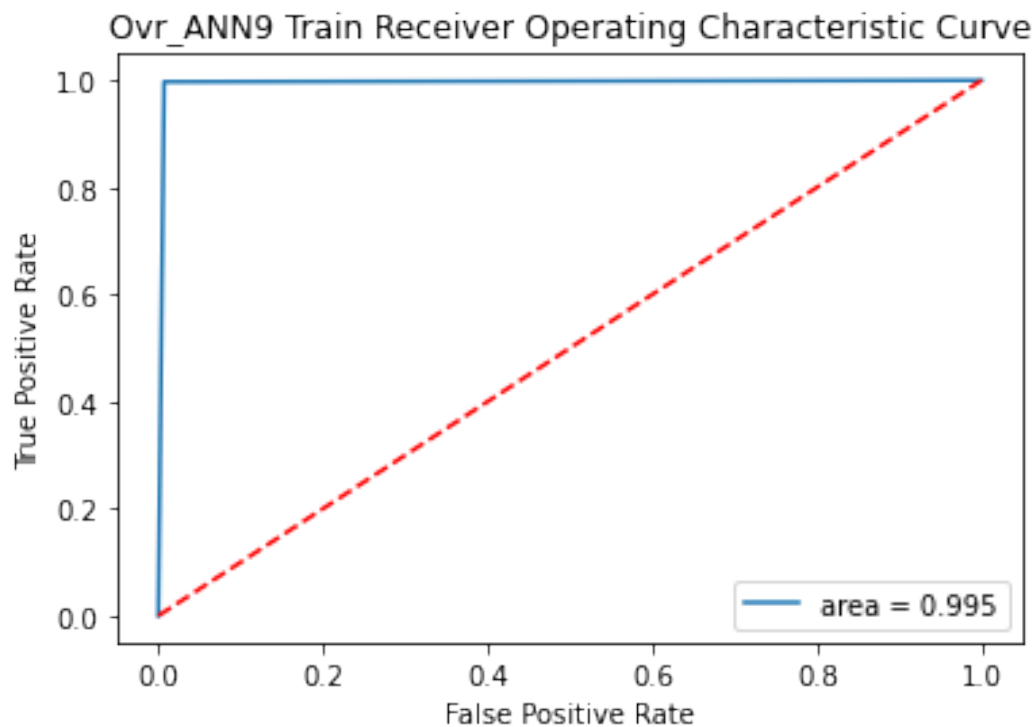
Train confusion matrix: Ovr_ANN9



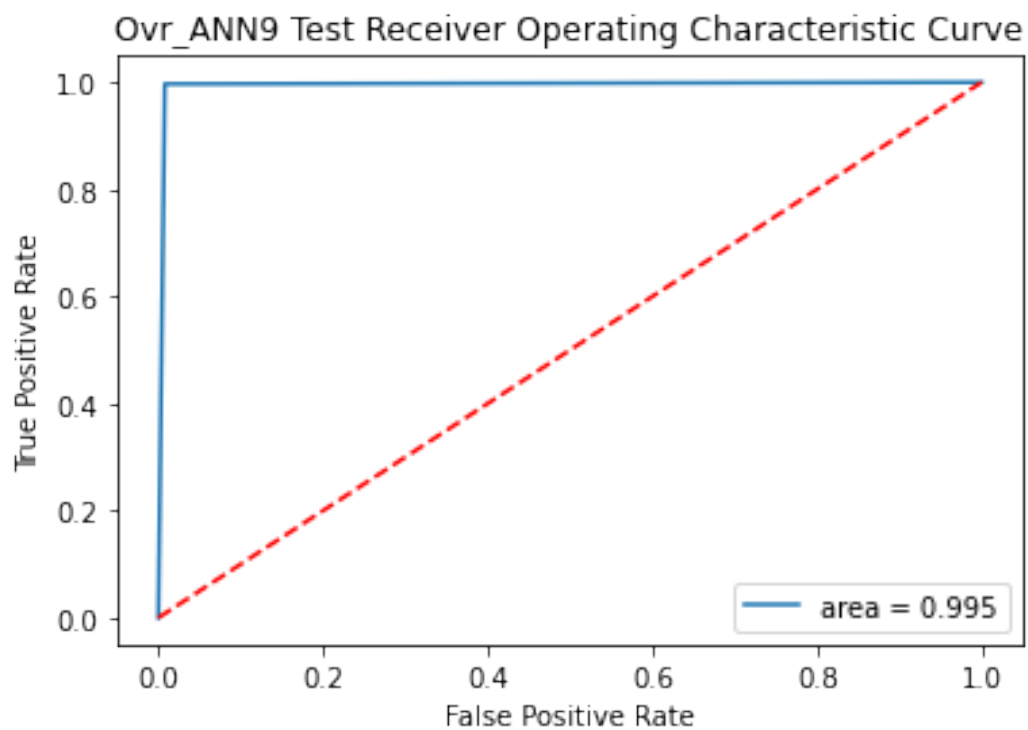
Test confusion matrix: Ovr_ANN9



roc auc score train 0.9951299854780935



roc auc score test 0.9945797324066564



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9923106632491837

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	1.00	56864
1	0.17	0.88	0.28	98
accuracy			0.99	56962
macro avg	0.58	0.94	0.64	56962
weighted avg	1.00	0.99	0.99	56962

Completed and saved for model Ovr_ANN9

```
buildANN(4, 256, 'relu', 'he_normal', 'l2', 'adam', 30, 10,  
'Ovr_ANN10', 0.3)
```

Model: "model_31"

Layer (type)	Output Shape	Param #
input_39 (InputLayer)	[(None, 30)]	0
dense_174 (Dense)	(None, 256)	7936
dense_175 (Dense)	(None, 128)	32896
dense_176 (Dense)	(None, 64)	8256
dense_177 (Dense)	(None, 32)	2080
dropout_11 (Dropout)	(None, 32)	0
batch_normalization_11 (Batch Normalization)	(None, 32)	128
dense_178 (Dense)	(None, 10)	330
dense_179 (Dense)	(None, 2)	22

Total params: 51,648

Trainable params: 51,584

Non-trainable params: 64

None

Epoch 1/10

12054/12054 [=====] - 48s 4ms/step - loss:

```

0.2785 - f1_score: 0.9837 - val_loss: 0.0701 - val_f1_score: 0.9936
Epoch 2/10
12054/12054 [=====] - 46s 4ms/step - loss:
0.0757 - f1_score: 0.9908 - val_loss: 0.0623 - val_f1_score: 0.9935
Epoch 3/10
12054/12054 [=====] - 44s 4ms/step - loss:
0.0738 - f1_score: 0.9913 - val_loss: 0.0630 - val_f1_score: 0.9950
Epoch 4/10
12054/12054 [=====] - 44s 4ms/step - loss:
0.0745 - f1_score: 0.9911 - val_loss: 0.0798 - val_f1_score: 0.9928
Epoch 5/10
12054/12054 [=====] - 45s 4ms/step - loss:
0.0773 - f1_score: 0.9906 - val_loss: 0.0589 - val_f1_score: 0.9961
Epoch 6/10
12054/12054 [=====] - 45s 4ms/step - loss:
0.0754 - f1_score: 0.9911 - val_loss: 0.0708 - val_f1_score: 0.9931
Epoch 7/10
12054/12054 [=====] - 45s 4ms/step - loss:
0.0724 - f1_score: 0.9915 - val_loss: 0.0623 - val_f1_score: 0.9945
Epoch 8/10
12054/12054 [=====] - 46s 4ms/step - loss:
0.0689 - f1_score: 0.9920 - val_loss: 0.0666 - val_f1_score: 0.9934
11301/11301 [=====] - 19s 2ms/step
2826/2826 [=====] - 5s 2ms/step

```

Model performance Ovr_ANN10

```

accuracy score train 0.9938080923448773
accuracy score test 0.9933629052775965

```

Train classification report: Ovr_ANN10

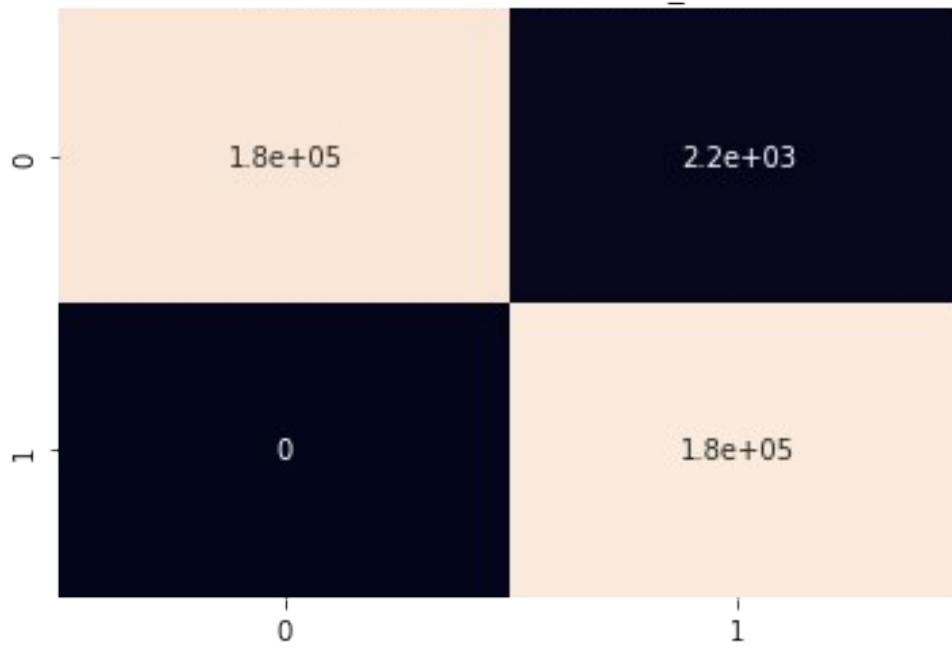
	precision	recall	f1-score	support
0	1.00	0.99	0.99	180800
1	0.99	1.00	0.99	180801
accuracy			0.99	361601
macro avg	0.99	0.99	0.99	361601
weighted avg	0.99	0.99	0.99	361601

Test classification report: Ovr_ANN10

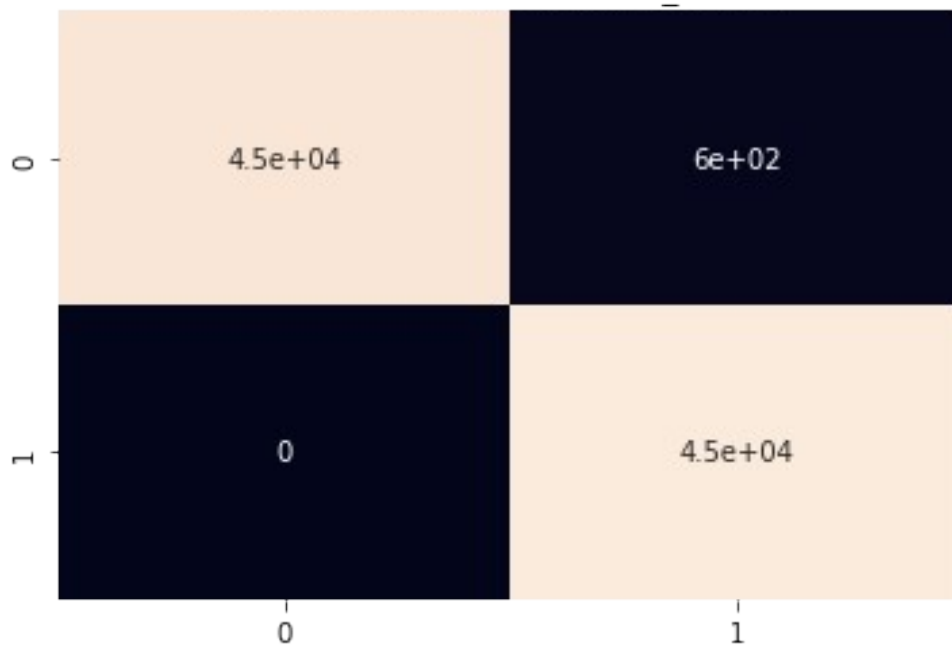
	precision	recall	f1-score	support
0	1.00	0.99	0.99	45201
1	0.99	1.00	0.99	45200

accuracy			0.99	90401
macro avg	0.99	0.99	0.99	90401
weighted avg	0.99	0.99	0.99	90401

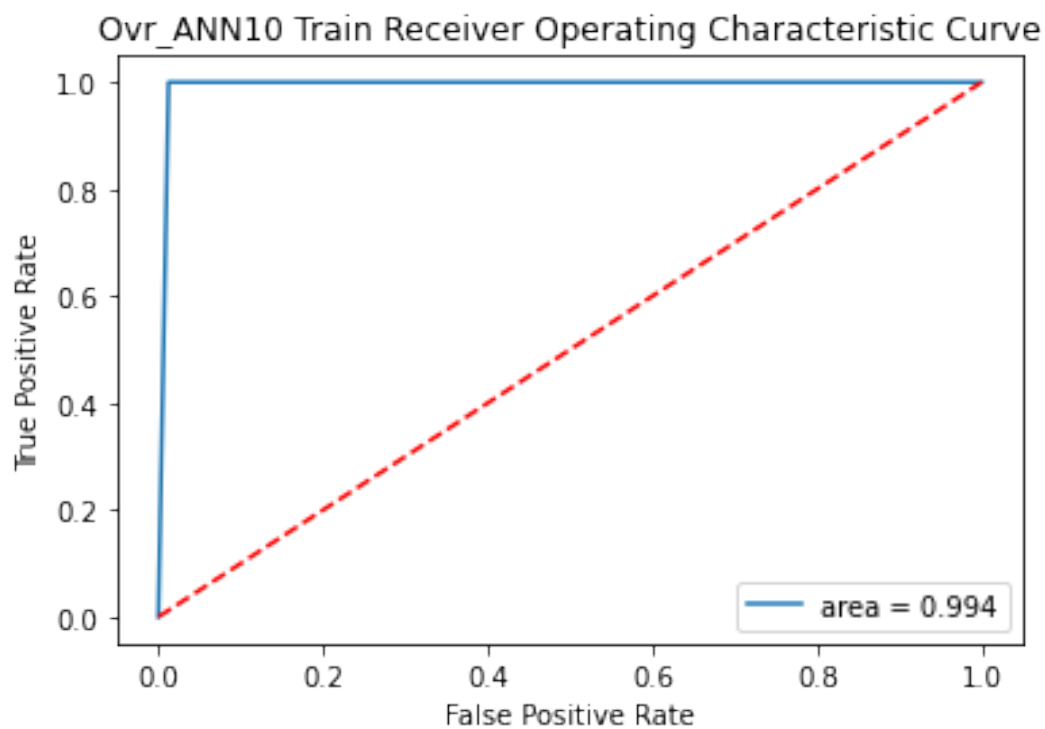
Train confusion matrix: Ovr_ANN10



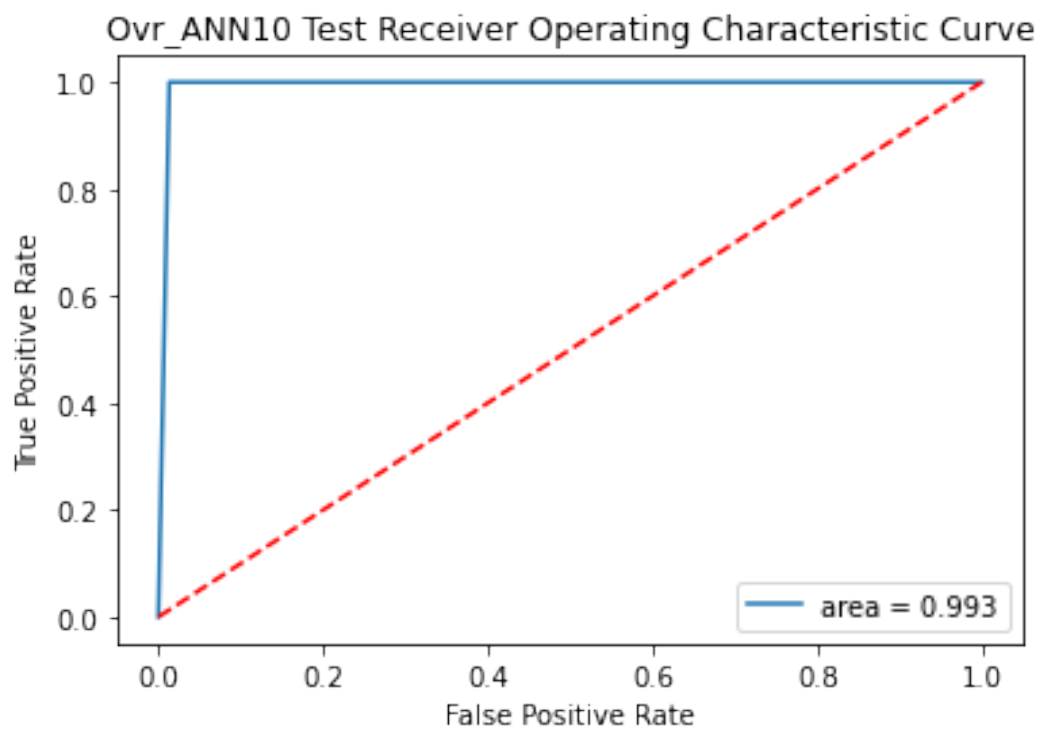
Test confusion matrix: Ovr_ANN10



roc auc score train 0.9938080752212389



roc auc score test 0.9933629786951615



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9870088831150592

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	56864
1	0.11	0.88	0.19	98
accuracy			0.99	56962
macro avg	0.55	0.93	0.59	56962
weighted avg	1.00	0.99	0.99	56962

Completed and saved for model Ovr_ANN10

```
buildANN(3, 128, 'relu', 'he_normal', 'l2', 'adam', 30, 10,  
'Ovr_ANN11')
```

Model: "model_32"

Layer (type)	Output Shape	Param #
input_40 (InputLayer)	[(None, 30)]	0
dense_180 (Dense)	(None, 128)	3968
dense_181 (Dense)	(None, 64)	8256
dense_182 (Dense)	(None, 32)	2080
dense_183 (Dense)	(None, 10)	330
dense_184 (Dense)	(None, 2)	22

=====
Total params: 14,656

Trainable params: 14,656

Non-trainable params: 0

None

Epoch 1/10

12054/12054 [=====] - 41s 3ms/step - loss:
0.2486 - f1_score: 0.9825 - val_loss: 0.0913 - val_f1_score: 0.9913

Epoch 2/10

12054/12054 [=====] - 37s 3ms/step - loss:
0.0810 - f1_score: 0.9921 - val_loss: 0.0717 - val_f1_score: 0.9944

Epoch 3/10

```

12054/12054 [=====] - 35s 3ms/step - loss:
0.0712 - f1_score: 0.9934 - val_loss: 0.0669 - val_f1_score: 0.9944
Epoch 4/10
12054/12054 [=====] - 35s 3ms/step - loss:
0.0656 - f1_score: 0.9941 - val_loss: 0.0598 - val_f1_score: 0.9965
Epoch 5/10
12054/12054 [=====] - 35s 3ms/step - loss:
0.0627 - f1_score: 0.9944 - val_loss: 0.0682 - val_f1_score: 0.9940
Epoch 6/10
12054/12054 [=====] - 35s 3ms/step - loss:
0.0599 - f1_score: 0.9946 - val_loss: 0.0574 - val_f1_score: 0.9944
Epoch 7/10
12054/12054 [=====] - 38s 3ms/step - loss:
0.0589 - f1_score: 0.9945 - val_loss: 0.0519 - val_f1_score: 0.9958
Epoch 8/10
12054/12054 [=====] - 37s 3ms/step - loss:
0.0574 - f1_score: 0.9944 - val_loss: 0.0614 - val_f1_score: 0.9925
Epoch 9/10
12054/12054 [=====] - 35s 3ms/step - loss:
0.0557 - f1_score: 0.9947 - val_loss: 0.0558 - val_f1_score: 0.9933
Epoch 10/10
12054/12054 [=====] - 35s 3ms/step - loss:
0.0558 - f1_score: 0.9945 - val_loss: 0.0633 - val_f1_score: 0.9964
11301/11301 [=====] - 17s 1ms/step
2826/2826 [=====] - 4s 1ms/step

```

Model performance Ovr_ANN11

```

accuracy score train 0.9966675977112895
accuracy score test 0.9963938452008274

```

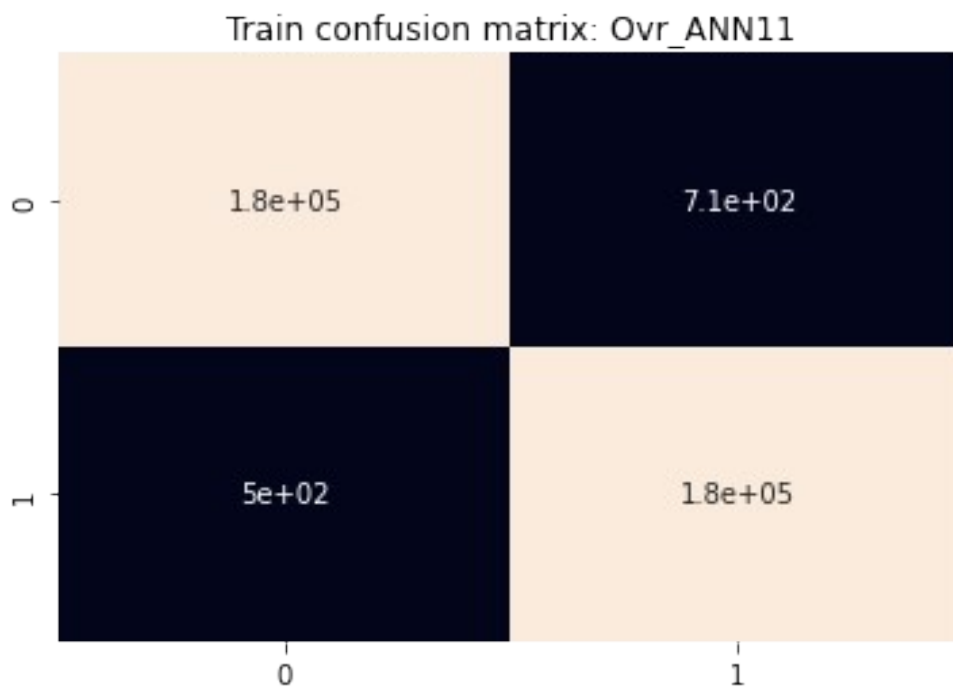
Train classification report: Ovr_ANN11

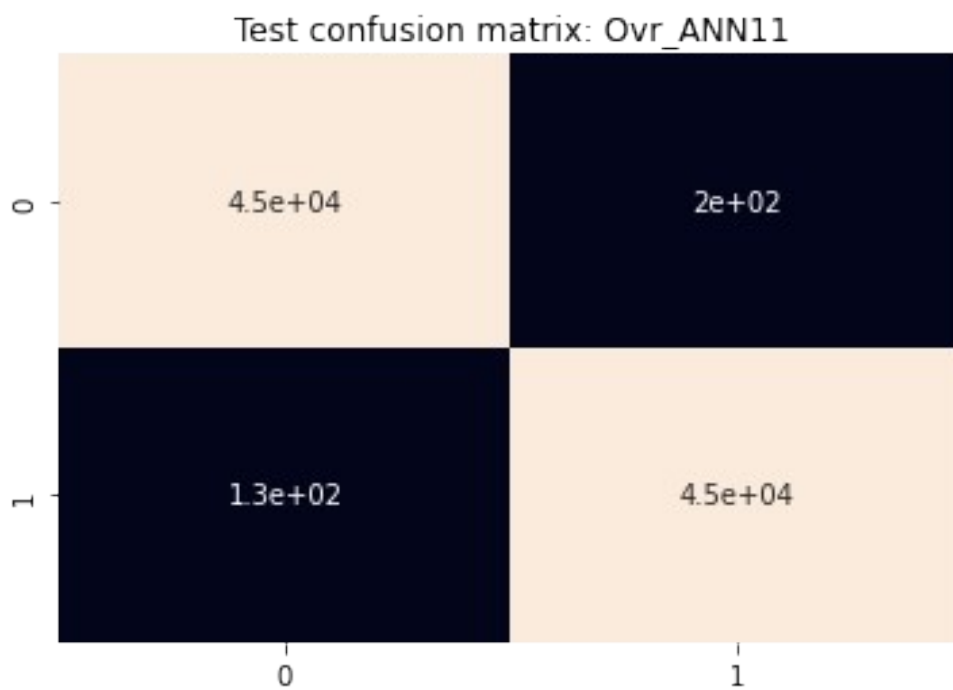
	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	1.00	1.00	1.00	180801
accuracy			1.00	361601
macro avg	1.00	1.00	1.00	361601
weighted avg	1.00	1.00	1.00	361601

Test classification report: Ovr_ANN11

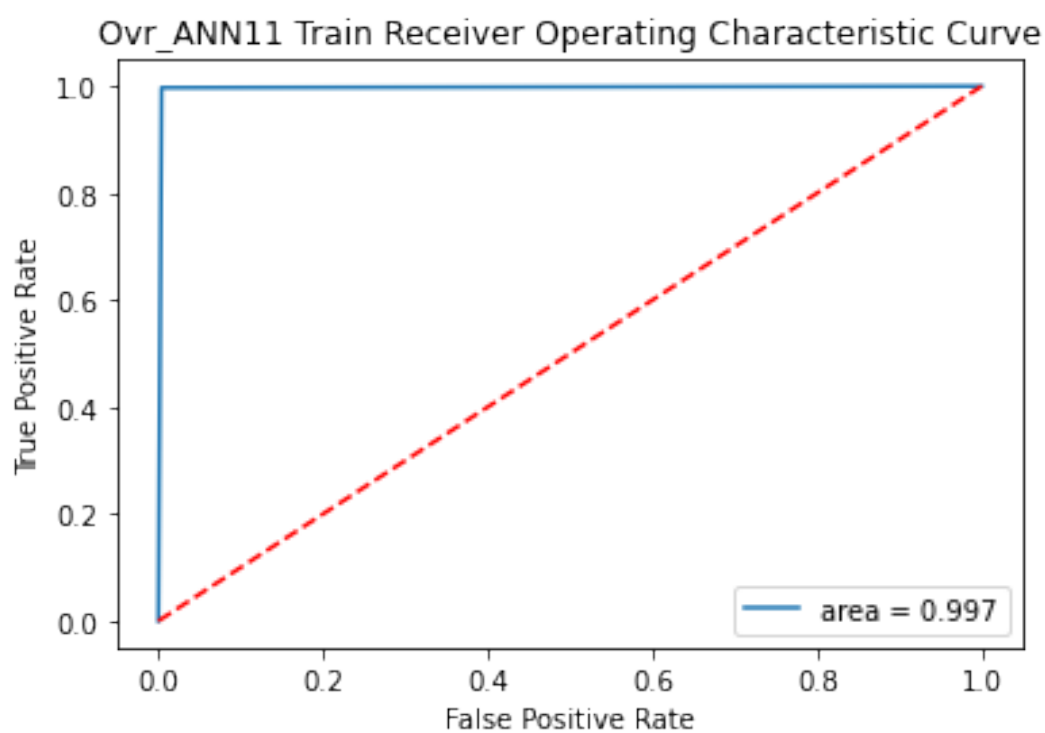
	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	1.00	1.00	1.00	45200

accuracy			1.00	90401
macro avg	1.00	1.00	1.00	90401
weighted avg	1.00	1.00	1.00	90401

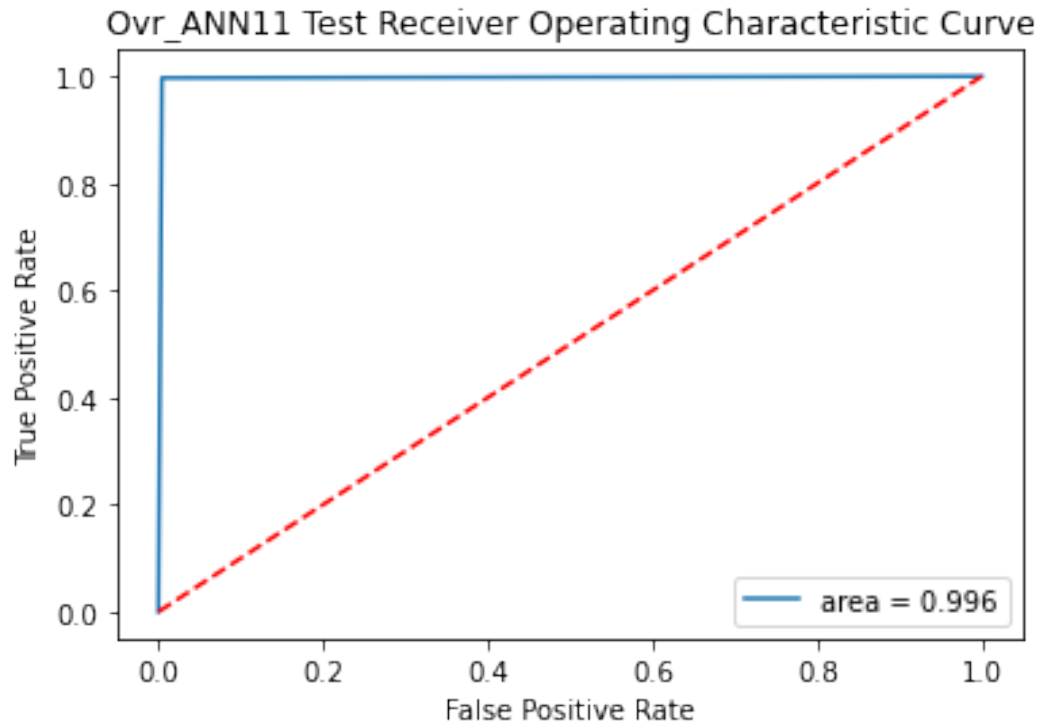




roc auc score train 0.9966675961128583



roc auc score test 0.9963938530316798



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9957339981039992

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.27	0.88	0.41	98
accuracy			1.00	56962
macro avg	0.64	0.94	0.71	56962
weighted avg	1.00	1.00	1.00	56962

Completed and saved for model Ovr_ANN11

We can select the model that gave higher macro f1-score on the test data. Model Ovr_ANN11 gave the best result till now (F1score macro= 0.71). So the number of layers and number of neurons mostly matters. Also its the optimizer that helps to get better performance.

So till now get the best result with 3 layers, (128, 64, 32) neurons respectively, relu activation, he_normal kernel initializer, l2 regularizer, adam optimizer, 30 batch size, 10 epochs.

The number of neurons also should be suitable for the input dimension.

Now we can try few models with undersampled data.

Undersampled data

```
finance_udr_train = pd.read_pickle('finance_udr_train.pkl')
finance_test = pd.read_pickle('finance_test.pkl')

train_udr_X = finance_udr_train.drop(['Class'], axis=1)
train_udr_y = finance_udr_train[['Class']]

test_X = finance_test.drop(['Class'], axis=1)
test_y = finance_test[['Class']]

x_train, x_test, y_train, y_test = train_test_split(train_udr_X,
train_udr_y,

stratify= train_udr_y,

test_size= 0.2, random_state= 0)

y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
test_y = to_categorical(test_y)

print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
print(test_X.shape)
print(test_y.shape)

(904, 30)
(904, 2)
(227, 30)
(227, 2)
(56962, 30)
(56962, 2)

ANN with undersampled data
buildANN(3, 128, 'relu', 'he_normal', 'l2', 'sgd', 30, 10, 'Udr_ANN1')

Model: "model_33"
```

Layer (type)	Output Shape	Param #
input_41 (InputLayer)	[(None, 30)]	0
dense_185 (Dense)	(None, 128)	3968
dense_186 (Dense)	(None, 64)	8256

dense_187 (Dense)	(None, 32)	2080
dense_188 (Dense)	(None, 10)	330
dense_189 (Dense)	(None, 2)	22

```

=====
Total params: 14,656
Trainable params: 14,656
Non-trainable params: 0

```

```

None
Epoch 1/10
31/31 [=====] - 1s 12ms/step - loss: 5.4097 -
f1_score: 0.4001 - val_loss: 5.2262 - val_f1_score: 0.3995
Epoch 2/10
31/31 [=====] - 0s 4ms/step - loss: 5.1789 -
f1_score: 0.4001 - val_loss: 5.1380 - val_f1_score: 0.3995
Epoch 3/10
31/31 [=====] - 0s 3ms/step - loss: 5.0930 -
f1_score: 0.4001 - val_loss: 5.0564 - val_f1_score: 0.3995
Epoch 4/10
31/31 [=====] - 0s 3ms/step - loss: 5.0094 -
f1_score: 0.4001 - val_loss: 4.9748 - val_f1_score: 0.3995
Epoch 5/10
31/31 [=====] - 0s 3ms/step - loss: 4.9277 -
f1_score: 0.4001 - val_loss: 4.8984 - val_f1_score: 0.3995
Epoch 6/10
31/31 [=====] - 0s 3ms/step - loss: 4.8461 -
f1_score: 0.4001 - val_loss: 4.8288 - val_f1_score: 0.3995
Epoch 7/10
31/31 [=====] - 0s 3ms/step - loss: 4.7681 -
f1_score: 0.4001 - val_loss: 4.7674 - val_f1_score: 0.3995
Epoch 8/10
31/31 [=====] - 0s 3ms/step - loss: 4.6935 -
f1_score: 0.7848 - val_loss: 4.6859 - val_f1_score: 0.9047
Epoch 9/10
31/31 [=====] - 0s 3ms/step - loss: 4.6200 -
f1_score: 0.9098 - val_loss: 4.6234 - val_f1_score: 0.8932
Epoch 10/10
31/31 [=====] - 0s 4ms/step - loss: 4.5514 -
f1_score: 0.9169 - val_loss: 4.5559 - val_f1_score: 0.9104
29/29 [=====] - 0s 2ms/step
8/8 [=====] - 0s 2ms/step

```

Model performance Udr_ANN1

```

accuracy score train 0.9314159292035398
accuracy score test 0.9251101321585903

```


Train classification report: Udr_ANN1

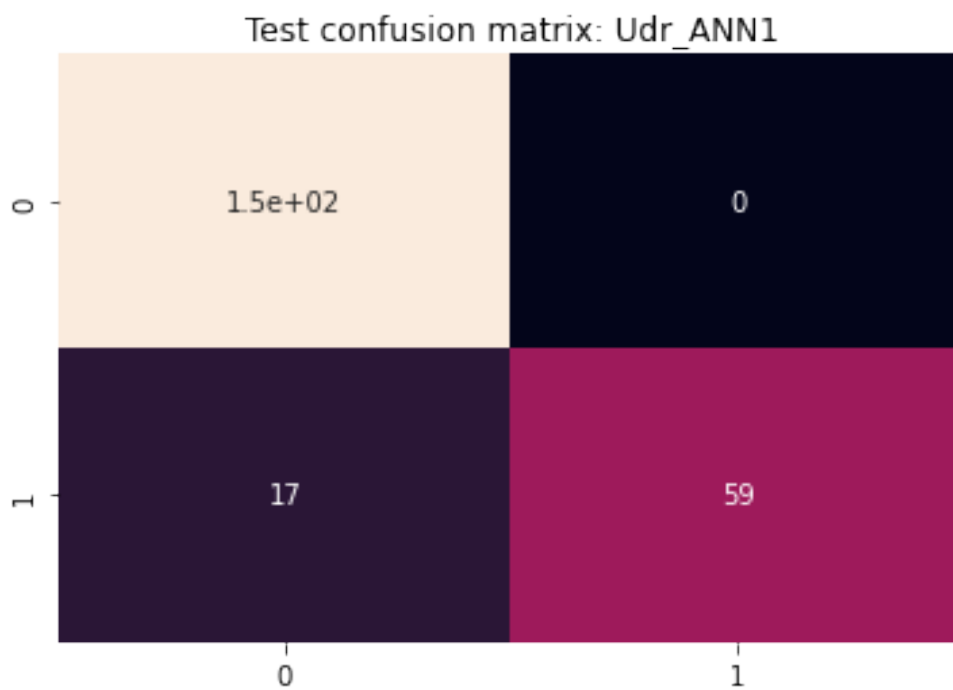
	precision	recall	f1-score	support
0	0.91	1.00	0.95	603
1	1.00	0.80	0.89	301
accuracy			0.93	904
macro avg	0.95	0.90	0.92	904
weighted avg	0.94	0.93	0.93	904

Test classification report: Udr_ANN1

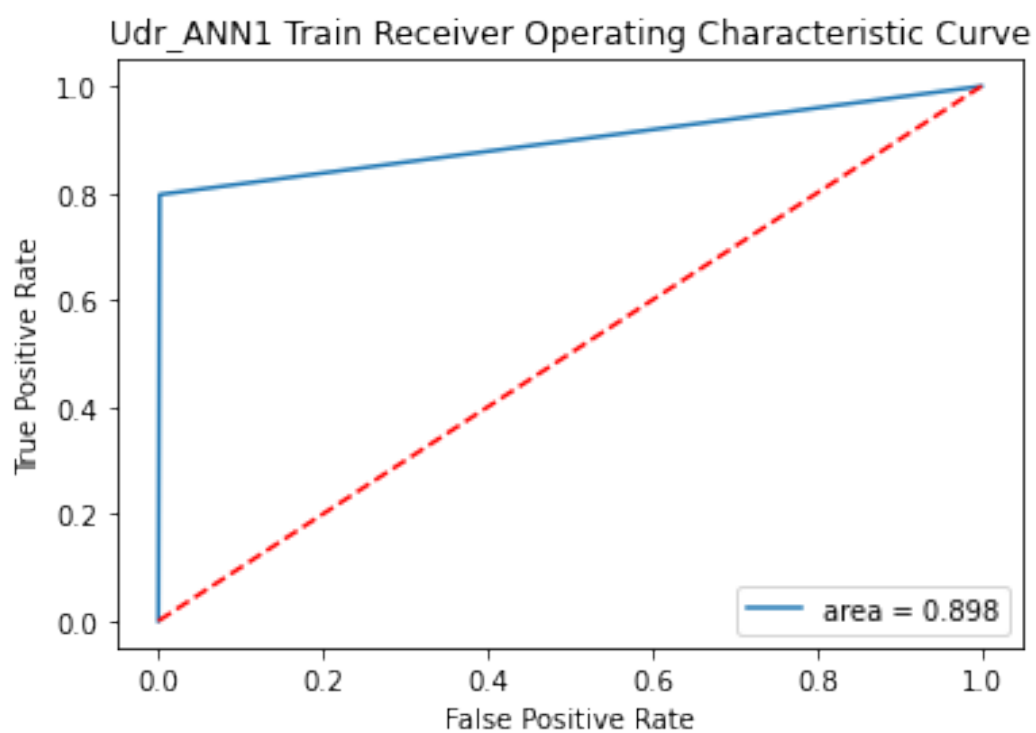
	precision	recall	f1-score	support
0	0.90	1.00	0.95	151
1	1.00	0.78	0.87	76
accuracy			0.93	227
macro avg	0.95	0.89	0.91	227
weighted avg	0.93	0.93	0.92	227

Train confusion matrix: Udr_ANN1

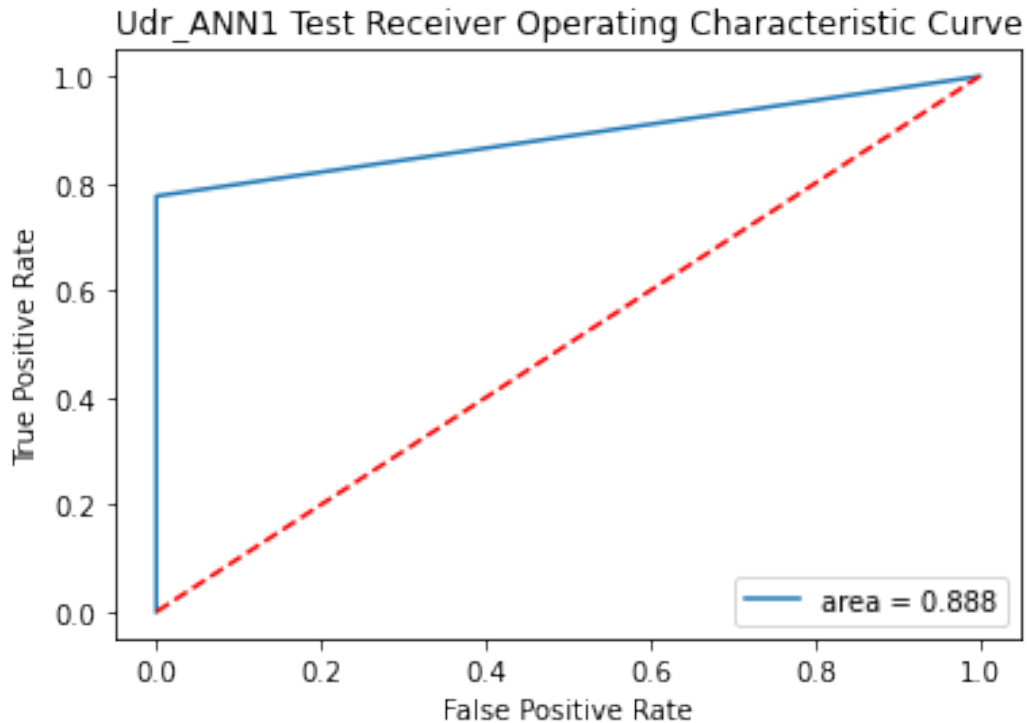




roc auc score train 0.8978419089491633



roc auc score test 0.888157894736842



1781/1781 [=====] - 3s 1ms/step

Test accuracy score 0.9979284435237527

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.44	0.71	0.54	98
accuracy			1.00	56962
macro avg	0.72	0.86	0.77	56962
weighted avg	1.00	1.00	1.00	56962

Completed and saved for model Udr_ANN1

```
buildANN(3, 128, 'relu', 'he_uniform', 'l2', 'adadelata', 30, 10,
'Udr_ANN2', 0.2)
```

Model: "model_34"

Layer (type)	Output Shape	Param #
input_42 (InputLayer)	[(None, 30)]	0

dense_190 (Dense)	(None, 128)	3968
dense_191 (Dense)	(None, 64)	8256
dense_192 (Dense)	(None, 32)	2080
dropout_12 (Dropout)	(None, 32)	0
batch_normalization_12 (Batch Normalization)	(None, 32)	128
dense_193 (Dense)	(None, 10)	330
dense_194 (Dense)	(None, 2)	22

```

=====
Total params: 14,784
Trainable params: 14,720
Non-trainable params: 64

```

```

None
Epoch 1/10
31/31 [=====] - 2s 13ms/step - loss: 5.3775 -
f1_score: 0.5585 - val_loss: 5.4278 - val_f1_score: 0.2914
Epoch 2/10
31/31 [=====] - 0s 4ms/step - loss: 5.3913 -
f1_score: 0.5718 - val_loss: 5.3019 - val_f1_score: 0.4803
Epoch 3/10
31/31 [=====] - 0s 4ms/step - loss: 5.3885 -
f1_score: 0.5638 - val_loss: 5.2665 - val_f1_score: 0.5845
Epoch 4/10
31/31 [=====] - 0s 4ms/step - loss: 5.3936 -
f1_score: 0.5658 - val_loss: 5.2557 - val_f1_score: 0.6431
Epoch 5/10
31/31 [=====] - 0s 4ms/step - loss: 5.3787 -
f1_score: 0.5796 - val_loss: 5.2520 - val_f1_score: 0.6644
Epoch 6/10
31/31 [=====] - 0s 4ms/step - loss: 5.3890 -
f1_score: 0.5660 - val_loss: 5.2516 - val_f1_score: 0.6641
Epoch 7/10
31/31 [=====] - 0s 4ms/step - loss: 5.3780 -
f1_score: 0.5701 - val_loss: 5.2525 - val_f1_score: 0.6722
Epoch 8/10
31/31 [=====] - 0s 4ms/step - loss: 5.3834 -
f1_score: 0.5658 - val_loss: 5.2552 - val_f1_score: 0.6675
Epoch 9/10
31/31 [=====] - 0s 4ms/step - loss: 5.3770 -
f1_score: 0.5835 - val_loss: 5.2573 - val_f1_score: 0.6670
29/29 [=====] - 0s 2ms/step
8/8 [=====] - 0s 2ms/step

```

Model performance Udr_ANN2

accuracy score train 0.6570796460176991

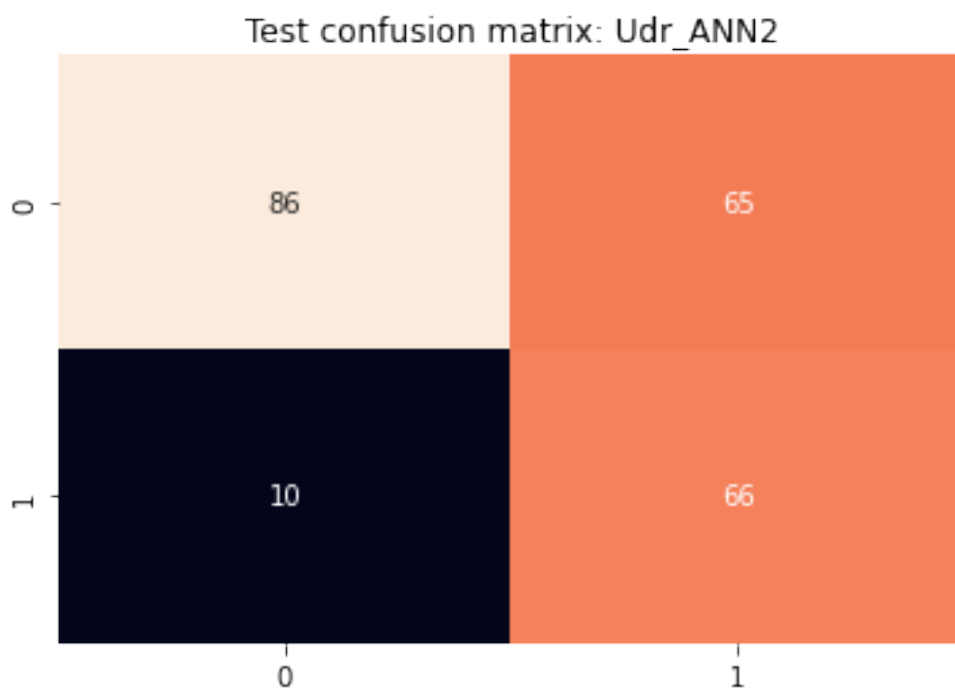
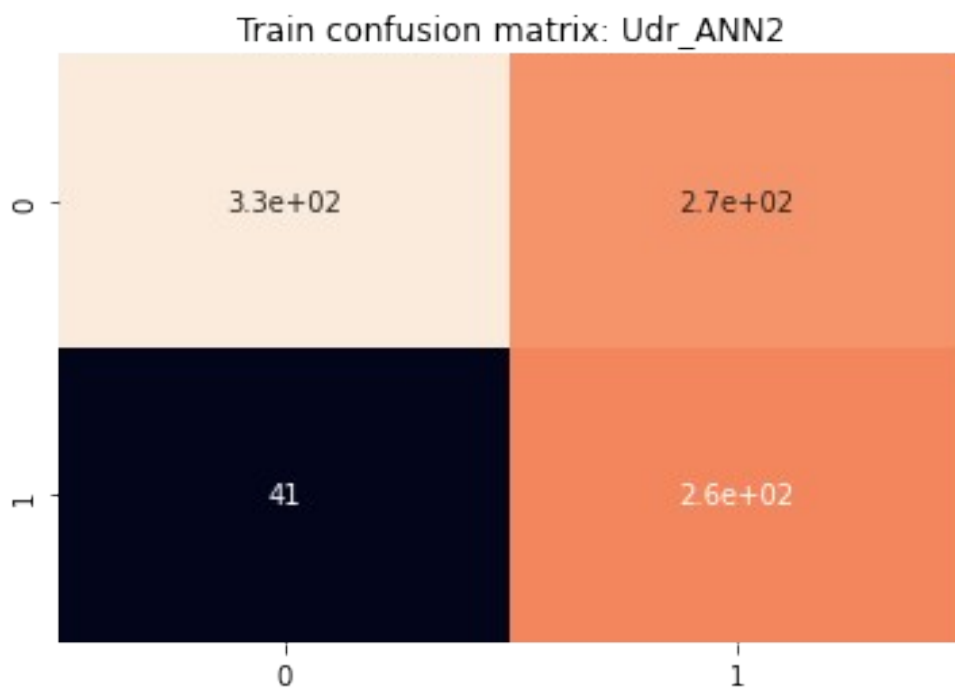
accuracy score test 0.6696035242290749

Train classification report: Udr_ANN2

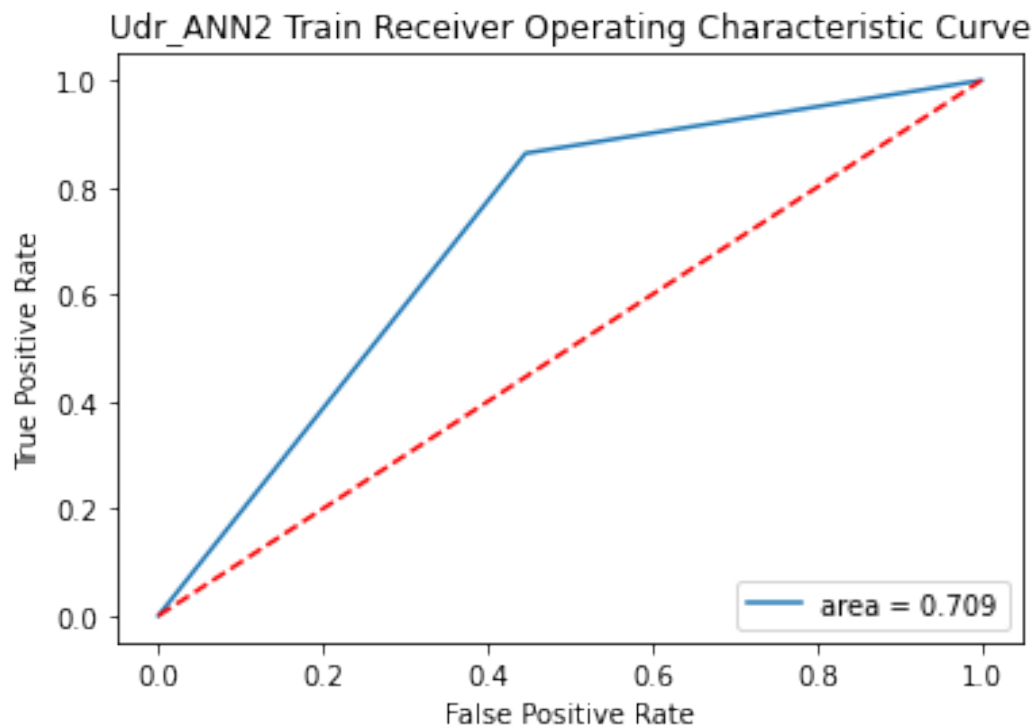
	precision	recall	f1-score	support
0	0.89	0.55	0.68	603
1	0.49	0.86	0.63	301
accuracy			0.66	904
macro avg	0.69	0.71	0.65	904
weighted avg	0.76	0.66	0.66	904

Test classification report: Udr_ANN2

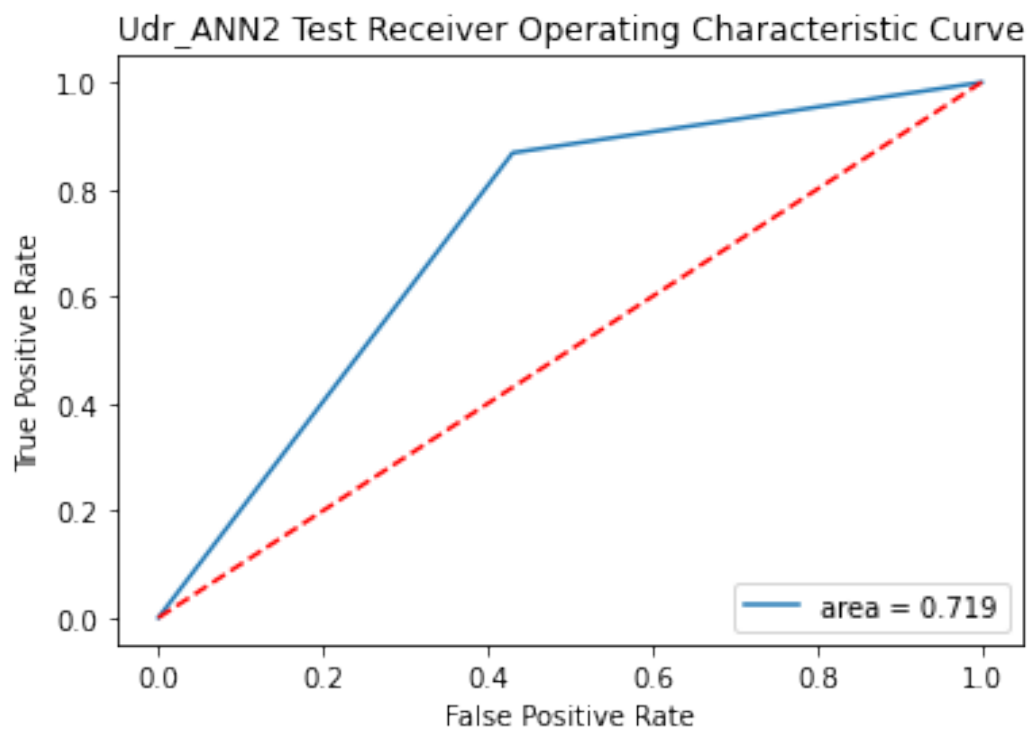
	precision	recall	f1-score	support
0	0.90	0.57	0.70	151
1	0.50	0.87	0.64	76
accuracy			0.67	227
macro avg	0.70	0.72	0.67	227
weighted avg	0.76	0.67	0.68	227



roc auc score train 0.7088422780890673



roc auc score test 0.7189787382363193



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.5401320178364524

Classification report

	precision	recall	f1-score	support
0	1.00	0.54	0.70	56864
1	0.00	0.83	0.01	98
accuracy			0.54	56962
macro avg	0.50	0.68	0.35	56962
weighted avg	1.00	0.54	0.70	56962

Completed and saved for model Udr_ANN2

```
buildANN(3, 128, 'relu', 'he_normal', 'l2', 'rmsprop', 30, 10, 'Udr_ANN3')
```

Model: "model_35"

Layer (type)	Output Shape	Param #
input_43 (InputLayer)	[(None, 30)]	0
dense_195 (Dense)	(None, 128)	3968
dense_196 (Dense)	(None, 64)	8256
dense_197 (Dense)	(None, 32)	2080
dense_198 (Dense)	(None, 10)	330
dense_199 (Dense)	(None, 2)	22

Total params: 14,656

Trainable params: 14,656

Non-trainable params: 0

None

Epoch 1/10

31/31 [=====] - 1s 12ms/step - loss: 4.6311 - f1_score: 0.8010 - val_loss: 4.0685 - val_f1_score: 0.9336

Epoch 2/10

31/31 [=====] - 0s 3ms/step - loss: 3.7022 - f1_score: 0.9410 - val_loss: 3.3467 - val_f1_score: 0.9341

Epoch 3/10

31/31 [=====] - 0s 4ms/step - loss: 3.0338 - f1_score: 0.9474 - val_loss: 2.7168 - val_f1_score: 0.9390


```

Epoch 4/10
31/31 [=====] - 0s 3ms/step - loss: 2.4700 -
f1_score: 0.9437 - val_loss: 2.2080 - val_f1_score: 0.9390
Epoch 5/10
31/31 [=====] - 0s 4ms/step - loss: 1.9993 -
f1_score: 0.9526 - val_loss: 1.7921 - val_f1_score: 0.9447
Epoch 6/10
31/31 [=====] - 0s 4ms/step - loss: 1.6236 -
f1_score: 0.9541 - val_loss: 1.4544 - val_f1_score: 0.9447
Epoch 7/10
31/31 [=====] - 0s 3ms/step - loss: 1.3098 -
f1_score: 0.9581 - val_loss: 1.1835 - val_f1_score: 0.9447
Epoch 8/10
31/31 [=====] - 0s 4ms/step - loss: 1.0586 -
f1_score: 0.9644 - val_loss: 0.9876 - val_f1_score: 0.9303
Epoch 9/10
31/31 [=====] - 0s 5ms/step - loss: 0.8678 -
f1_score: 0.9605 - val_loss: 0.8091 - val_f1_score: 0.9447
Epoch 10/10
31/31 [=====] - 0s 4ms/step - loss: 0.7142 -
f1_score: 0.9581 - val_loss: 0.6705 - val_f1_score: 0.9447
29/29 [=====] - 0s 1ms/step
8/8 [=====] - 0s 2ms/step

```

Model performance Udr_ANN3

```

accuracy score train 0.9701327433628318
accuracy score test 0.9515418502202643

```

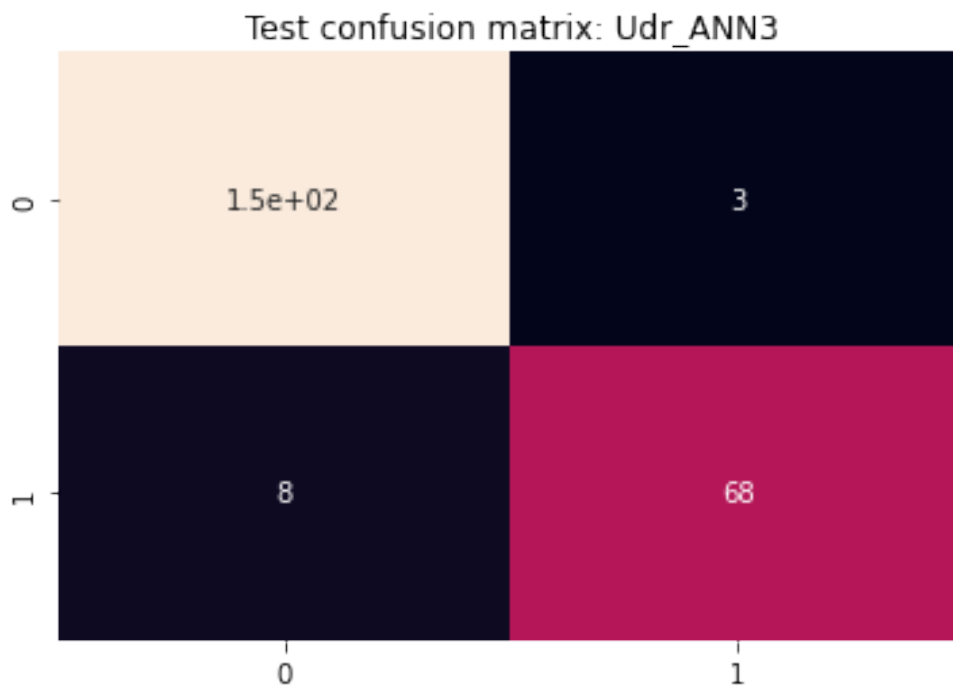
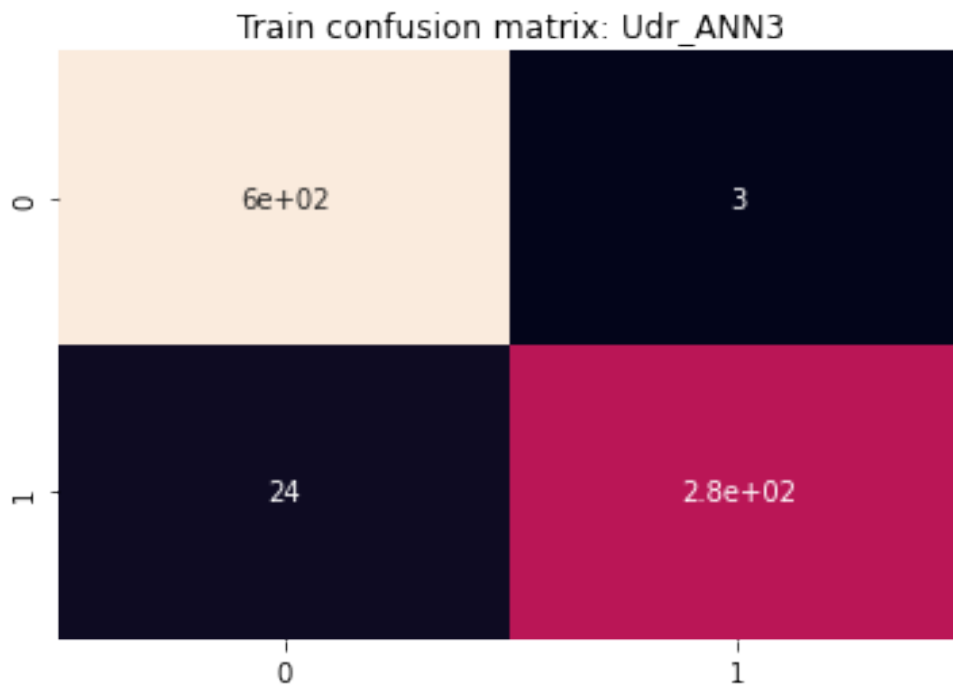
Train classification report: Udr_ANN3

	precision	recall	f1-score	support
0	0.96	1.00	0.98	603
1	0.99	0.92	0.95	301
accuracy			0.97	904
macro avg	0.98	0.96	0.97	904
weighted avg	0.97	0.97	0.97	904

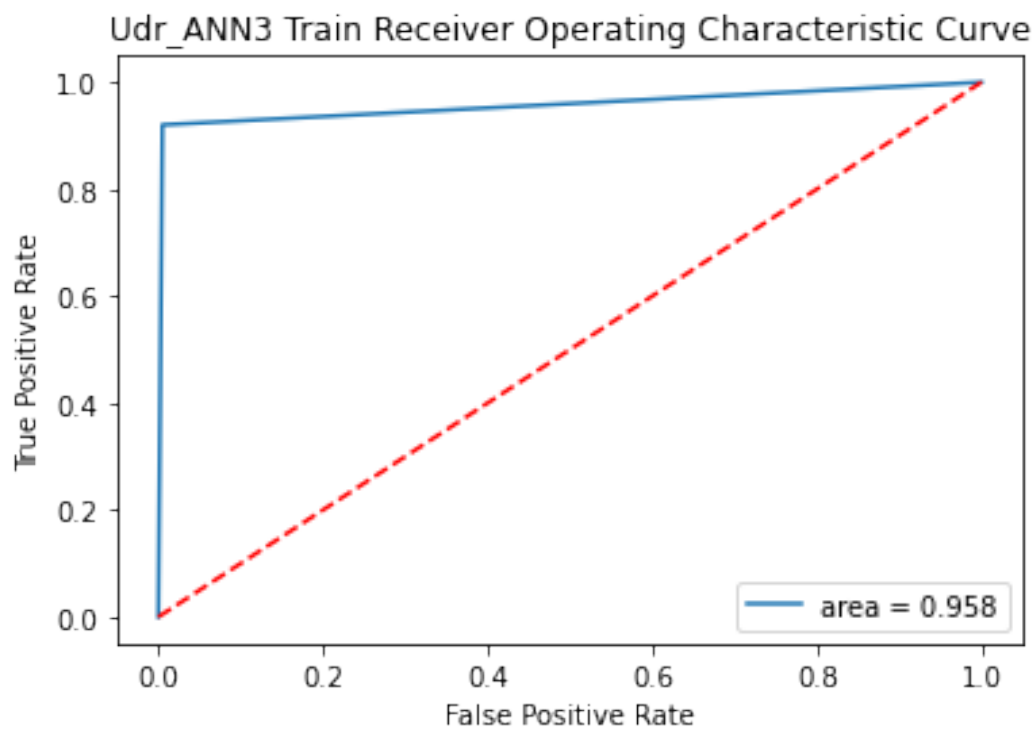
Test classification report: Udr_ANN3

	precision	recall	f1-score	support
0	0.95	0.98	0.96	151
1	0.96	0.89	0.93	76
accuracy			0.95	227

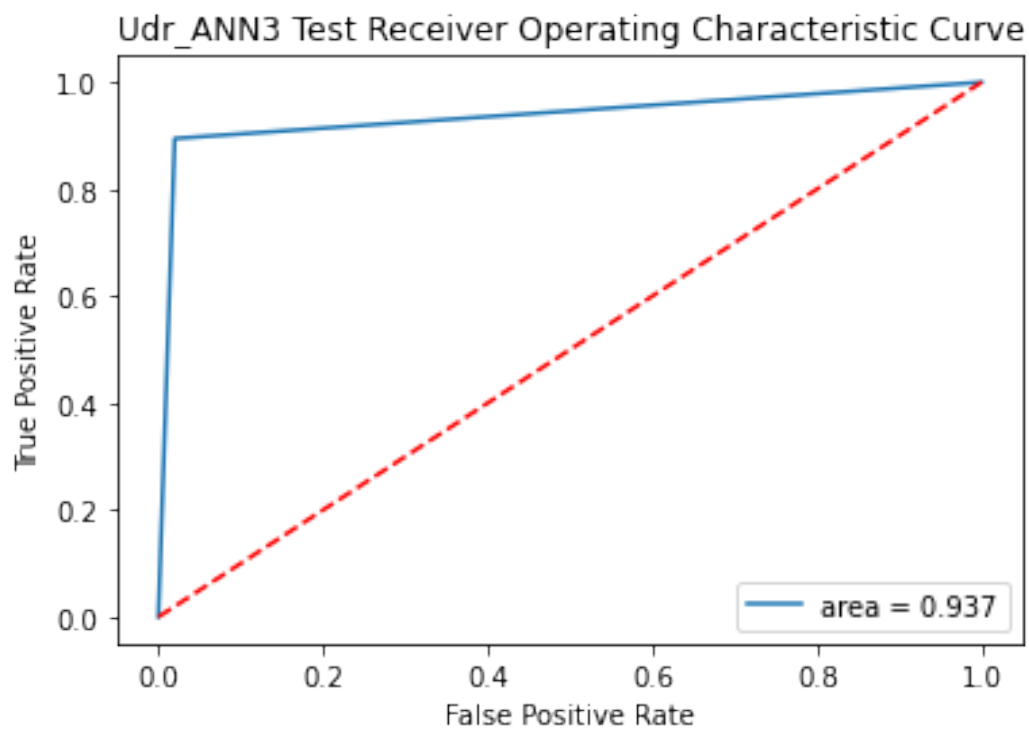
macro avg	0.95	0.94	0.94	227
weighted avg	0.95	0.95	0.95	227



roc auc score train 0.9576453281763938



roc auc score test 0.9374346462181945



1781/1781 [=====] - 3s 1ms/step

Test accuracy score 0.9858151048067132

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	56864
1	0.10	0.87	0.17	98
accuracy			0.99	56962
macro avg	0.55	0.93	0.58	56962
weighted avg	1.00	0.99	0.99	56962

Completed and saved for model Udr_ANN3

```
buildANN(3, 128, 'relu', 'he_normal', 'l1', 'rmsprop', 40, 10, 'Udr_ANN4')
```

Model: "model_36"

Layer (type)	Output Shape	Param #
input_44 (InputLayer)	[(None, 30)]	0
dense_200 (Dense)	(None, 128)	3968
dense_201 (Dense)	(None, 64)	8256
dense_202 (Dense)	(None, 32)	2080
dense_203 (Dense)	(None, 10)	330
dense_204 (Dense)	(None, 2)	22

=====
Total params: 14,656

Trainable params: 14,656

Non-trainable params: 0

None

Epoch 1/10

23/23 [=====] - 1s 15ms/step - loss: 19.3082
- f1_score: 0.8279 - val_loss: 17.7791 - val_f1_score: 0.9341

Epoch 2/10

23/23 [=====] - 0s 4ms/step - loss: 16.7145 -
f1_score: 0.9356 - val_loss: 15.5046 - val_f1_score: 0.9385

Epoch 3/10

```

23/23 [=====] - 0s 4ms/step - loss: 14.4683 -
f1_score: 0.9340 - val_loss: 13.3429 - val_f1_score: 0.9434
Epoch 4/10
23/23 [=====] - 0s 5ms/step - loss: 12.3721 -
f1_score: 0.9418 - val_loss: 11.3592 - val_f1_score: 0.9390
Epoch 5/10
23/23 [=====] - 0s 4ms/step - loss: 10.5088 -
f1_score: 0.9417 - val_loss: 9.6300 - val_f1_score: 0.9390
Epoch 6/10
23/23 [=====] - 0s 4ms/step - loss: 8.8789 -
f1_score: 0.9407 - val_loss: 8.1111 - val_f1_score: 0.9390
Epoch 7/10
23/23 [=====] - 0s 4ms/step - loss: 7.4636 -
f1_score: 0.9448 - val_loss: 6.7906 - val_f1_score: 0.9390
Epoch 8/10
23/23 [=====] - 0s 4ms/step - loss: 6.2296 -
f1_score: 0.9460 - val_loss: 5.6514 - val_f1_score: 0.9390
Epoch 9/10
23/23 [=====] - 0s 4ms/step - loss: 5.1736 -
f1_score: 0.9406 - val_loss: 4.6817 - val_f1_score: 0.9390
Epoch 10/10
23/23 [=====] - 0s 5ms/step - loss: 4.2913 -
f1_score: 0.9418 - val_loss: 3.8814 - val_f1_score: 0.9390
29/29 [=====] - 0s 1ms/step
8/8 [=====] - 0s 2ms/step

```

Model performance Udr_ANN4

```

accuracy score train 0.9557522123893806
accuracy score test 0.947136563876652

```

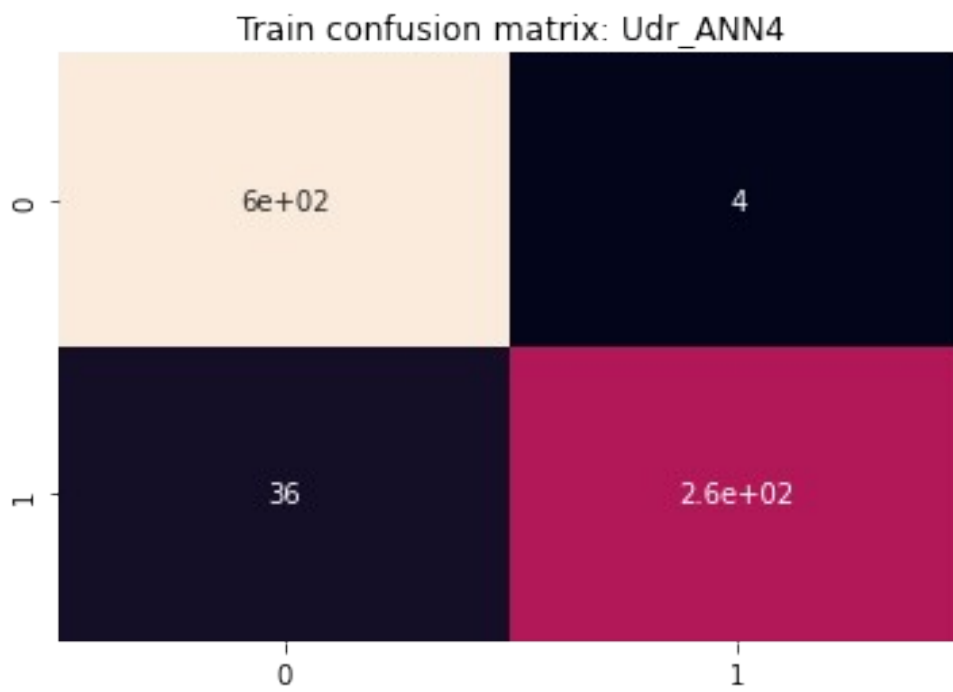
Train classification report: Udr_ANN4

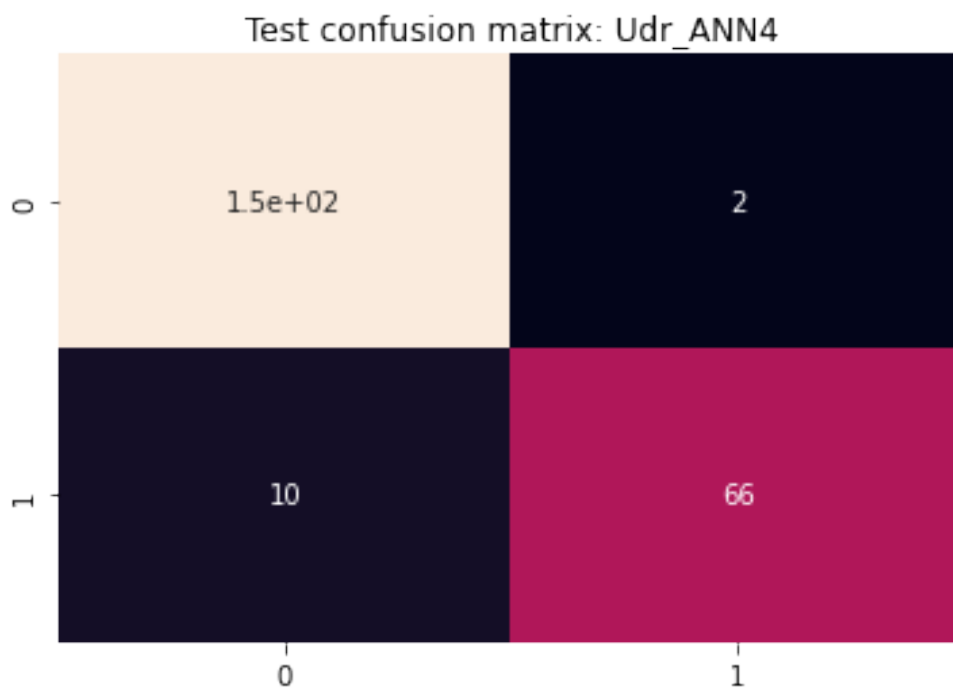
	precision	recall	f1-score	support
0	0.94	0.99	0.97	603
1	0.99	0.88	0.93	301
accuracy			0.96	904
macro avg	0.96	0.94	0.95	904
weighted avg	0.96	0.96	0.96	904

Test classification report: Udr_ANN4

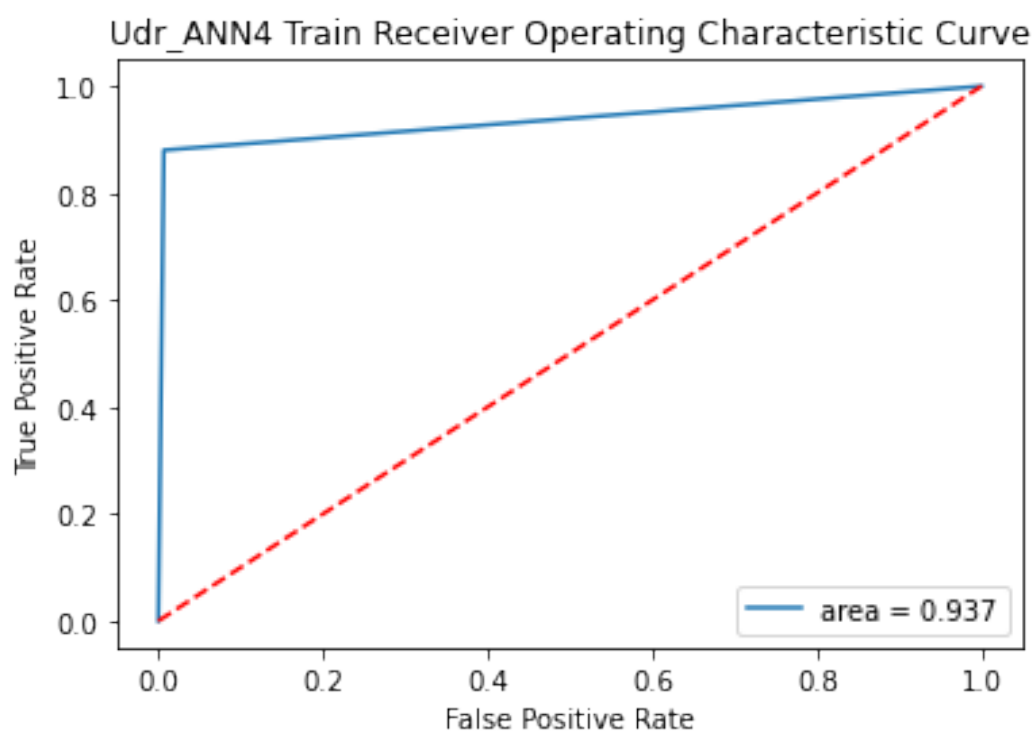
	precision	recall	f1-score	support
0	0.94	0.99	0.96	151
1	0.97	0.87	0.92	76

accuracy			0.95	227
macro avg	0.95	0.93	0.94	227
weighted avg	0.95	0.95	0.95	227

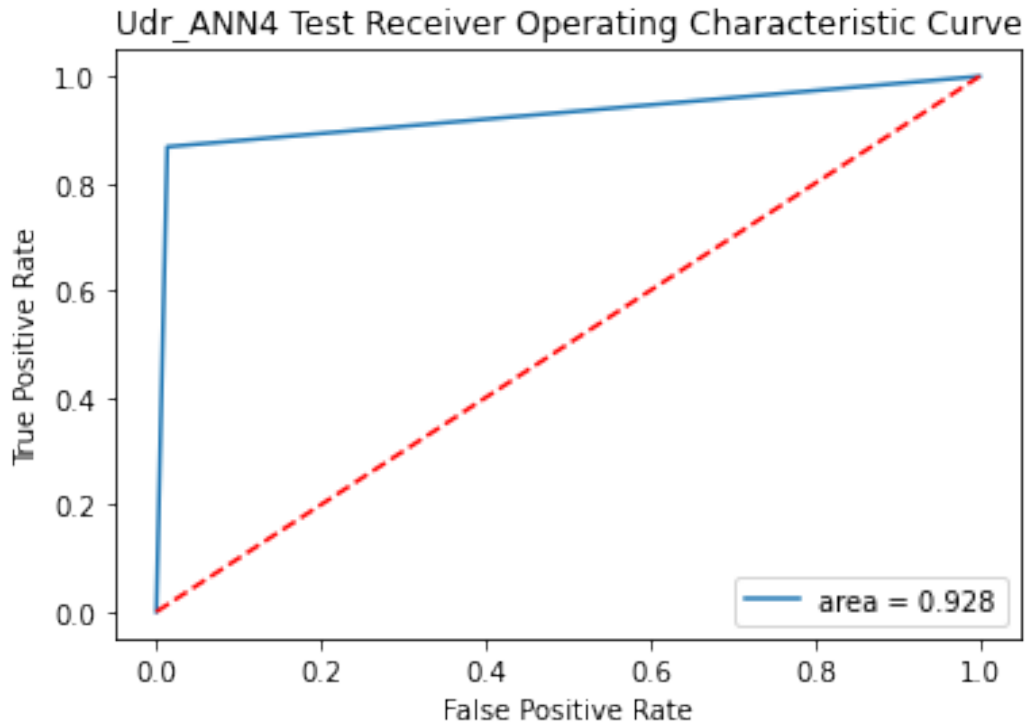




roc auc score train 0.9368825859627665



roc auc score test 0.9275880097594982



1781/1781 [=====] - 3s 1ms/step

Test accuracy score 0.9876584389593062

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	56864
1	0.11	0.84	0.19	98
accuracy			0.99	56962
macro avg	0.55	0.91	0.59	56962
weighted avg	1.00	0.99	0.99	56962

Completed and saved for model Udr_ANN4

buildANN(3, 128, 'relu', 'he_normal', 'l2', 'adam', 30, 10, 'Udr_ANN5')

Model: "model_37"

Layer (type)	Output Shape	Param #
input_45 (InputLayer)	[(None, 30)]	0

dense_205 (Dense)	(None, 128)	3968
dense_206 (Dense)	(None, 64)	8256
dense_207 (Dense)	(None, 32)	2080
dense_208 (Dense)	(None, 10)	330
dense_209 (Dense)	(None, 2)	22

```

=====
Total params: 14,656
Trainable params: 14,656
Non-trainable params: 0

```

```

None
Epoch 1/10
31/31 [=====] - 1s 12ms/step - loss: 4.8078 -
f1_score: 0.8938 - val_loss: 4.3735 - val_f1_score: 0.9390
Epoch 2/10
31/31 [=====] - 0s 4ms/step - loss: 4.0840 -
f1_score: 0.9441 - val_loss: 3.8031 - val_f1_score: 0.9390
Epoch 3/10
31/31 [=====] - 0s 4ms/step - loss: 3.5507 -
f1_score: 0.9544 - val_loss: 3.3117 - val_f1_score: 0.9443
Epoch 4/10
31/31 [=====] - 0s 4ms/step - loss: 3.0805 -
f1_score: 0.9605 - val_loss: 2.8854 - val_f1_score: 0.9443
Epoch 5/10
31/31 [=====] - 0s 4ms/step - loss: 2.6728 -
f1_score: 0.9605 - val_loss: 2.5073 - val_f1_score: 0.9491
Epoch 6/10
31/31 [=====] - 0s 4ms/step - loss: 2.3267 -
f1_score: 0.9619 - val_loss: 2.1998 - val_f1_score: 0.9443
Epoch 7/10
31/31 [=====] - 0s 4ms/step - loss: 2.0173 -
f1_score: 0.9621 - val_loss: 1.9312 - val_f1_score: 0.9491
Epoch 8/10
31/31 [=====] - 0s 4ms/step - loss: 1.7644 -
f1_score: 0.9633 - val_loss: 1.6844 - val_f1_score: 0.9443
Epoch 9/10
31/31 [=====] - 0s 4ms/step - loss: 1.5358 -
f1_score: 0.9658 - val_loss: 1.4827 - val_f1_score: 0.9491
Epoch 10/10
31/31 [=====] - 0s 4ms/step - loss: 1.3435 -
f1_score: 0.9671 - val_loss: 1.3004 - val_f1_score: 0.9443
29/29 [=====] - 0s 2ms/step
8/8 [=====] - 0s 2ms/step

```

Model performance Udr_ANN5

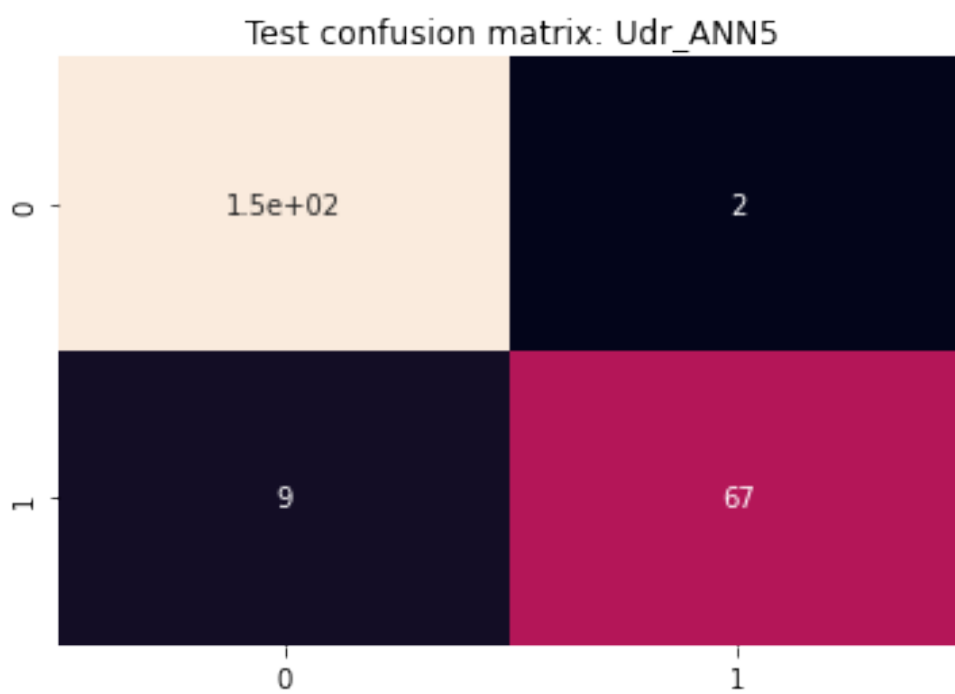
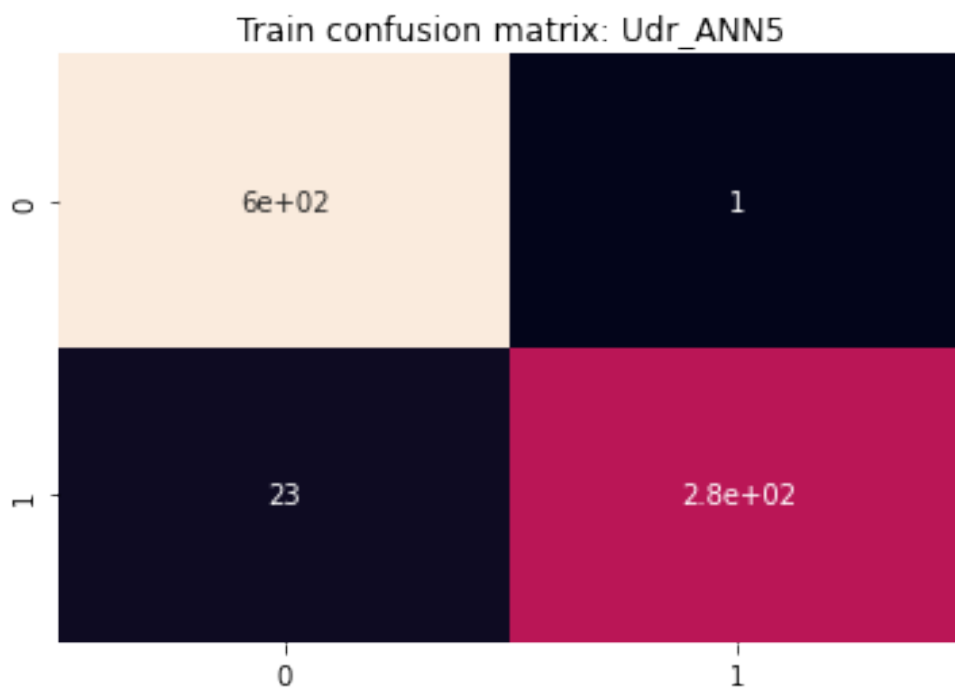
accuracy score train 0.9734513274336283
accuracy score test 0.9515418502202643

Train classification report: Udr_ANN5

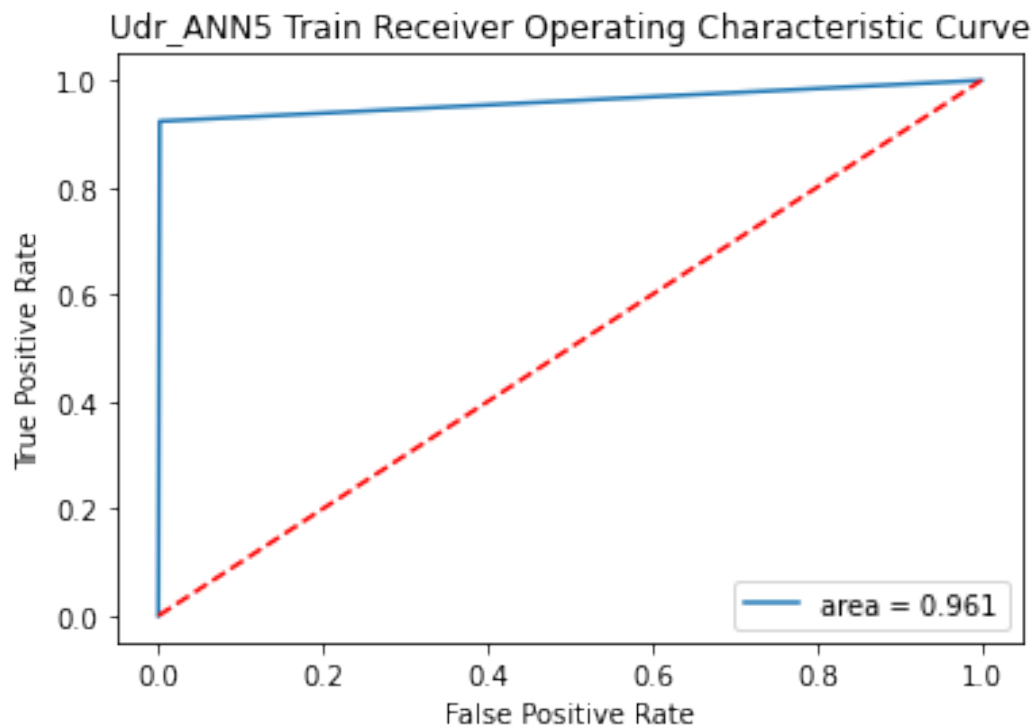
	precision	recall	f1-score	support
0	0.96	1.00	0.98	603
1	1.00	0.92	0.96	301
accuracy			0.97	904
macro avg	0.98	0.96	0.97	904
weighted avg	0.97	0.97	0.97	904

Test classification report: Udr_ANN5

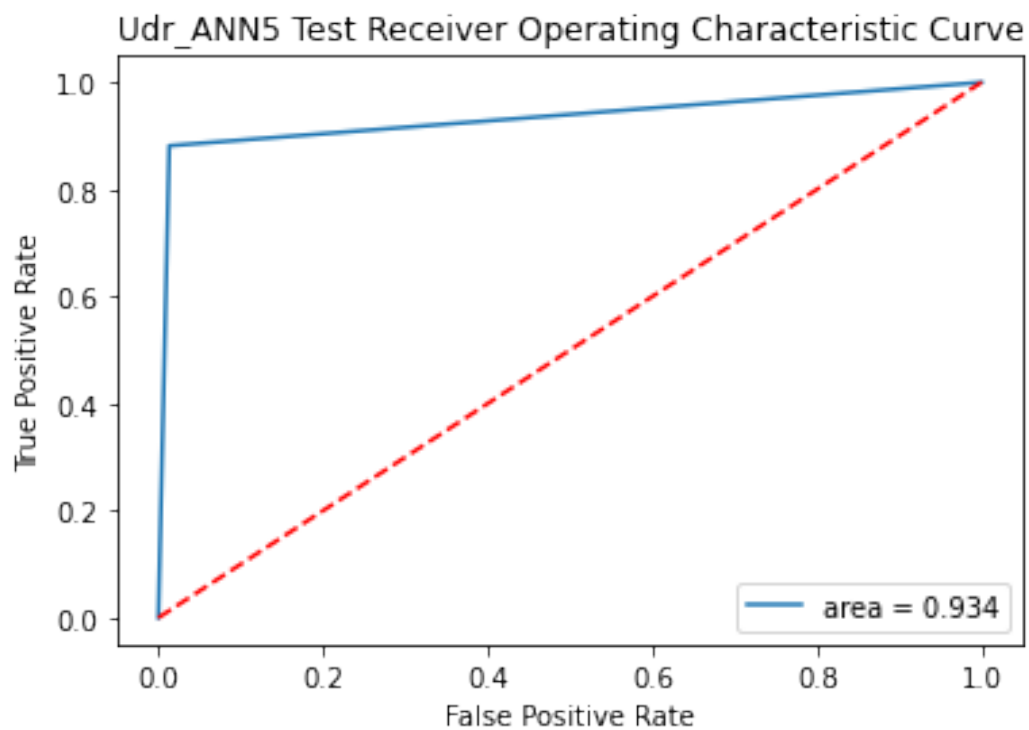
	precision	recall	f1-score	support
0	0.94	0.99	0.96	151
1	0.97	0.88	0.92	76
accuracy			0.95	227
macro avg	0.96	0.93	0.94	227
weighted avg	0.95	0.95	0.95	227



roc auc score train 0.9609648325372033



roc auc score test 0.9341669571279192



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9893086619149608

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	56864
1	0.12	0.87	0.22	98
accuracy			0.99	56962
macro avg	0.56	0.93	0.61	56962
weighted avg	1.00	0.99	0.99	56962

Completed and saved for model Udr_ANN5

```
buildANN(3, 128, 'relu', 'he_normal', 'l2', 'adam', 40, 20,  
'Udr_ANN6', 0.2)
```

Model: "model_38"

Layer (type)	Output Shape	Param #
input_46 (InputLayer)	[(None, 30)]	0
dense_210 (Dense)	(None, 128)	3968
dense_211 (Dense)	(None, 64)	8256
dense_212 (Dense)	(None, 32)	2080
dropout_13 (Dropout)	(None, 32)	0
batch_normalization_13 (Batch Normalization)	(None, 32)	128
dense_213 (Dense)	(None, 10)	330
dense_214 (Dense)	(None, 2)	22

Total params: 14,784

Trainable params: 14,720

Non-trainable params: 64

None

Epoch 1/20

23/23 [=====] - 1s 18ms/step - loss: 5.0495 -

f1_score: 0.7302 - val_loss: 4.7523 - val_f1_score: 0.8971

Epoch 2/20

23/23 [=====] - 0s 5ms/step - loss: 4.5570 -
f1_score: 0.9019 - val_loss: 4.3585 - val_f1_score: 0.9443
Epoch 3/20
23/23 [=====] - 0s 5ms/step - loss: 4.1544 -
f1_score: 0.9327 - val_loss: 3.9809 - val_f1_score: 0.9390
Epoch 4/20
23/23 [=====] - 0s 5ms/step - loss: 3.8134 -
f1_score: 0.9341 - val_loss: 3.6527 - val_f1_score: 0.9390
Epoch 5/20
23/23 [=====] - 0s 4ms/step - loss: 3.5031 -
f1_score: 0.9501 - val_loss: 3.3595 - val_f1_score: 0.9390
Epoch 6/20
23/23 [=====] - 0s 4ms/step - loss: 3.2158 -
f1_score: 0.9464 - val_loss: 3.0960 - val_f1_score: 0.9439
Epoch 7/20
23/23 [=====] - 0s 5ms/step - loss: 2.9510 -
f1_score: 0.9582 - val_loss: 2.8505 - val_f1_score: 0.9390
Epoch 8/20
23/23 [=====] - 0s 4ms/step - loss: 2.7148 -
f1_score: 0.9569 - val_loss: 2.6244 - val_f1_score: 0.9390
Epoch 9/20
23/23 [=====] - 0s 5ms/step - loss: 2.4912 -
f1_score: 0.9608 - val_loss: 2.4151 - val_f1_score: 0.9390
Epoch 10/20
23/23 [=====] - 0s 5ms/step - loss: 2.2849 -
f1_score: 0.9634 - val_loss: 2.2253 - val_f1_score: 0.9443
Epoch 11/20
23/23 [=====] - 0s 5ms/step - loss: 2.0902 -
f1_score: 0.9722 - val_loss: 2.0528 - val_f1_score: 0.9443
Epoch 12/20
23/23 [=====] - 0s 5ms/step - loss: 1.9234 -
f1_score: 0.9711 - val_loss: 1.8977 - val_f1_score: 0.9443
Epoch 13/20
23/23 [=====] - 0s 5ms/step - loss: 1.7654 -
f1_score: 0.9674 - val_loss: 1.7534 - val_f1_score: 0.9394
Epoch 14/20
23/23 [=====] - 0s 4ms/step - loss: 1.6299 -
f1_score: 0.9648 - val_loss: 1.6256 - val_f1_score: 0.9346
Epoch 15/20
23/23 [=====] - 0s 5ms/step - loss: 1.4813 -
f1_score: 0.9775 - val_loss: 1.5027 - val_f1_score: 0.9394
Epoch 16/20
23/23 [=====] - 0s 4ms/step - loss: 1.3544 -
f1_score: 0.9862 - val_loss: 1.3976 - val_f1_score: 0.9394
Epoch 17/20
23/23 [=====] - 0s 4ms/step - loss: 1.2577 -
f1_score: 0.9799 - val_loss: 1.3013 - val_f1_score: 0.9346
Epoch 18/20
23/23 [=====] - 0s 4ms/step - loss: 1.1614 -
f1_score: 0.9825 - val_loss: 1.2115 - val_f1_score: 0.9443

Epoch 19/20
 23/23 [=====] - 0s 4ms/step - loss: 1.0664 -
 f1_score: 0.9775 - val_loss: 1.1294 - val_f1_score: 0.9443
 Epoch 20/20
 23/23 [=====] - 0s 4ms/step - loss: 0.9909 -
 f1_score: 0.9788 - val_loss: 1.0726 - val_f1_score: 0.9346
 29/29 [=====] - 0s 2ms/step
 8/8 [=====] - 0s 2ms/step

Model performance Udr_ANN6

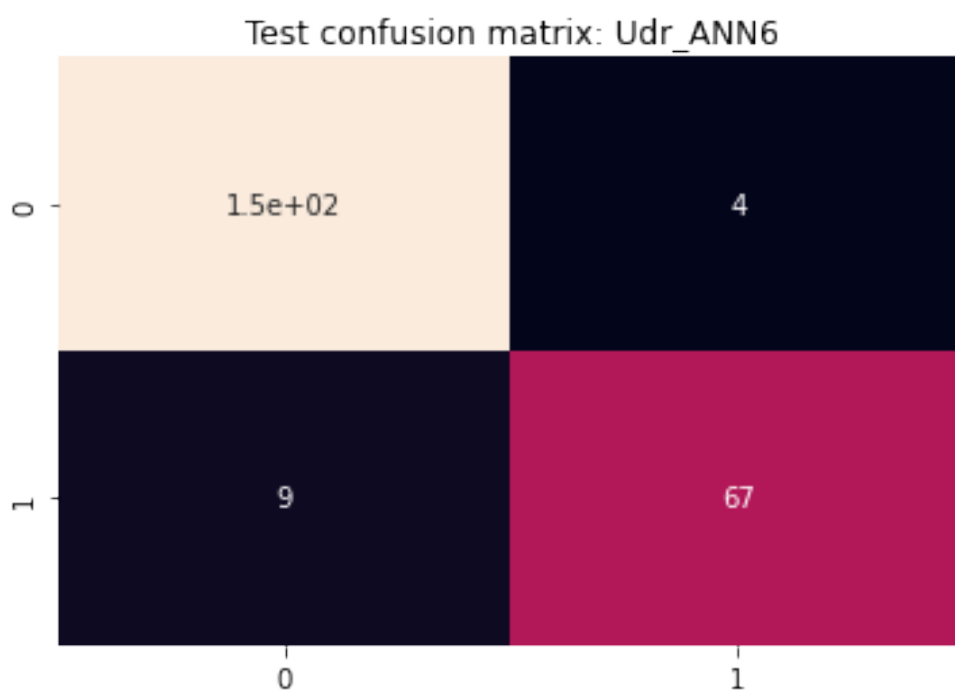
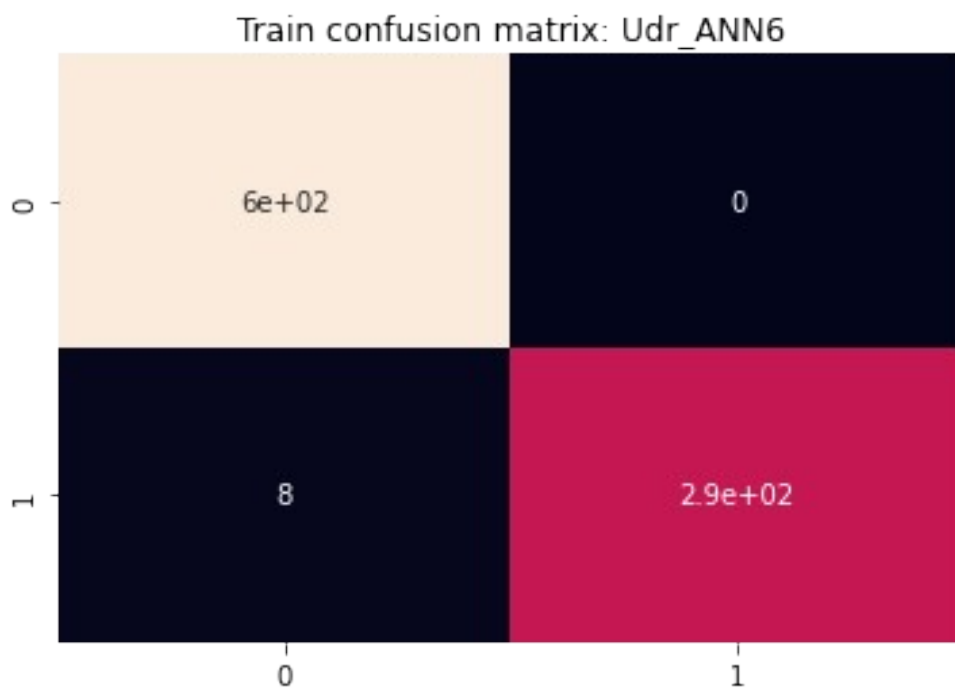
accuracy score train 0.9911504424778761
 accuracy score test 0.9427312775330396

Train classification report: Udr_ANN6

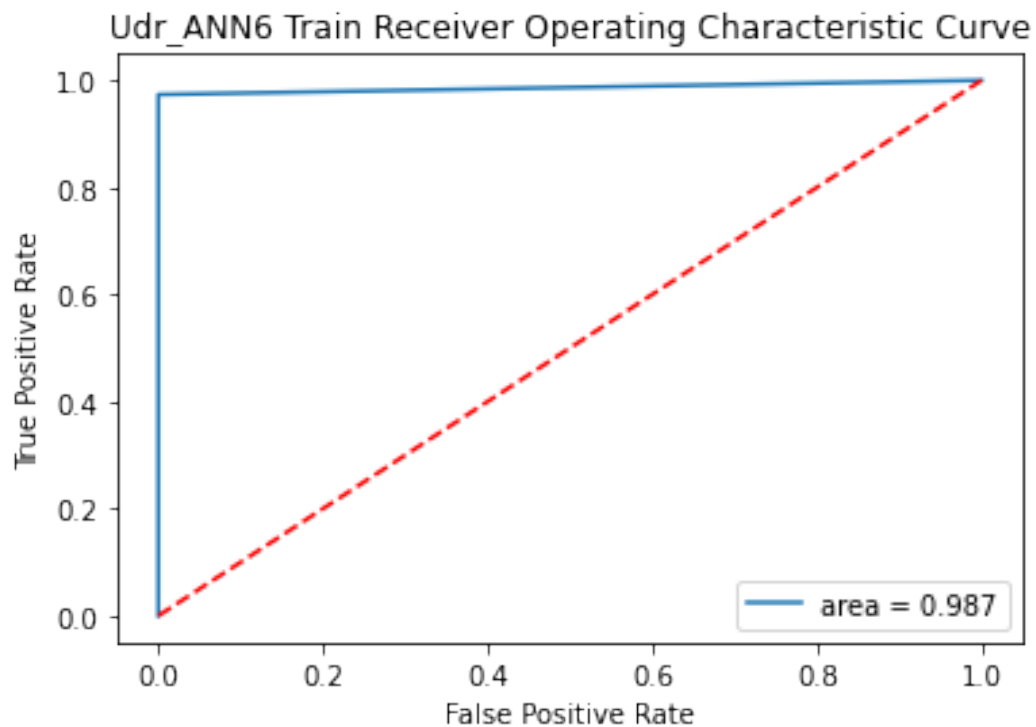
	precision	recall	f1-score	support
0	0.99	1.00	0.99	603
1	1.00	0.97	0.99	301
accuracy			0.99	904
macro avg	0.99	0.99	0.99	904
weighted avg	0.99	0.99	0.99	904

Test classification report: Udr_ANN6

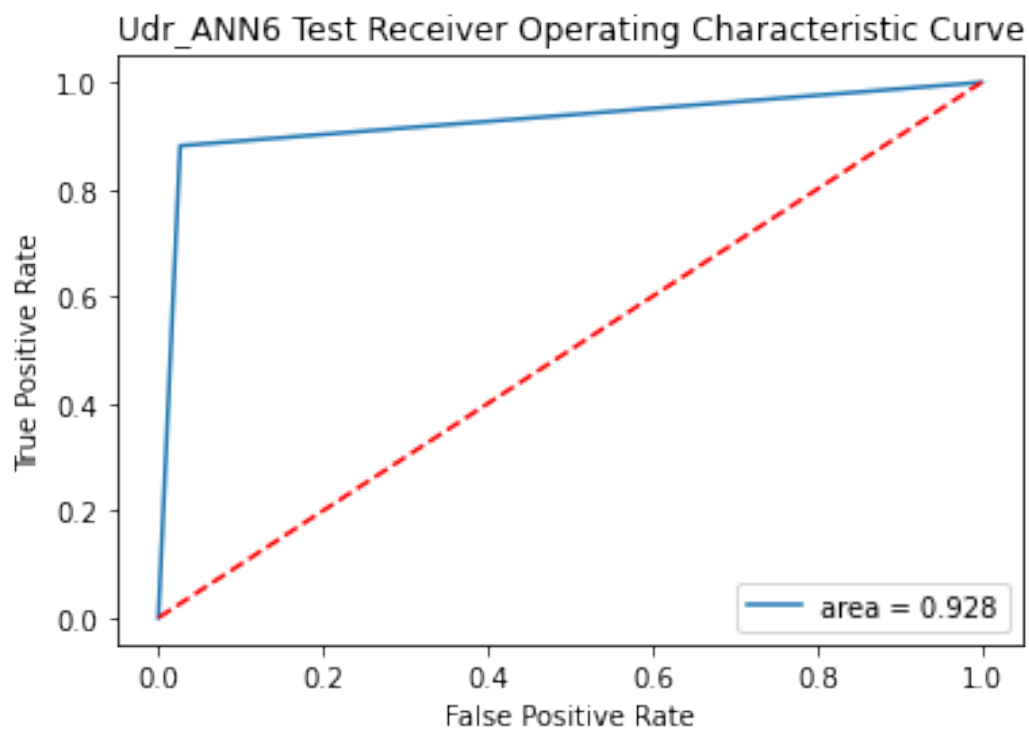
	precision	recall	f1-score	support
0	0.94	0.97	0.96	151
1	0.94	0.88	0.91	76
accuracy			0.94	227
macro avg	0.94	0.93	0.93	227
weighted avg	0.94	0.94	0.94	227



roc auc score train 0.9867109634551495



roc auc score test 0.9275444405716278



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9871142164952074

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	56864
1	0.11	0.88	0.19	98
accuracy			0.99	56962
macro avg	0.55	0.93	0.59	56962
weighted avg	1.00	0.99	0.99	56962

Completed and saved for model Udr_ANN6

```
buildANN(4, 128, 'relu', 'he_normal', 'l2', 'adam', 30, 10, 'Udr_ANN7')
```

Model: "model_39"

Layer (type)	Output Shape	Param #
input_47 (InputLayer)	[(None, 30)]	0
dense_215 (Dense)	(None, 128)	3968
dense_216 (Dense)	(None, 64)	8256
dense_217 (Dense)	(None, 32)	2080
dense_218 (Dense)	(None, 16)	528
dense_219 (Dense)	(None, 10)	170
dense_220 (Dense)	(None, 2)	22

=====
Total params: 15,024

Trainable params: 15,024

Non-trainable params: 0

None

Epoch 1/10

31/31 [=====] - 2s 14ms/step - loss: 5.1768 -
f1_score: 0.8608 - val_loss: 4.7930 - val_f1_score: 0.9341

Epoch 2/10

31/31 [=====] - 0s 4ms/step - loss: 4.5212 -
f1_score: 0.9450 - val_loss: 4.3060 - val_f1_score: 0.9390

Epoch 3/10

```

31/31 [=====] - 0s 4ms/step - loss: 4.0416 -
f1_score: 0.9541 - val_loss: 3.8510 - val_f1_score: 0.9390
Epoch 4/10
31/31 [=====] - 0s 4ms/step - loss: 3.6087 -
f1_score: 0.9606 - val_loss: 3.4518 - val_f1_score: 0.9390
Epoch 5/10
31/31 [=====] - 0s 4ms/step - loss: 3.2220 -
f1_score: 0.9632 - val_loss: 3.1023 - val_f1_score: 0.9390
Epoch 6/10
31/31 [=====] - 0s 4ms/step - loss: 2.8798 -
f1_score: 0.9632 - val_loss: 2.7689 - val_f1_score: 0.9341
Epoch 7/10
31/31 [=====] - 0s 4ms/step - loss: 2.5693 -
f1_score: 0.9671 - val_loss: 2.4943 - val_f1_score: 0.9390
Epoch 8/10
31/31 [=====] - 0s 4ms/step - loss: 2.2997 -
f1_score: 0.9608 - val_loss: 2.2250 - val_f1_score: 0.9341
Epoch 9/10
31/31 [=====] - 0s 4ms/step - loss: 2.0626 -
f1_score: 0.9684 - val_loss: 2.0094 - val_f1_score: 0.9390
Epoch 10/10
31/31 [=====] - 0s 4ms/step - loss: 1.8514 -
f1_score: 0.9722 - val_loss: 1.8076 - val_f1_score: 0.9447
29/29 [=====] - 0s 2ms/step
8/8 [=====] - 0s 3ms/step

```

Model performance Udr_ANN7

```

accuracy score train 0.9767699115044248
accuracy score test 0.9515418502202643

```

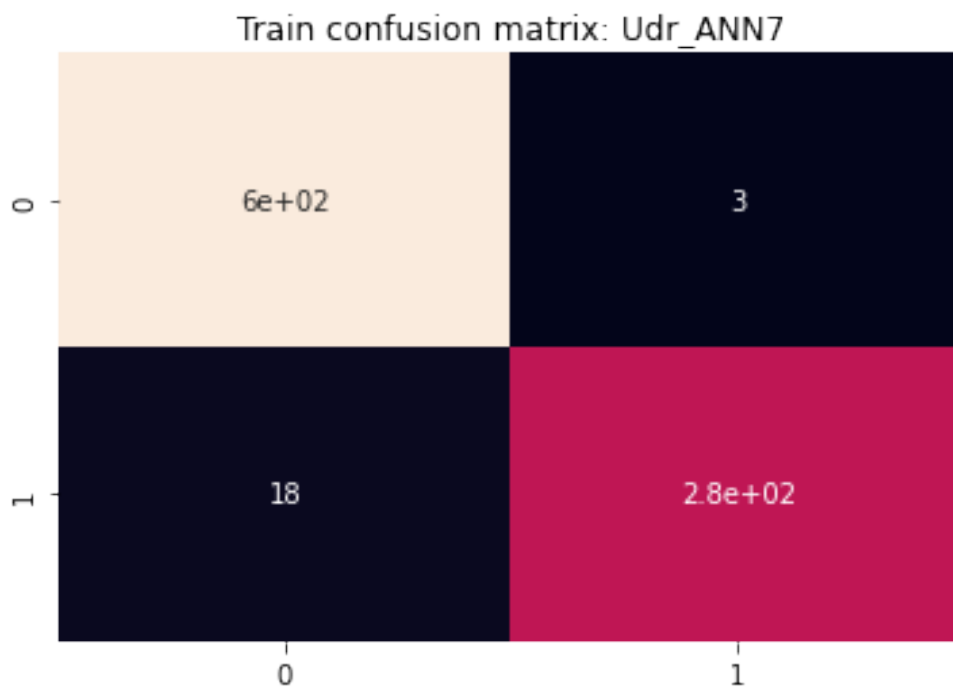
Train classification report: Udr_ANN7

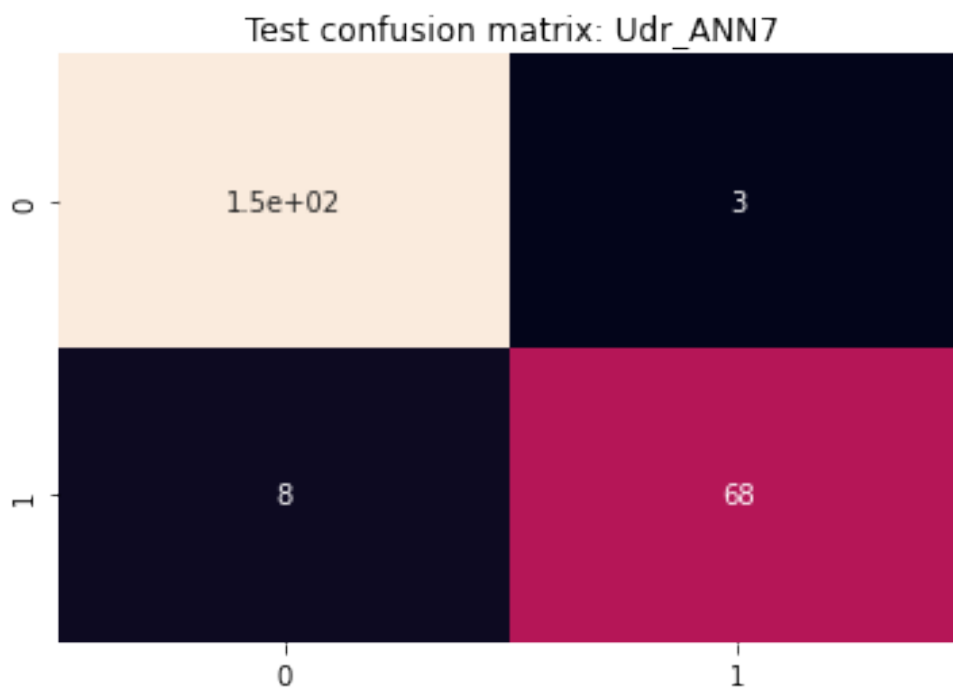
	precision	recall	f1-score	support
0	0.97	1.00	0.98	603
1	0.99	0.94	0.96	301
accuracy			0.98	904
macro avg	0.98	0.97	0.97	904
weighted avg	0.98	0.98	0.98	904

Test classification report: Udr_ANN7

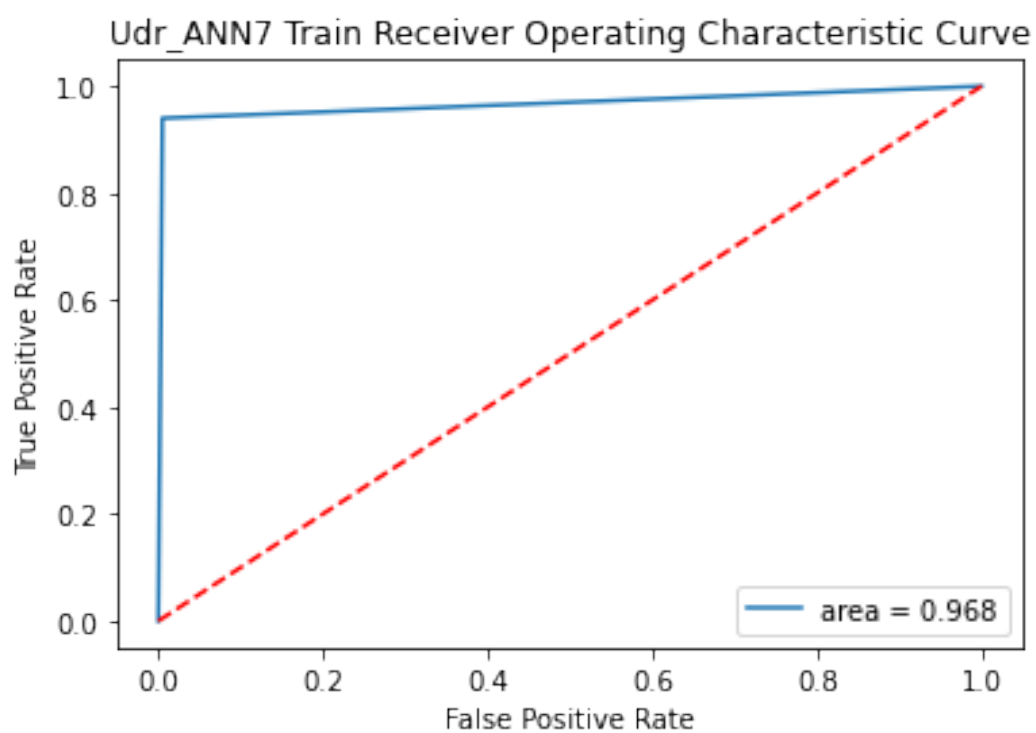
	precision	recall	f1-score	support
0	0.95	0.98	0.96	151
1	0.96	0.89	0.93	76

accuracy			0.95	227
macro avg	0.95	0.94	0.94	227
weighted avg	0.95	0.95	0.95	227

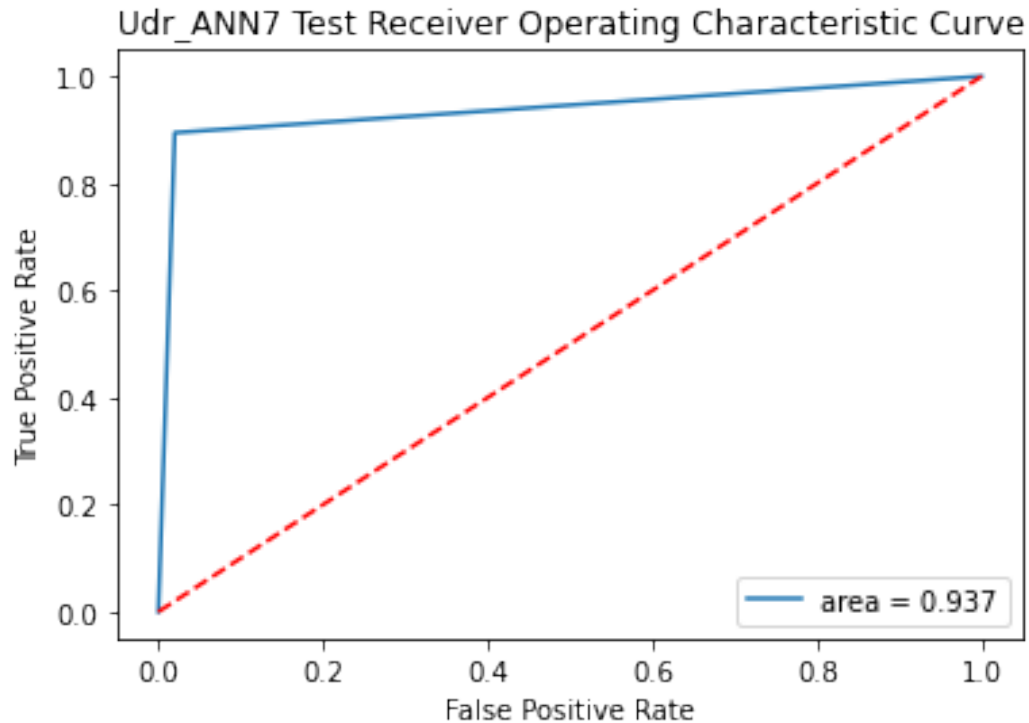




roc auc score train 0.9676121055850317



roc auc score test 0.9374346462181945



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9850777711456761

Classification report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	56864
1	0.09	0.87	0.17	98
accuracy			0.99	56962
macro avg	0.55	0.93	0.58	56962
weighted avg	1.00	0.99	0.99	56962

Completed and saved for model Udr_ANN7

```
buildANN(4, 256, 'relu', 'he_normal', 'l2', 'adam', 30, 10,
'Udr_ANN8', 0.2)
```

Model: "model_40"

Layer (type)	Output Shape	Param #
input_48 (InputLayer)	[(None, 30)]	0

dense_221 (Dense)	(None, 256)	7936
dense_222 (Dense)	(None, 128)	32896
dense_223 (Dense)	(None, 64)	8256
dense_224 (Dense)	(None, 32)	2080
dropout_14 (Dropout)	(None, 32)	0
batch_normalization_14 (Batch Normalization)	(None, 32)	128
dense_225 (Dense)	(None, 10)	330
dense_226 (Dense)	(None, 2)	22

```

=====
Total params: 51,648
Trainable params: 51,584
Non-trainable params: 64

```

```

None
Epoch 1/10
31/31 [=====] - 2s 15ms/step - loss: 9.7260 -
f1_score: 0.8183 - val_loss: 8.7859 - val_f1_score: 0.9126
Epoch 2/10
31/31 [=====] - 0s 5ms/step - loss: 8.1771 -
f1_score: 0.9132 - val_loss: 7.3770 - val_f1_score: 0.9390
Epoch 3/10
31/31 [=====] - 0s 7ms/step - loss: 6.8184 -
f1_score: 0.9398 - val_loss: 6.1774 - val_f1_score: 0.9390
Epoch 4/10
31/31 [=====] - 0s 5ms/step - loss: 5.7595 -
f1_score: 0.9427 - val_loss: 5.3181 - val_f1_score: 0.9488
Epoch 5/10
31/31 [=====] - 0s 5ms/step - loss: 4.9396 -
f1_score: 0.9380 - val_loss: 4.5652 - val_f1_score: 0.9488
Epoch 6/10
31/31 [=====] - 0s 5ms/step - loss: 4.2270 -
f1_score: 0.9467 - val_loss: 3.9231 - val_f1_score: 0.9439
Epoch 7/10
31/31 [=====] - 0s 5ms/step - loss: 3.6413 -
f1_score: 0.9483 - val_loss: 3.4173 - val_f1_score: 0.9380
Epoch 8/10
31/31 [=====] - 0s 5ms/step - loss: 3.1325 -
f1_score: 0.9453 - val_loss: 2.9751 - val_f1_score: 0.9434
Epoch 9/10
31/31 [=====] - 0s 5ms/step - loss: 2.7314 -
f1_score: 0.9342 - val_loss: 2.6309 - val_f1_score: 0.9160

```

Epoch 10/10
31/31 [=====] - 0s 5ms/step - loss: 2.3701 -
f1_score: 0.9532 - val_loss: 2.2774 - val_f1_score: 0.9491
29/29 [=====] - 0s 2ms/step
8/8 [=====] - 0s 3ms/step

Model performance Udr_ANN8

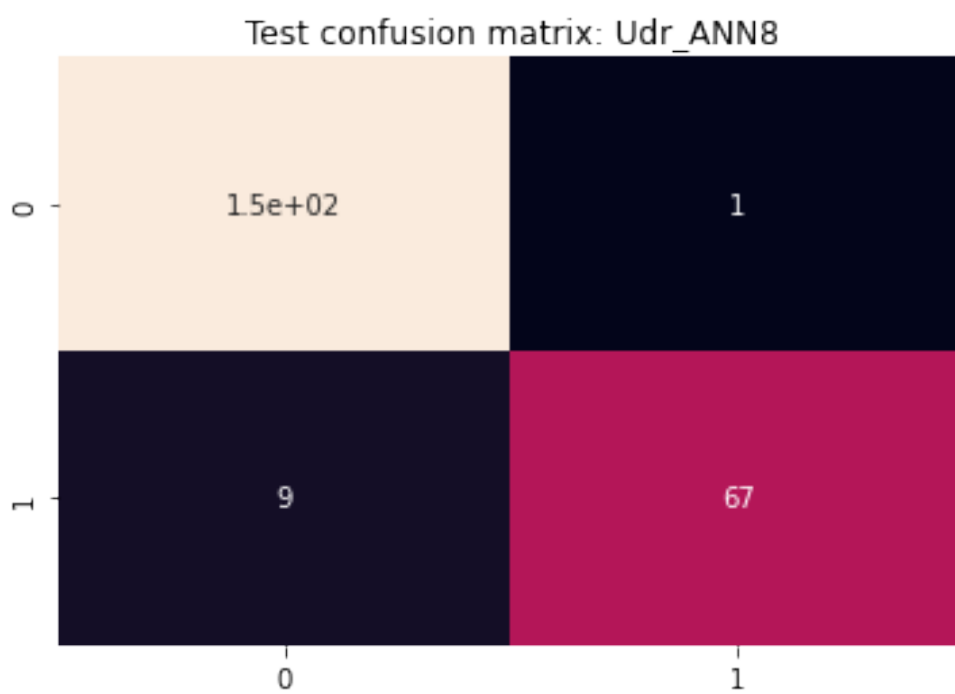
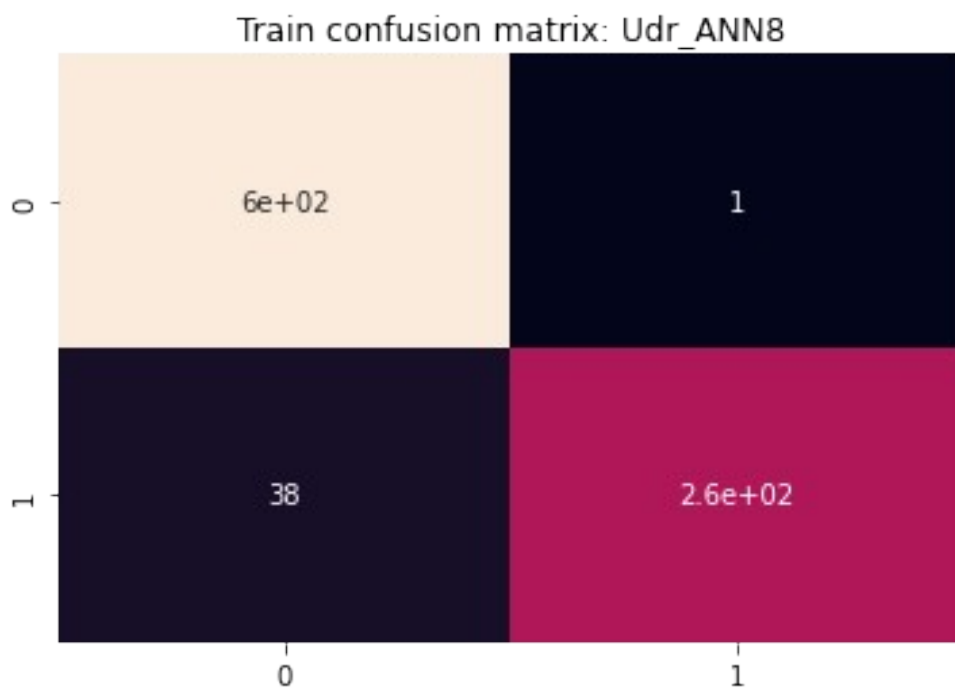
accuracy score train 0.956858407079646
accuracy score test 0.9559471365638766

Train classification report: Udr_ANN8

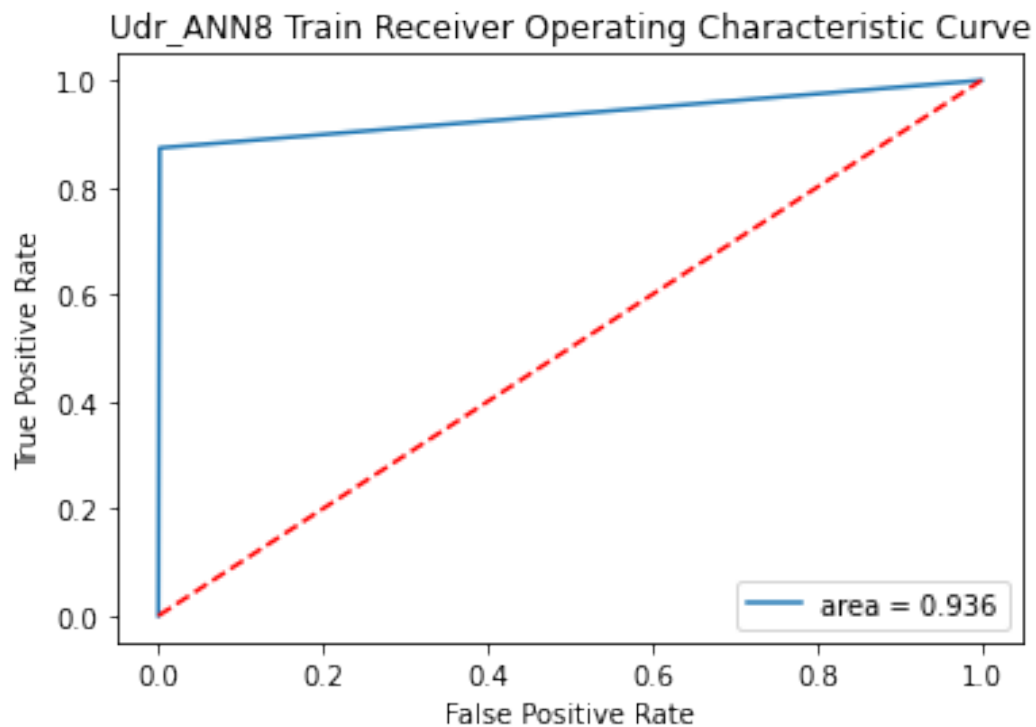
	precision	recall	f1-score	support
0	0.94	1.00	0.97	603
1	1.00	0.87	0.93	301
accuracy			0.96	904
macro avg	0.97	0.94	0.95	904
weighted avg	0.96	0.96	0.96	904

Test classification report: Udr_ANN8

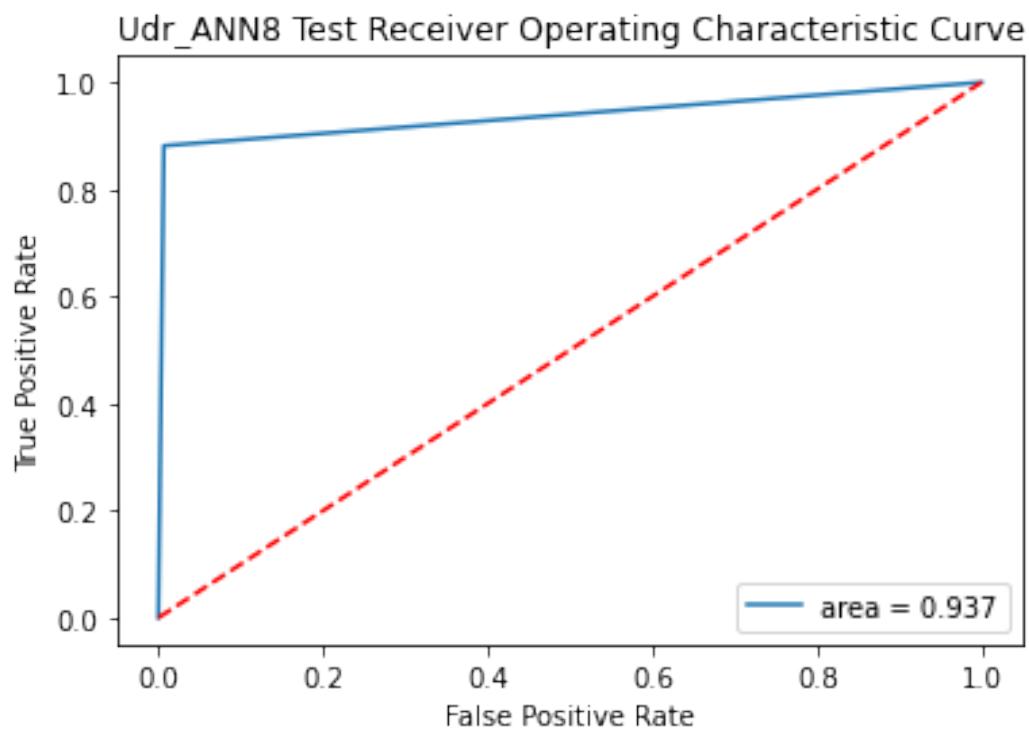
	precision	recall	f1-score	support
0	0.94	0.99	0.97	151
1	0.99	0.88	0.93	76
accuracy			0.96	227
macro avg	0.96	0.94	0.95	227
weighted avg	0.96	0.96	0.96	227



roc auc score train 0.9360478890156085



roc auc score test 0.9374782154060647



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.996892665285629

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.34	0.83	0.48	98
accuracy			1.00	56962
macro avg	0.67	0.91	0.74	56962
weighted avg	1.00	1.00	1.00	56962

Completed and saved for model Udr_ANN8

With undersampled data, Udr_ANN1 gave better result than the other undersampled models (f1-score macro= 0.77).

Also by comparing the performance with the oversampled models, undersampled ANN8 model gave the best performance.

So till now get the best result with 3 layers, (128, 64, 32) neurons respectively, relu activation, he_normal kernel initializer, l2 regularizer, sgd optimizer, 30 batch size, 10 epochs.

Further we can try with original data.

Original data

```
finance_train = pd.read_pickle('finance_train.pkl')
finance_test = pd.read_pickle('finance_test.pkl')

train_X = finance_train.drop(['Class'], axis=1)
train_y = finance_train[['Class']]

test_X = finance_test.drop(['Class'], axis=1)
test_y = finance_test[['Class']]

x_train, x_test, y_train, y_test = train_test_split(train_X, train_y,
stratify= train_y,

test_size= 0.2, random_state= 0)

y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
test_y = to_categorical(test_y)

print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
```

```
print(y_test.shape)
print(test_X.shape)
print(test_y.shape)
```

```
(181102, 30)
(181102, 2)
(45276, 30)
(45276, 2)
(56962, 30)
(56962, 2)
```

ANN with original data

```
buildANN(3, 128, 'relu', 'he_normal', 'l2', 'sgd', 30, 10, 'ANN1',
0.2)
```

Model: "model_41"

Layer (type)	Output Shape	Param #
input_49 (InputLayer)	[(None, 30)]	0
dense_227 (Dense)	(None, 128)	3968
dense_228 (Dense)	(None, 64)	8256
dense_229 (Dense)	(None, 32)	2080
dropout_15 (Dropout)	(None, 32)	0
batch_normalization_15 (Batch Normalization)	(None, 32)	128
dense_230 (Dense)	(None, 10)	330
dense_231 (Dense)	(None, 2)	22

Total params: 14,784

Trainable params: 14,720

Non-trainable params: 64

None

Epoch 1/10

6037/6037 [=====] - 18s 3ms/step - loss: 1.8209 - f1_score: 0.5611 - val_loss: 0.4391 - val_f1_score: 0.7854

Epoch 2/10

6037/6037 [=====] - 16s 3ms/step - loss: 0.1710 - f1_score: 0.6288 - val_loss: 0.0473 - val_f1_score: 0.6731

Epoch 3/10

6037/6037 [=====] - 16s 3ms/step - loss: 0.0224 - f1_score: 0.6568 - val_loss: 0.0119 - val_f1_score: 0.7146

```

Epoch 4/10
6037/6037 [=====] - 16s 3ms/step - loss:
0.0088 - f1_score: 0.7596 - val_loss: 0.0084 - val_f1_score: 0.7756
Epoch 5/10
6037/6037 [=====] - 15s 3ms/step - loss:
0.0073 - f1_score: 0.8247 - val_loss: 0.0081 - val_f1_score: 0.8143
Epoch 6/10
6037/6037 [=====] - 16s 3ms/step - loss:
0.0070 - f1_score: 0.8399 - val_loss: 0.0080 - val_f1_score: 0.8648
Epoch 7/10
6037/6037 [=====] - 15s 3ms/step - loss:
0.0069 - f1_score: 0.8645 - val_loss: 0.0078 - val_f1_score: 0.8456
Epoch 8/10
6037/6037 [=====] - 16s 3ms/step - loss:
0.0067 - f1_score: 0.8715 - val_loss: 0.0078 - val_f1_score: 0.8739
Epoch 9/10
6037/6037 [=====] - 16s 3ms/step - loss:
0.0067 - f1_score: 0.8762 - val_loss: 0.0077 - val_f1_score: 0.8739
Epoch 10/10
6037/6037 [=====] - 16s 3ms/step - loss:
0.0065 - f1_score: 0.8801 - val_loss: 0.0076 - val_f1_score: 0.8601
5660/5660 [=====] - 9s 2ms/step
1415/1415 [=====] - 2s 2ms/step

```

Model performance ANN1

```

accuracy score train 0.9993649987299975
accuracy score test 0.9991607032423359

```

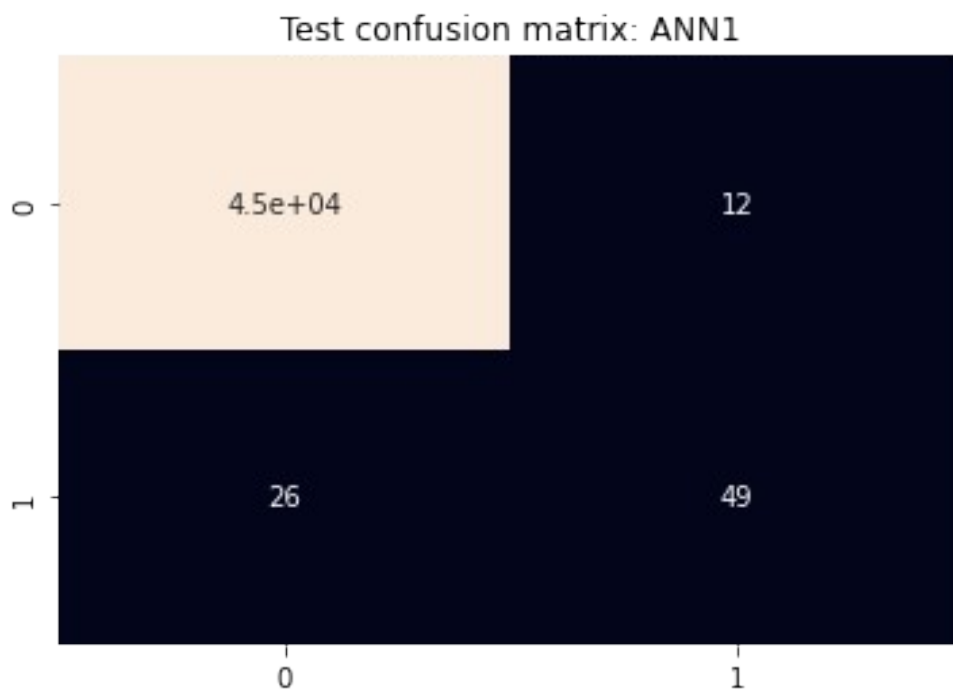
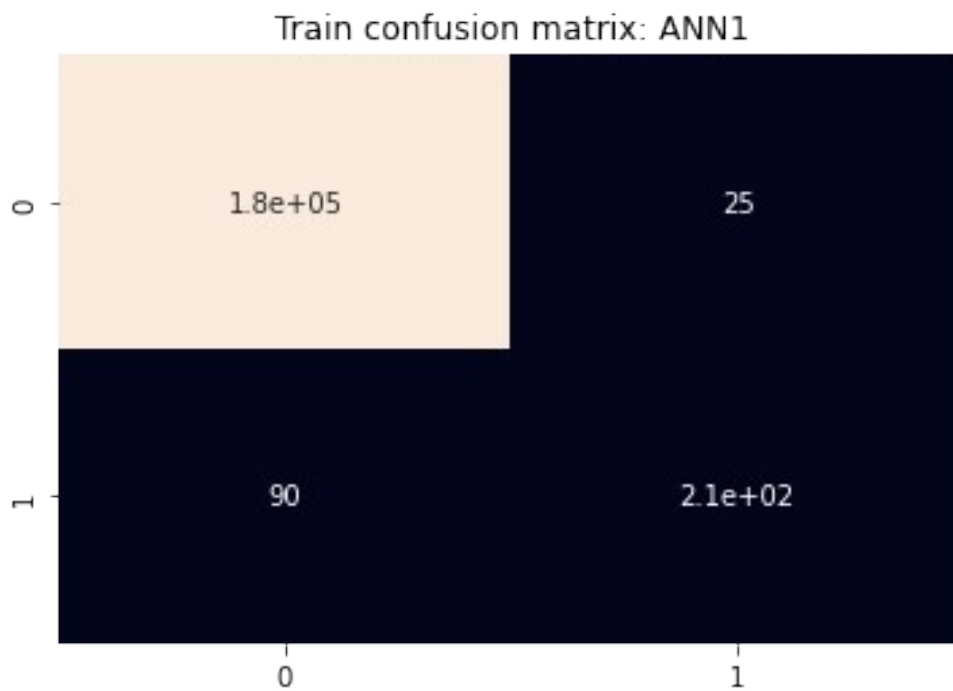
Train classification report: ANN1

	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	0.89	0.70	0.79	302
accuracy			1.00	181102
macro avg	0.95	0.85	0.89	181102
weighted avg	1.00	1.00	1.00	181102

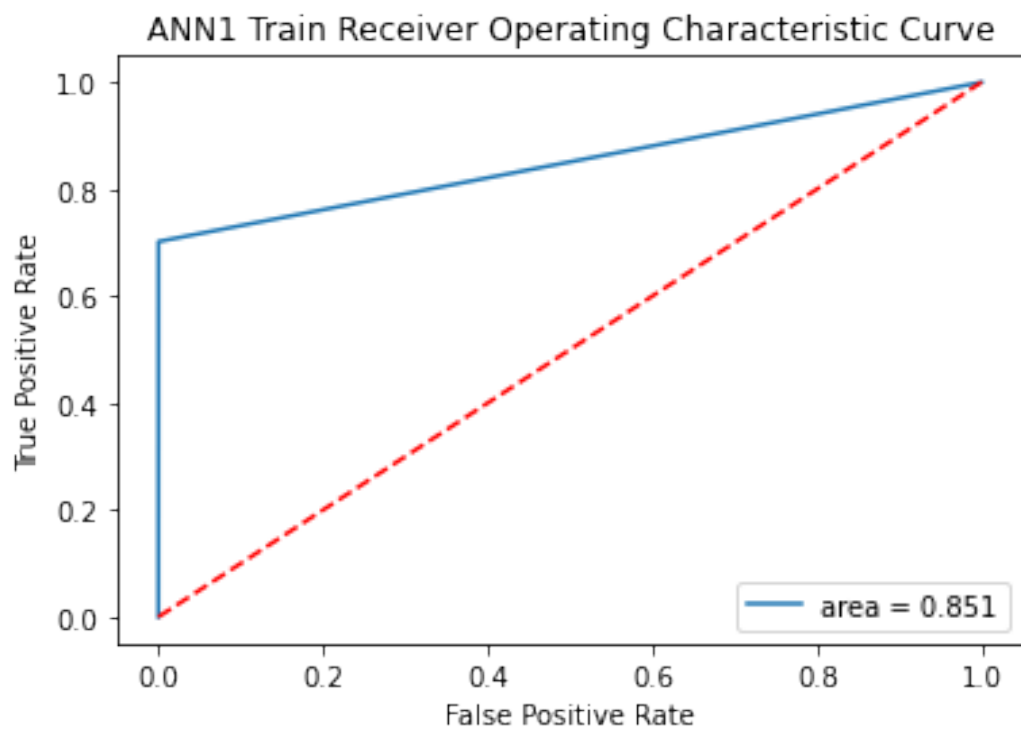
Test classification report: ANN1

	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	0.80	0.65	0.72	75
accuracy			1.00	45276

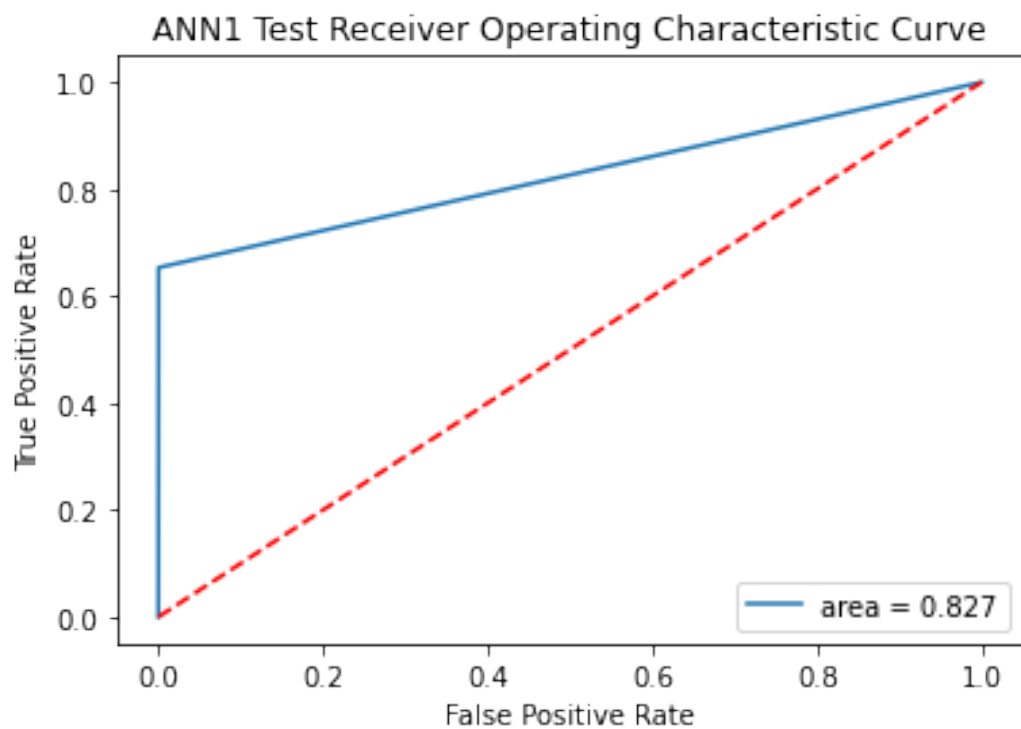
macro avg	0.90	0.83	0.86	45276
weighted avg	1.00	1.00	1.00	45276



roc auc score train 0.8509242403153021



roc auc score test 0.8265339262405699



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9991924440855307

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.85	0.64	0.73	98
accuracy			1.00	56962
macro avg	0.93	0.82	0.87	56962
weighted avg	1.00	1.00	1.00	56962

Completed and saved for model ANN1

buildANN(3, 128, 'relu', 'he_uniform', 'l2', 'adadelata', 30, 10, 'ANN2')

Model: "model_42"

Layer (type)	Output Shape	Param #
input_50 (InputLayer)	[(None, 30)]	0
dense_232 (Dense)	(None, 128)	3968
dense_233 (Dense)	(None, 64)	8256
dense_234 (Dense)	(None, 32)	2080
dense_235 (Dense)	(None, 10)	330
dense_236 (Dense)	(None, 2)	22

=====
Total params: 14,656

Trainable params: 14,656

Non-trainable params: 0

None

Epoch 1/10

6037/6037 [=====] - 17s 3ms/step - loss: 5.3073 - f1_score: 0.4093 - val_loss: 5.0166 - val_f1_score: 0.4858

Epoch 2/10

6037/6037 [=====] - 16s 3ms/step - loss: 4.7432 - f1_score: 0.4971 - val_loss: 4.4870 - val_f1_score: 0.4994

Epoch 3/10


```

6037/6037 [=====] - 16s 3ms/step - loss:
4.2634 - f1_score: 0.4995 - val_loss: 4.0395 - val_f1_score: 0.4996
Epoch 4/10
6037/6037 [=====] - 16s 3ms/step - loss:
3.8236 - f1_score: 0.4996 - val_loss: 3.6098 - val_f1_score: 0.4996
Epoch 5/10
6037/6037 [=====] - 15s 3ms/step - loss:
3.4094 - f1_score: 0.4996 - val_loss: 3.2148 - val_f1_score: 0.4996
Epoch 6/10
6037/6037 [=====] - 16s 3ms/step - loss:
3.0436 - f1_score: 0.4996 - val_loss: 2.8752 - val_f1_score: 0.4996
Epoch 7/10
6037/6037 [=====] - 18s 3ms/step - loss:
2.7290 - f1_score: 0.4996 - val_loss: 2.5823 - val_f1_score: 0.4996
Epoch 8/10
6037/6037 [=====] - 16s 3ms/step - loss:
2.4535 - f1_score: 0.4996 - val_loss: 2.3272 - val_f1_score: 0.4996
Epoch 9/10
6037/6037 [=====] - 15s 3ms/step - loss:
2.2171 - f1_score: 0.4996 - val_loss: 2.1089 - val_f1_score: 0.4996
Epoch 10/10
6037/6037 [=====] - 15s 3ms/step - loss:
2.0155 - f1_score: 0.4996 - val_loss: 1.9215 - val_f1_score: 0.4996
5660/5660 [=====] - 8s 1ms/step
1415/1415 [=====] - 2s 2ms/step

```

Model performance ANN2

```

accuracy score train 0.9983324314474716
accuracy score test 0.9983434932414524

```

Train classification report: ANN2

```

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_
_classification.py:1318: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification

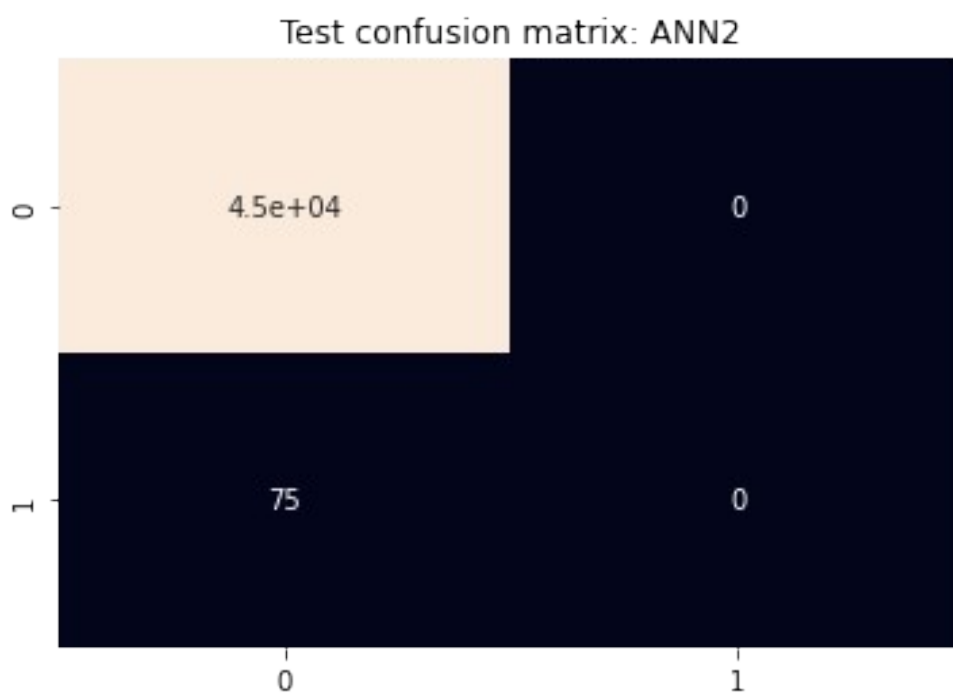
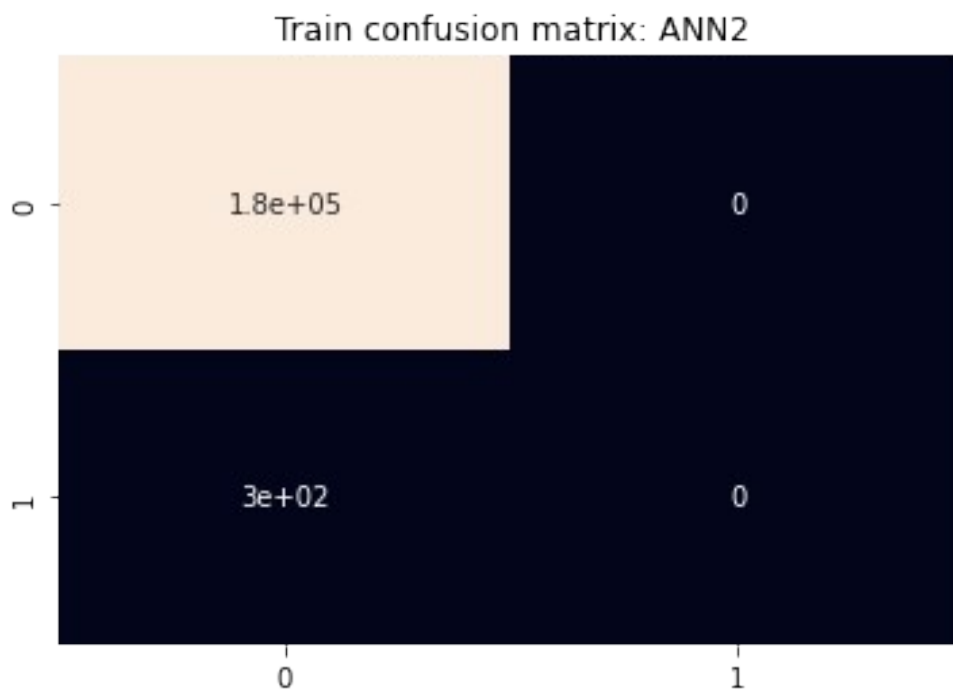
```

```
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

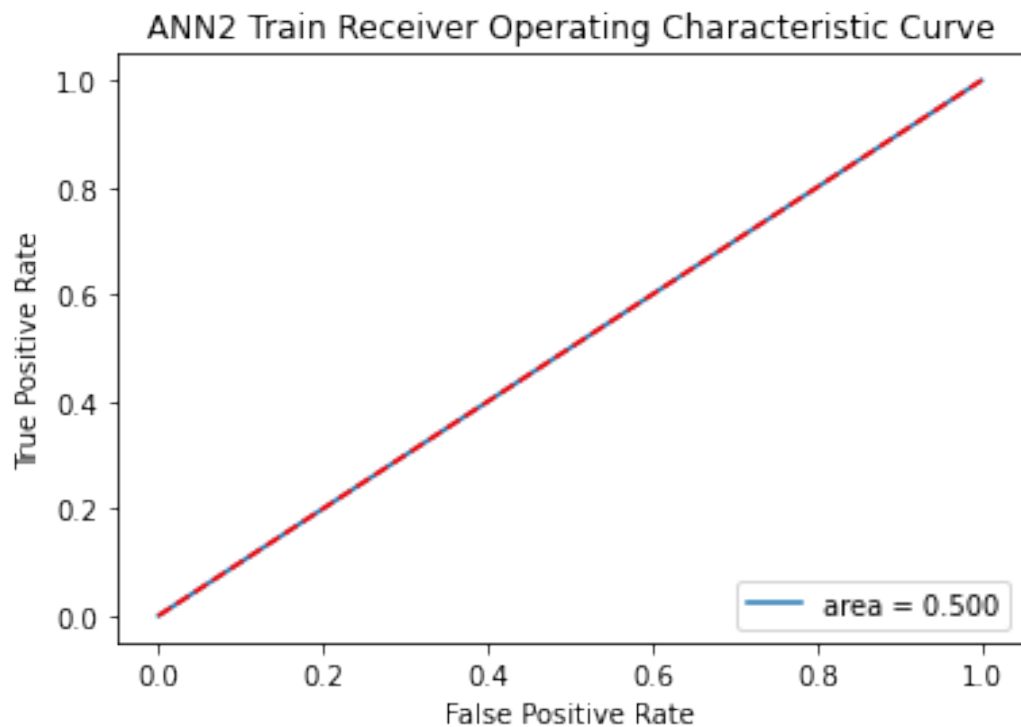
	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	0.00	0.00	0.00	302
accuracy			1.00	181102
macro avg	0.50	0.50	0.50	181102
weighted avg	1.00	1.00	1.00	181102

Test classification report: ANN2

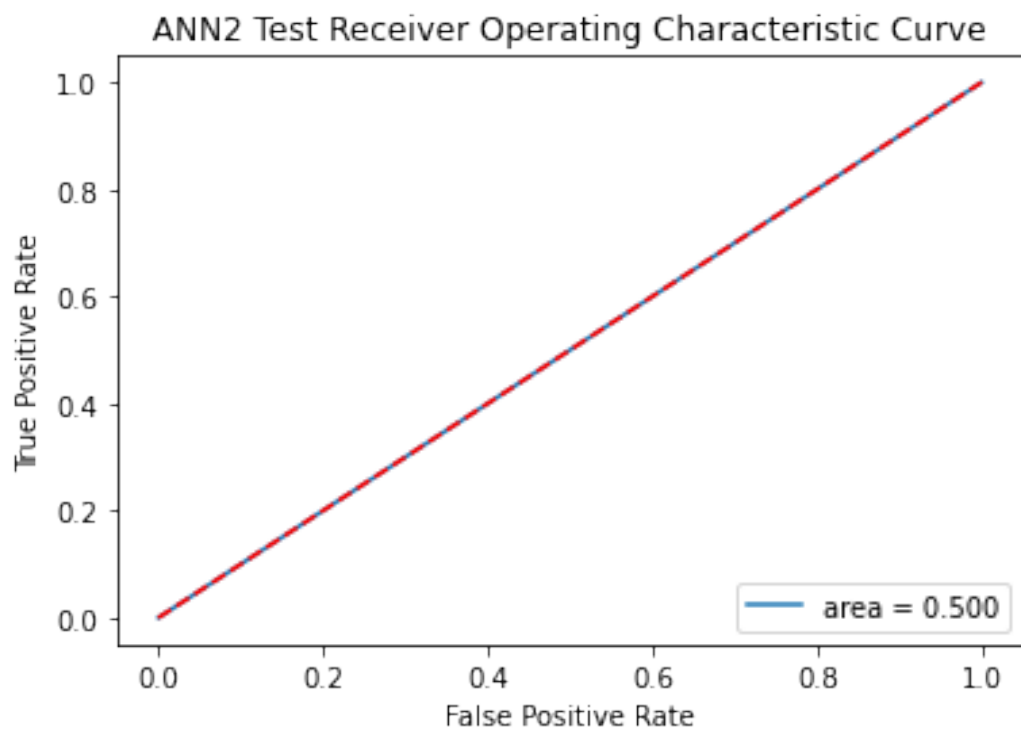
	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	0.00	0.00	0.00	75
accuracy			1.00	45276
macro avg	0.50	0.50	0.50	45276
weighted avg	1.00	1.00	1.00	45276



roc auc score train 0.5



roc auc score test 0.5



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9982795547909132

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.00	0.00	0.00	98
accuracy			1.00	56962
macro avg	0.50	0.50	0.50	56962
weighted avg	1.00	1.00	1.00	56962

Completed and saved for model ANN2

```
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
buildANN(3, 64, 'relu', 'he_normal', 'l1', 'rmsprop', 30, 10, 'ANN3')
Model: "model_43"
```

Layer (type)	Output Shape	Param #
input_51 (InputLayer)	[(None, 30)]	0
dense_237 (Dense)	(None, 64)	1984
dense_238 (Dense)	(None, 32)	2080
dense_239 (Dense)	(None, 16)	528
dense_240 (Dense)	(None, 10)	170
dense_241 (Dense)	(None, 2)	22

```

=====
Total params: 4,784
Trainable params: 4,784
Non-trainable params: 0

None
Epoch 1/10
6037/6037 [=====] - 16s 3ms/step - loss:
0.2765 - f1_score: 0.5012 - val_loss: 0.0367 - val_f1_score: 0.4996
Epoch 2/10
6037/6037 [=====] - 15s 3ms/step - loss:
0.0369 - f1_score: 0.4996 - val_loss: 0.0360 - val_f1_score: 0.4996
Epoch 3/10
6037/6037 [=====] - 16s 3ms/step - loss:
0.0367 - f1_score: 0.4996 - val_loss: 0.0372 - val_f1_score: 0.4996
Epoch 4/10
6037/6037 [=====] - 15s 2ms/step - loss:
0.0366 - f1_score: 0.4996 - val_loss: 0.0362 - val_f1_score: 0.4996
Epoch 5/10
6037/6037 [=====] - 15s 3ms/step - loss:
0.0366 - f1_score: 0.4996 - val_loss: 0.0364 - val_f1_score: 0.4996
5660/5660 [=====] - 8s 1ms/step
1415/1415 [=====] - 2s 1ms/step

```

Model performance ANN3

```

accuracy score train 0.9983324314474716
accuracy score test 0.9983434932414524

```

Train classification report: ANN3

```

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

```

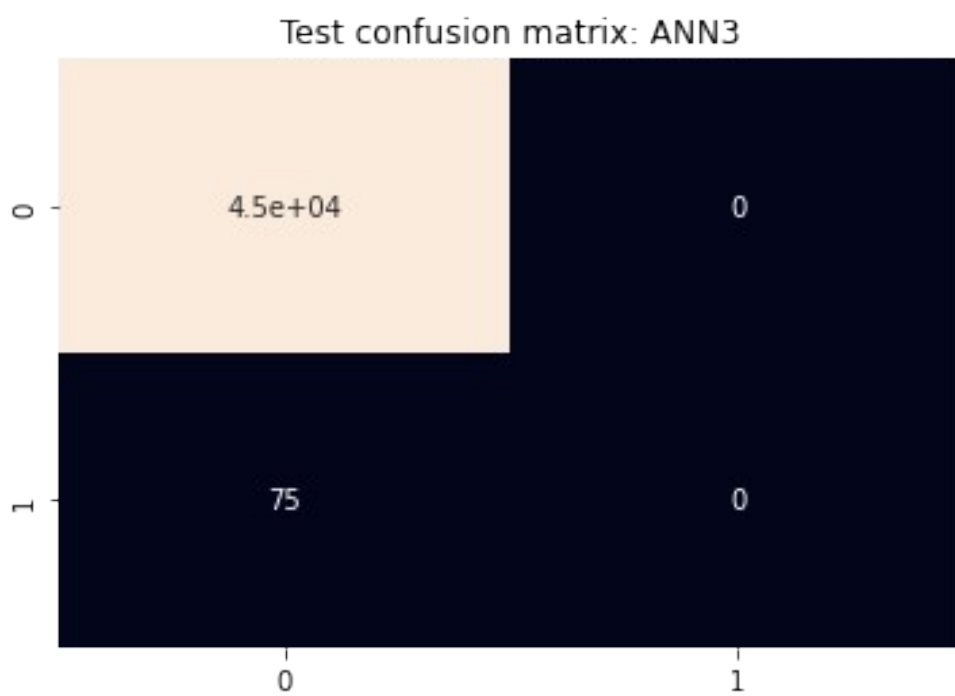
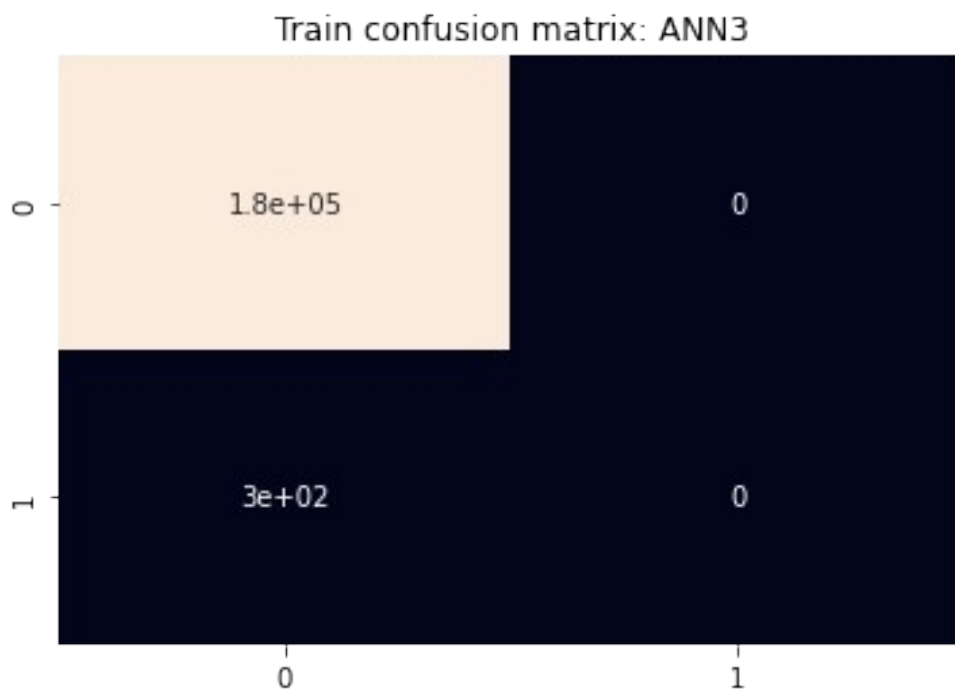
	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	0.00	0.00	0.00	302
accuracy			1.00	181102
macro avg	0.50	0.50	0.50	181102

weighted avg	1.00	1.00	1.00	181102
--------------	------	------	------	--------

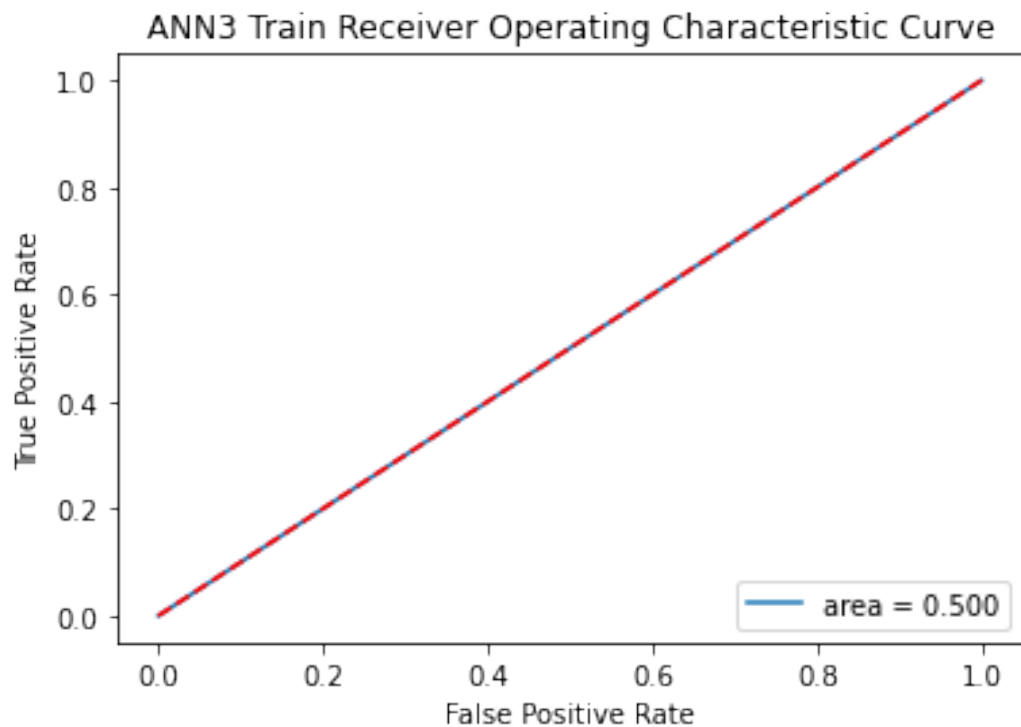
Test classification report: ANN3

	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	0.00	0.00	0.00	75
accuracy			1.00	45276
macro avg	0.50	0.50	0.50	45276
weighted avg	1.00	1.00	1.00	45276

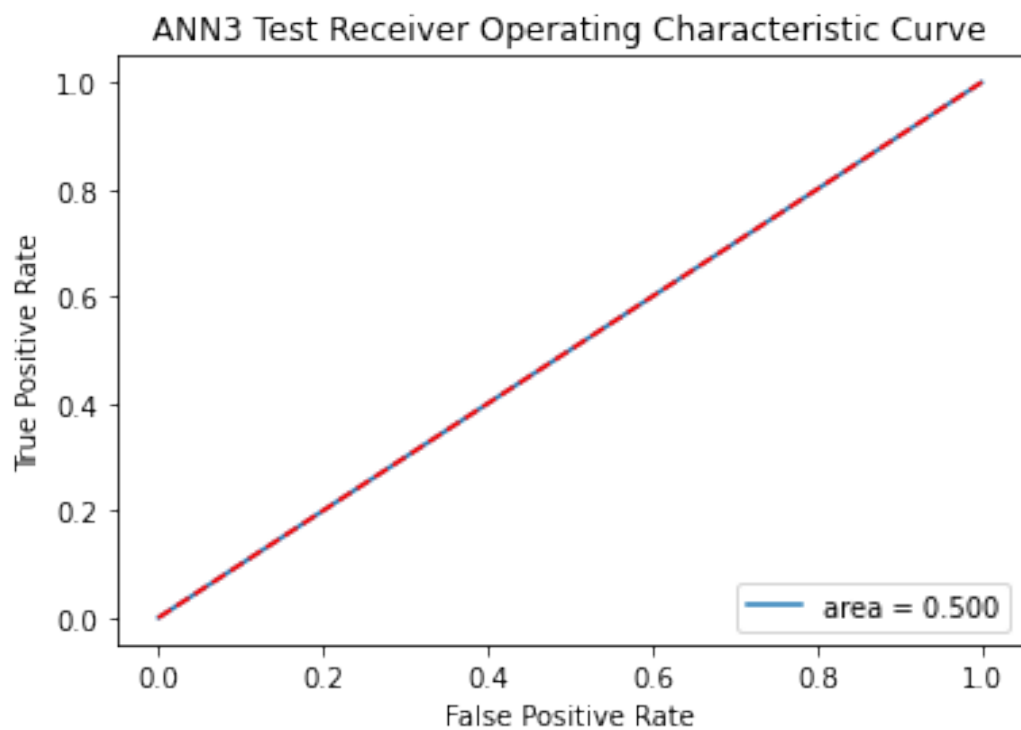
```
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
```



roc auc score train 0.5



roc auc score test 0.5



1781/1781 [=====] - 3s 1ms/step

Test accuracy score 0.9982795547909132

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.00	0.00	0.00	98
accuracy			1.00	56962
macro avg	0.50	0.50	0.50	56962
weighted avg	1.00	1.00	1.00	56962

Completed and saved for model ANN3

```
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
buildANN(3, 128, 'relu', 'he_normal', 'l2', 'rmsprop', 30, 10, 'ANN4')
Model: "model_44"
```

Layer (type)	Output Shape	Param #
input_52 (InputLayer)	[(None, 30)]	0
dense_242 (Dense)	(None, 128)	3968
dense_243 (Dense)	(None, 64)	8256
dense_244 (Dense)	(None, 32)	2080
dense_245 (Dense)	(None, 10)	330
dense_246 (Dense)	(None, 2)	22

```

=====
Total params: 14,656
Trainable params: 14,656
Non-trainable params: 0

None
Epoch 1/10
6037/6037 [=====] - 17s 3ms/step - loss:
0.1142 - f1_score: 0.5013 - val_loss: 0.0133 - val_f1_score: 0.4996
Epoch 2/10
6037/6037 [=====] - 16s 3ms/step - loss:
0.0136 - f1_score: 0.4996 - val_loss: 0.0137 - val_f1_score: 0.4996
Epoch 3/10
6037/6037 [=====] - 15s 3ms/step - loss:
0.0135 - f1_score: 0.4996 - val_loss: 0.0138 - val_f1_score: 0.4996
Epoch 4/10
6037/6037 [=====] - 16s 3ms/step - loss:
0.0134 - f1_score: 0.4996 - val_loss: 0.0128 - val_f1_score: 0.4996
Epoch 5/10
6037/6037 [=====] - 16s 3ms/step - loss:
0.0134 - f1_score: 0.4996 - val_loss: 0.0125 - val_f1_score: 0.4996
Epoch 6/10
6037/6037 [=====] - 15s 3ms/step - loss:
0.0134 - f1_score: 0.4996 - val_loss: 0.0126 - val_f1_score: 0.4996
Epoch 7/10
6037/6037 [=====] - 16s 3ms/step - loss:
0.0135 - f1_score: 0.4996 - val_loss: 0.0132 - val_f1_score: 0.4996
Epoch 8/10
6037/6037 [=====] - 16s 3ms/step - loss:
0.0137 - f1_score: 0.4996 - val_loss: 0.0132 - val_f1_score: 0.4996
5660/5660 [=====] - 8s 1ms/step
1415/1415 [=====] - 2s 1ms/step

```

Model performance ANN4

```

accuracy score train 0.9983324314474716
accuracy score test 0.9983434932414524

```

Train classification report: ANN4

```

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.

```

```

_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))

```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	0.00	0.00	0.00	302
accuracy			1.00	181102
macro avg	0.50	0.50	0.50	181102
weighted avg	1.00	1.00	1.00	181102

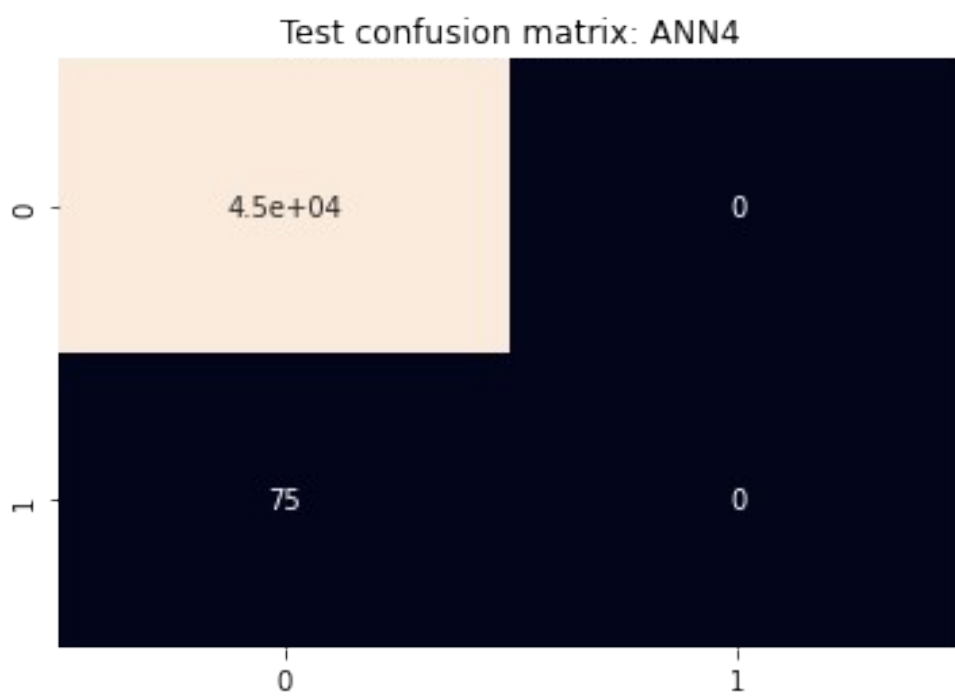
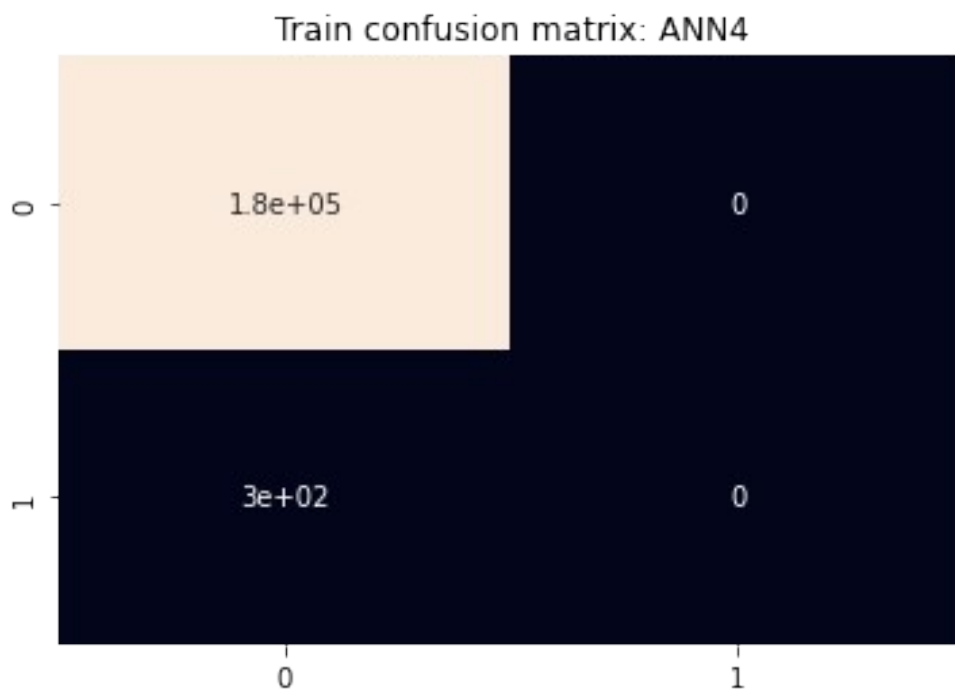
Test classification report: ANN4

	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	0.00	0.00	0.00	75
accuracy			1.00	45276
macro avg	0.50	0.50	0.50	45276
weighted avg	1.00	1.00	1.00	45276

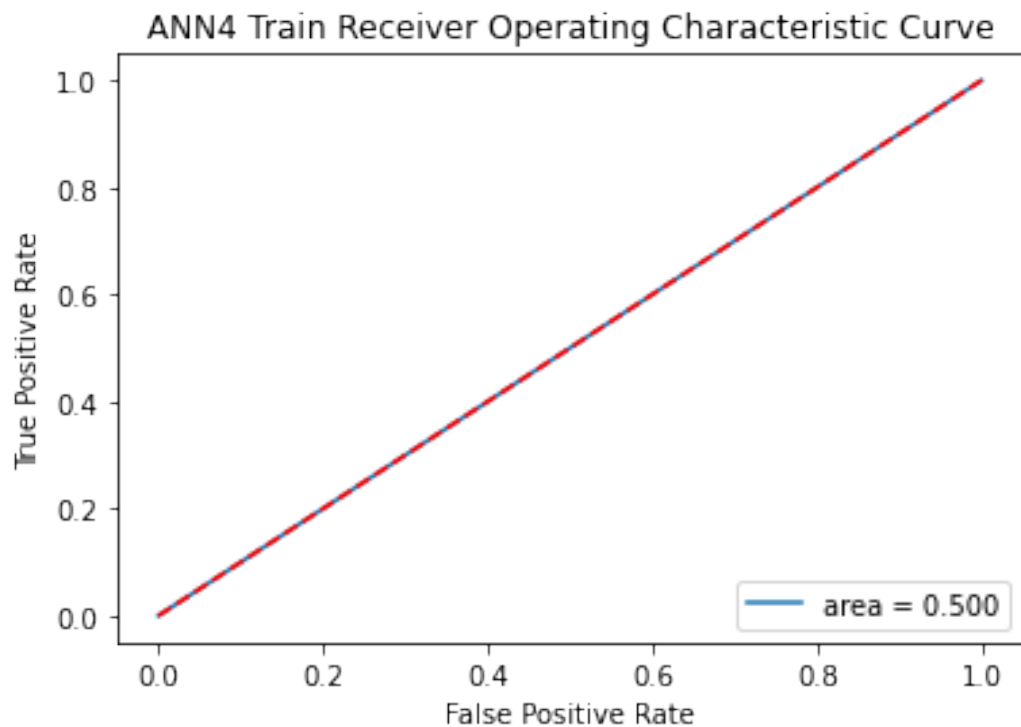
```

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/
_classification.py:1318: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))

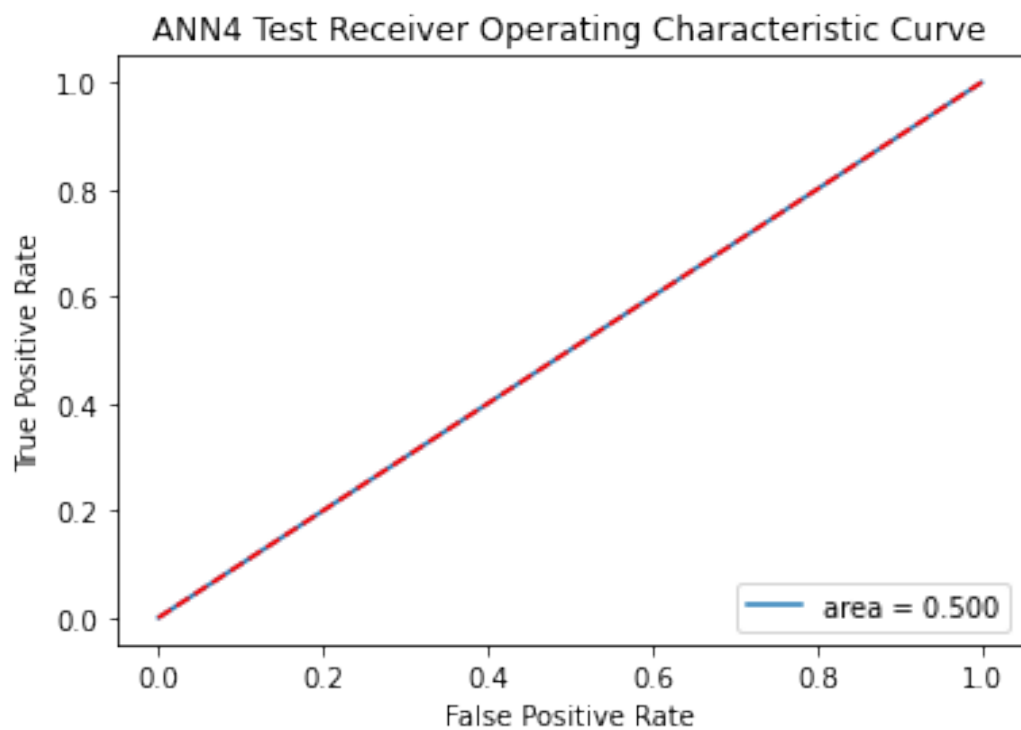
```



roc auc score train 0.5



roc auc score test 0.5



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9982795547909132

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.00	0.00	0.00	98
accuracy			1.00	56962
macro avg	0.50	0.50	0.50	56962
weighted avg	1.00	1.00	1.00	56962

Completed and saved for model ANN4

```
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
buildANN(3, 128, 'relu', 'he_normal', 'l2', 'adam', 30, 20, 'ANN5')
Model: "model_45"
```

Layer (type)	Output Shape	Param #
input_53 (InputLayer)	[(None, 30)]	0
dense_247 (Dense)	(None, 128)	3968
dense_248 (Dense)	(None, 64)	8256
dense_249 (Dense)	(None, 32)	2080
dense_250 (Dense)	(None, 10)	330
dense_251 (Dense)	(None, 2)	22

```

=====
Total params: 14,656
Trainable params: 14,656
Non-trainable params: 0
=====
None
Epoch 1/20
6037/6037 [=====] - 18s 3ms/step - loss:
0.1524 - f1_score: 0.5254 - val_loss: 0.0125 - val_f1_score: 0.4996
Epoch 2/20
6037/6037 [=====] - 18s 3ms/step - loss:
0.0125 - f1_score: 0.4996 - val_loss: 0.0124 - val_f1_score: 0.4996
Epoch 3/20
6037/6037 [=====] - 17s 3ms/step - loss:
0.0124 - f1_score: 0.4996 - val_loss: 0.0123 - val_f1_score: 0.4996
Epoch 4/20
6037/6037 [=====] - 17s 3ms/step - loss:
0.0124 - f1_score: 0.4996 - val_loss: 0.0123 - val_f1_score: 0.4996
Epoch 5/20
6037/6037 [=====] - 18s 3ms/step - loss:
0.0124 - f1_score: 0.4996 - val_loss: 0.0123 - val_f1_score: 0.4996
Epoch 6/20
6037/6037 [=====] - 18s 3ms/step - loss:
0.0124 - f1_score: 0.4996 - val_loss: 0.0123 - val_f1_score: 0.4996
5660/5660 [=====] - 9s 2ms/step
1415/1415 [=====] - 2s 1ms/step

```

Model performance ANN5

```

accuracy score train 0.9983324314474716
accuracy score test 0.9983434932414524

```

Train classification report: ANN5

```

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

```



```

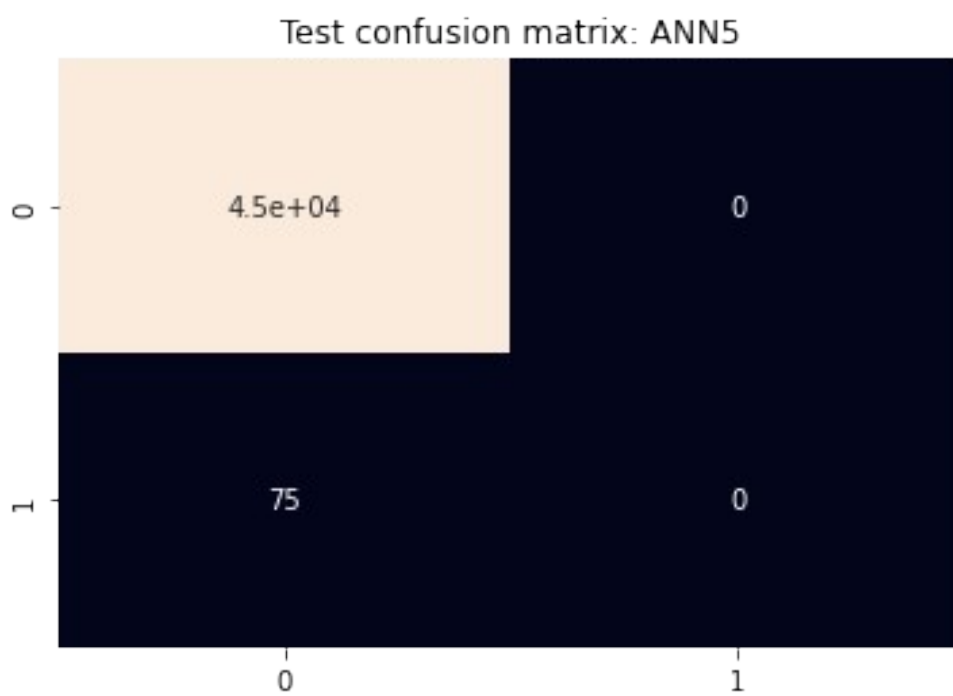
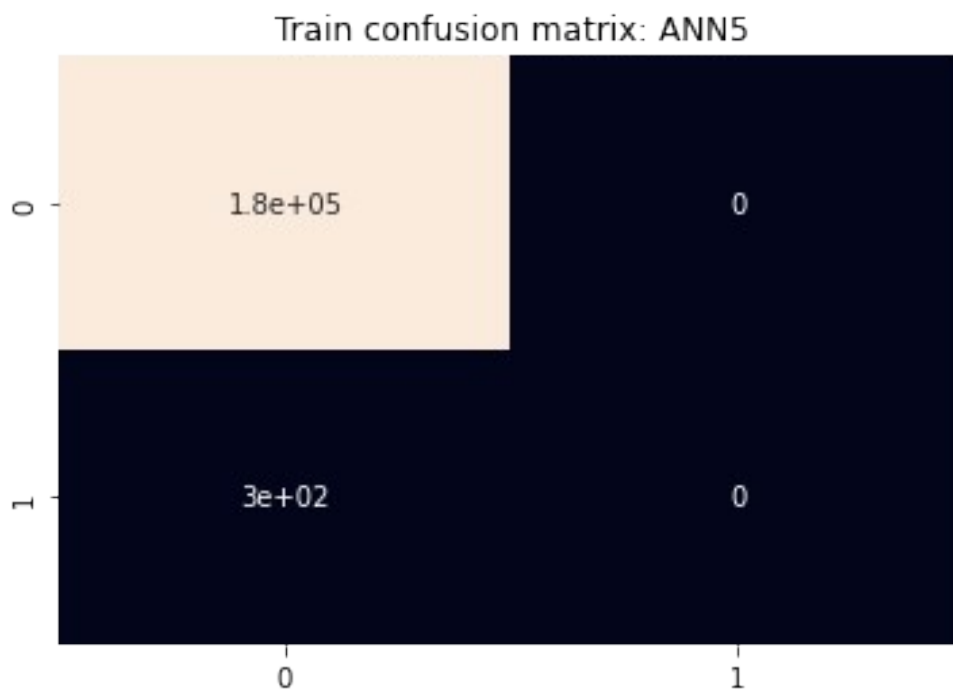
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, msg_start, len(result))

```

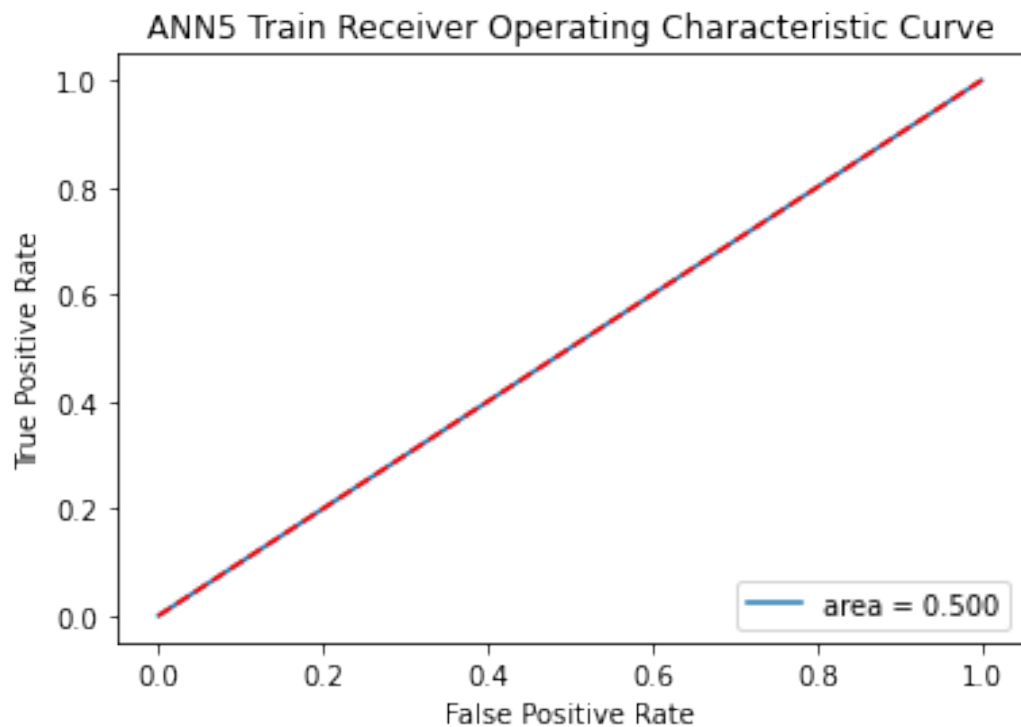
	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	0.00	0.00	0.00	302
accuracy			1.00	181102
macro avg	0.50	0.50	0.50	181102
weighted avg	1.00	1.00	1.00	181102

Test classification report: ANN5

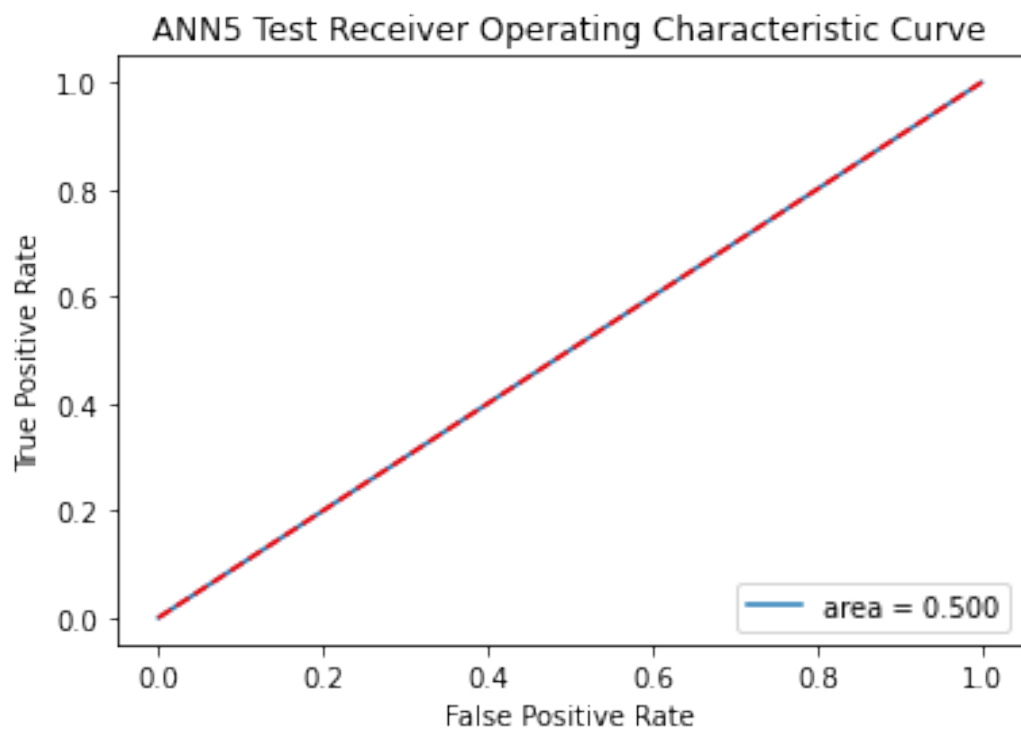
	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	0.00	0.00	0.00	75
accuracy			1.00	45276
macro avg	0.50	0.50	0.50	45276
weighted avg	1.00	1.00	1.00	45276



roc auc score train 0.5



roc auc score test 0.5



1781/1781 [=====] - 3s 1ms/step

Test accuracy score 0.9982795547909132

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.00	0.00	0.00	98
accuracy			1.00	56962
macro avg	0.50	0.50	0.50	56962
weighted avg	1.00	1.00	1.00	56962

Completed and saved for model ANN5

```
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
buildANN(4, 256, 'relu', 'he_normal', 'l2', 'adam', 30, 10, 'ANN6', 0.2)
```

Model: "model_46"

Layer (type)	Output Shape	Param #
input_54 (InputLayer)	[(None, 30)]	0
dense_252 (Dense)	(None, 256)	7936
dense_253 (Dense)	(None, 128)	32896
dense_254 (Dense)	(None, 64)	8256
dense_255 (Dense)	(None, 32)	2080
dropout_16 (Dropout)	(None, 32)	0

batch_normalization_16 (Batch Normalization)	(None, 32)	128
dense_256 (Dense)	(None, 10)	330
dense_257 (Dense)	(None, 2)	22

```

=====
Total params: 51,648
Trainable params: 51,584
Non-trainable params: 64

```

```

None
Epoch 1/10
6037/6037 [=====] - 28s 5ms/step - loss:
0.3764 - f1_score: 0.5799 - val_loss: 0.0126 - val_f1_score: 0.8648
Epoch 2/10
6037/6037 [=====] - 24s 4ms/step - loss:
0.0097 - f1_score: 0.8228 - val_loss: 0.0103 - val_f1_score: 0.7497
Epoch 3/10
6037/6037 [=====] - 24s 4ms/step - loss:
0.0086 - f1_score: 0.8558 - val_loss: 0.0089 - val_f1_score: 0.8381
Epoch 4/10
6037/6037 [=====] - 24s 4ms/step - loss:
0.0082 - f1_score: 0.8608 - val_loss: 0.0094 - val_f1_score: 0.7261
Epoch 5/10
6037/6037 [=====] - 25s 4ms/step - loss:
0.0080 - f1_score: 0.8610 - val_loss: 0.0084 - val_f1_score: 0.8784
Epoch 6/10
6037/6037 [=====] - 24s 4ms/step - loss:
0.0079 - f1_score: 0.8615 - val_loss: 0.0084 - val_f1_score: 0.7647
Epoch 7/10
6037/6037 [=====] - 23s 4ms/step - loss:
0.0075 - f1_score: 0.8675 - val_loss: 0.0085 - val_f1_score: 0.8784
Epoch 8/10
6037/6037 [=====] - 23s 4ms/step - loss:
0.0072 - f1_score: 0.8827 - val_loss: 0.0096 - val_f1_score: 0.7072
Epoch 9/10
6037/6037 [=====] - 23s 4ms/step - loss:
0.0073 - f1_score: 0.8788 - val_loss: 0.0086 - val_f1_score: 0.8818
5660/5660 [=====] - 10s 2ms/step
1415/1415 [=====] - 3s 2ms/step

```

Model performance ANN6

```

accuracy score train 0.9994478249826065
accuracy score test 0.9992490502694584

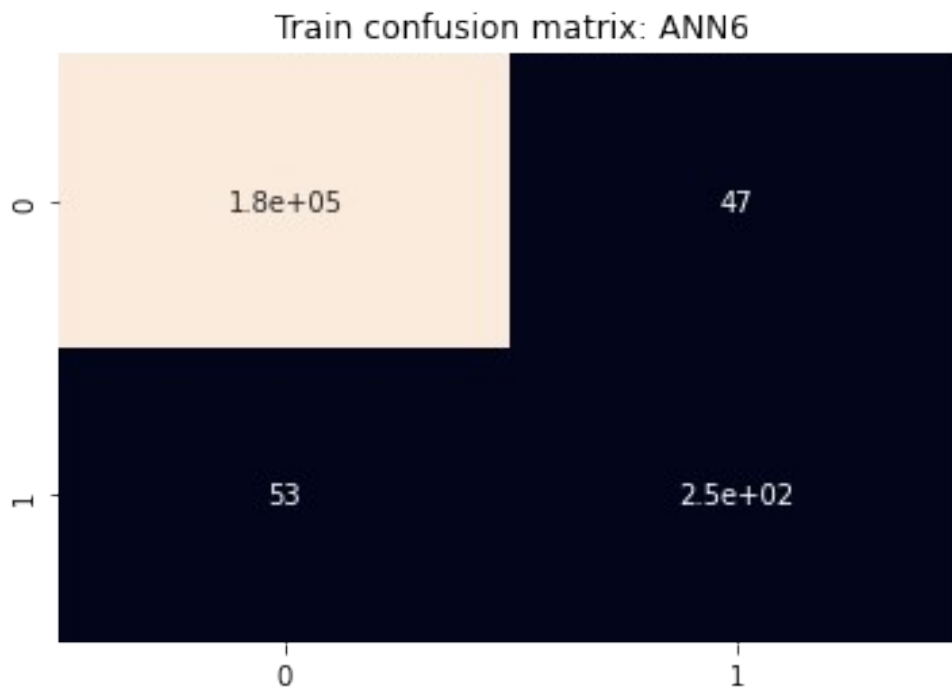
```

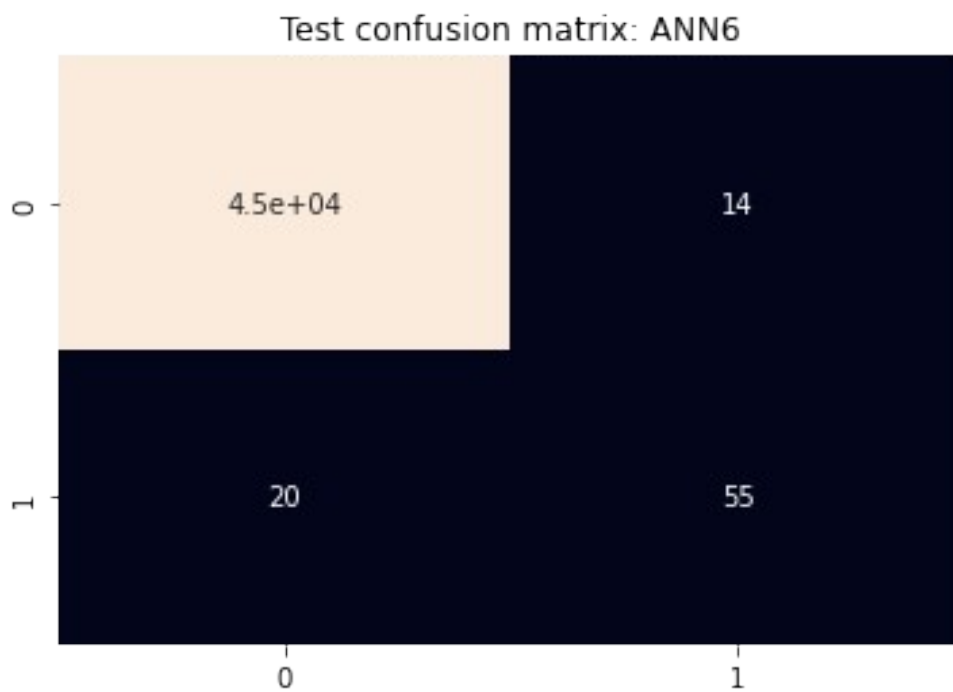
Train classification report: ANN6

	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	0.84	0.82	0.83	302
accuracy			1.00	181102
macro avg	0.92	0.91	0.92	181102
weighted avg	1.00	1.00	1.00	181102

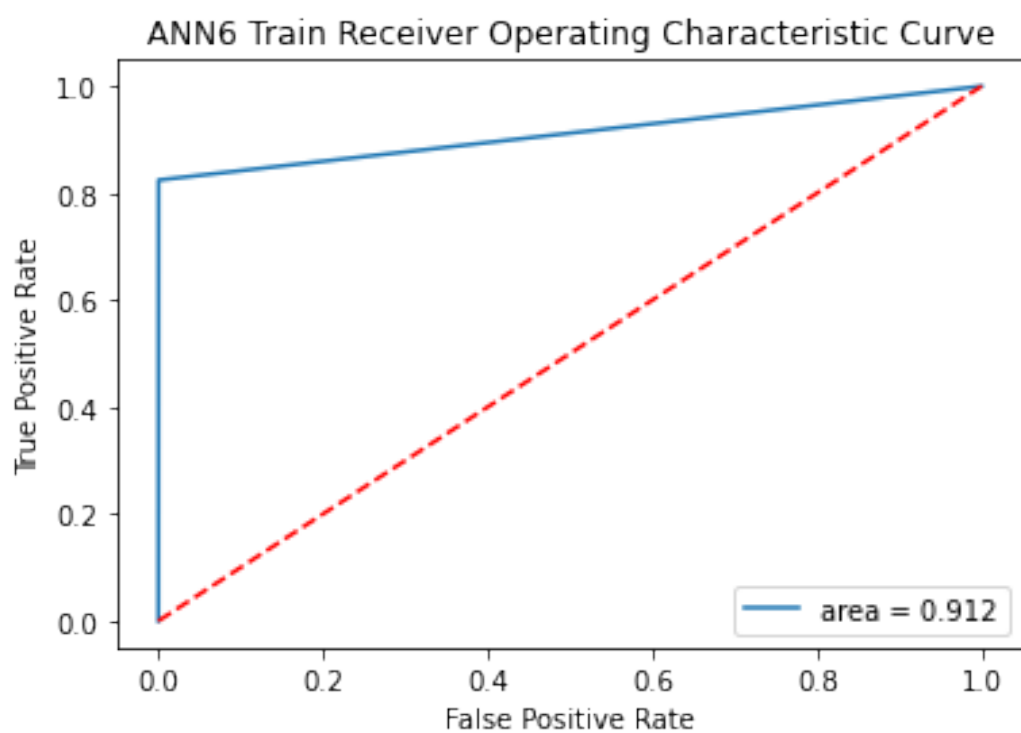
Test classification report: ANN6

	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	0.80	0.73	0.76	75
accuracy			1.00	45276
macro avg	0.90	0.87	0.88	45276
weighted avg	1.00	1.00	1.00	45276

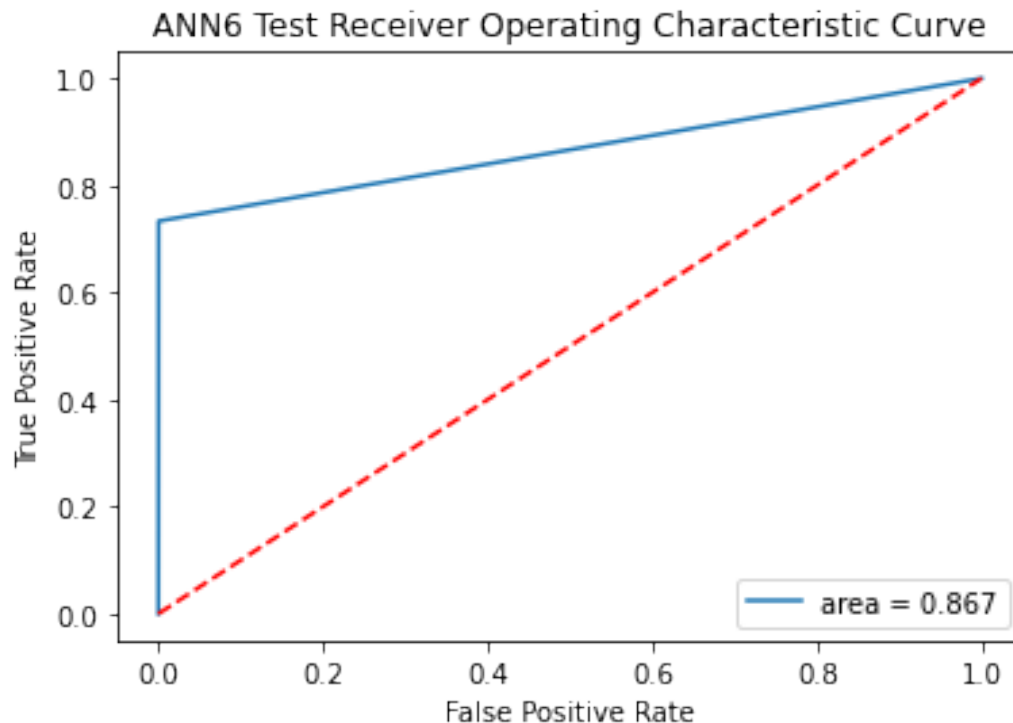




roc auc score train 0.9121216777530329



roc auc score test 0.8665118028362204



1781/1781 [=====] - 3s 2ms/step

Test accuracy score 0.9993153330290369

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.82	0.77	0.79	98
accuracy			1.00	56962
macro avg	0.91	0.88	0.90	56962
weighted avg	1.00	1.00	1.00	56962

Completed and saved for model ANN6

Among all the models with oversampled, undersampled and original inputs, we got the best model with highest performance.

ANN6 with original input gave best score (f1-score macro= 0.90).

So going forward, for fraud prediction, we can use this model.

Now with the original input data, we can do hyper-parameter tuning.

Hyper-parameter tuning for ANN models

```
finance_train = pd.read_pickle('finance_train.pkl')
finance_test = pd.read_pickle('finance_test.pkl')

train_X = finance_train.drop(['Class'], axis=1)
train_y = finance_train[['Class']]

test_X = finance_test.drop(['Class'], axis=1)
test_y = finance_test[['Class']]

x_train, x_test, y_train, y_test = train_test_split(train_X, train_y,
stratify= train_y,

test_size= 0.2, random_state= 0)

y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
test_y = to_categorical(test_y)

print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
print(test_X.shape)
print(test_y.shape)

(181102, 30)
(181102, 2)
(45276, 30)
(45276, 2)
(56962, 30)
(56962, 2)

def modelBuilder(hy_param):
    # regularization param
    regL1 = hy_param.Float('regularization1', 0.0, 0.1, step=0.005)
    regL2 = hy_param.Float('regularization2', 0.0, 0.1, step=0.005)
    # kernel initialization param
    kernel_initializers = hy_param.Choice('kernel_initializer',
['he_uniform', 'he_normal'])
    # dropout param
    dropout = hy_param.Float('dropout', 0, 0.5, step=0.2)
    # actiation
    activation_fn = hy_param.Choice('activation', ['relu', 'tanh'])
    # kernel initializer
    initializer = hy_param.Choice('kernel initializer', ['he_normal',
'he_uniform', 'glorot_uniform', 'glorot_normal'])
    # Number of neurons and number of layers
    num_neuron = hy_param.Choice('nmber of neurons', [32, 64, 128,
256])
```

```

    nu_num = num_neuron
    num_layer = hy_param.Int('dense_layers', 1, math.log2(num_neuron
// 16))
    num_neuron_last = hy_param.Choice('number of neurons', [5, 10, 15])
    # Optimizers
    optimizerName = hy_param.Choice('optimizer', ['sgd', 'adadelta',
'adagrad', 'rmsprop', 'adam'])

    input = Input(x_train.shape[-1],)
    x = input

    for i in range(num_layer):
        x = Dense(units = nu_num, activation = activation_fn,
                kernel_initializer = initializer, kernel_regularizer =
L1L2(l1=regL1, l2=regL2))(x)
        nu_num //= 2

    x = Dropout(dropout)(x)
    x = BatchNormalization()(x)

    x = Dense(units = num_neuron_last, activation = activation_fn,
            kernel_initializer = initializer, kernel_regularizer =
L1L2(l1=regL1, l2=regL2))(x)
    output = Dense(2, activation = 'softmax')(x)

    model = Model(input, output)
    model.compile(loss='categorical_crossentropy', optimizer=
optimizerName, metrics=[F1Score(num_classes= 2, average= 'macro')])
    return model

tuner = BayesianOptimization(modelBuilder, objective='val_loss',
max_trials=3,
                        project_name='Finance ANN Result')

tuner.search_space_summary()

Search space summary
Default search space size: 9
regularization1 (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.1,
'step': 0.005, 'sampling': None}
regularization2 (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.1,
'step': 0.005, 'sampling': None}
kernel_initializer (Choice)
{'default': 'he_uniform', 'conditions': [], 'values': ['he_uniform',
'he_normal'], 'ordered': False}
dropout (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.5,
'step': 0.2, 'sampling': None}

```

```

activation (Choice)
{'default': 'relu', 'conditions': [], 'values': ['relu', 'tanh'],
 'ordered': False}
kernel_initializer (Choice)
{'default': 'he_normal', 'conditions': [], 'values': ['he_normal',
 'he_uniform', 'glorot_uniform', 'glorot_normal'], 'ordered': False}
number of neurons (Choice)
{'default': 32, 'conditions': [], 'values': [32, 64, 128, 256],
 'ordered': True}
dense_layers (Int)
{'default': None, 'conditions': [], 'min_value': 1, 'max_value': 1,
 'step': 1, 'sampling': None}
optimizer (Choice)
{'default': 'sgd', 'conditions': [], 'values': ['sgd', 'adadelata',
 'adagrad', 'rmsprop', 'adam'], 'ordered': False}

callback = EarlyStopping(monitor='val_loss', patience=4)

tuner.search(x_train, y_train, batch_size=30, epochs=10,
             validation_data=(x_test, y_test), callbacks=[callback])

```

```

Trial 3 Complete [00h 05m 23s]
val_loss: 0.003881769487634301

```

```

Best val_loss So Far: 0.003881769487634301
Total elapsed time: 00h 09m 54s

```

```
tuner.results_summary()
```

```

Results summary
Results in ./Finance ANN Result
Showing 10 best trials
<keras_tuner.engine.objective.Objective object at 0x7f00556e3110>
Trial summary
Hyperparameters:
regularization1: 0.0
regularization2: 0.0
kernel_initializer: he_normal
dropout: 0.2
activation: tanh
kernel_initializer: he_uniform
number of neurons: 256
dense_layers: 1
optimizer: sgd
Score: 0.003881769487634301
Trial summary
Hyperparameters:
regularization1: 0.045
regularization2: 0.015
kernel_initializer: he_normal
dropout: 0.2

```

```

activation: tanh
kernel_initializer: he_uniform
number of neurons: 128
dense_layers: 1
optimizer: sgd
Score: 0.21482113003730774
Trial summary
Hyperparameters:
regularization1: 0.085
regularization2: 0.03
kernel_initializer: he_uniform
dropout: 0.2
activation: relu
kernel_initializer: he_uniform
number of neurons: 64
dense_layers: 1
optimizer: sgd
Score: 0.22776171565055847

```

```

tunned_neural_model = tuner.get_best_models(num_models=1)[0]
tunned_neural_model.summary()

```

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 30)]	0
dense (Dense)	(None, 256)	7936
dropout (Dropout)	(None, 256)	0
batch_normalization (Batch Normalization)	(None, 256)	1024
dense_1 (Dense)	(None, 256)	65792
dense_2 (Dense)	(None, 2)	514
Total params: 75,266		
Trainable params: 74,754		
Non-trainable params: 512		

```

y_train_pred = tunned_neural_model.predict(x_train)
y_test_pred = tunned_neural_model.predict(x_test)
y_train_label = np.argmax(y_train, axis= 1)
y_train_pred = np.argmax(y_train_pred, axis= 1)
y_test_label = np.argmax(y_test, axis= 1)
y_test_pred = np.argmax(y_test_pred, axis= 1)

```

```
getPerformance(y_train_label, y_train_pred, y_test_label, y_test_pred,
'Tunned ANN')
```

```
test_y_pred = tuned_neural_model.predict(test_X)
test_y_label = np.argmax(test_y, axis= 1)
test_y_pred = np.argmax(test_y_pred, axis= 1)
```

```
print('\nTest accuracy score {} \
n'.format(accuracy_score(test_y_label, test_y_pred)))
print('Classification report\n')
print(classification_report(test_y_label, test_y_pred))
print('\nCompleted and saved for model Tunned ANN')
tuned_neural_model.save('Tunned ANN')
```

```
5660/5660 [=====] - 11s 2ms/step
1415/1415 [=====] - 3s 2ms/step
```

Model performance Tunned ANN

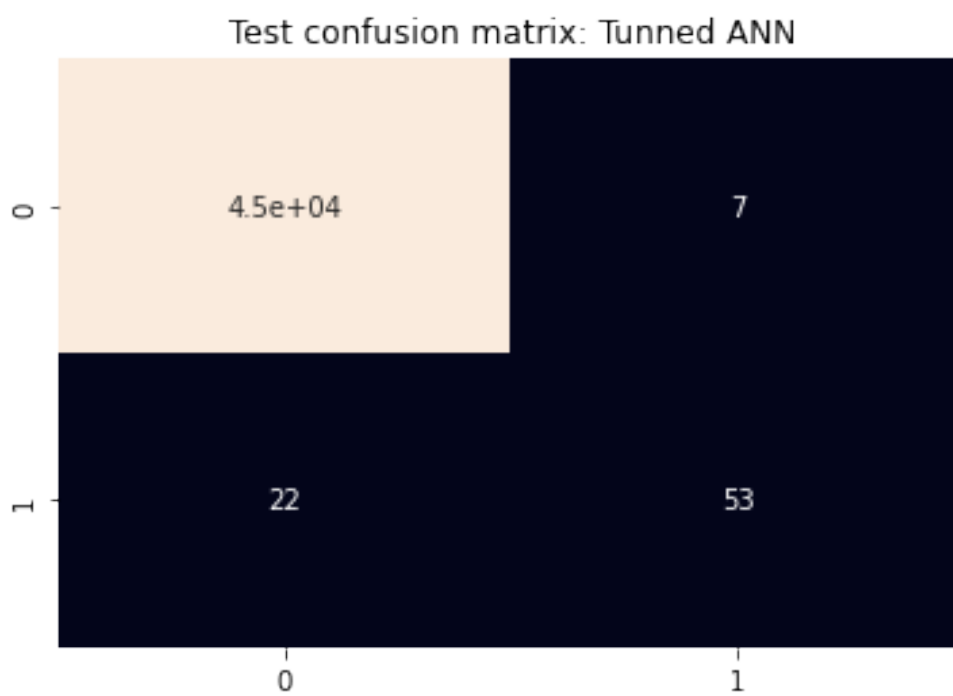
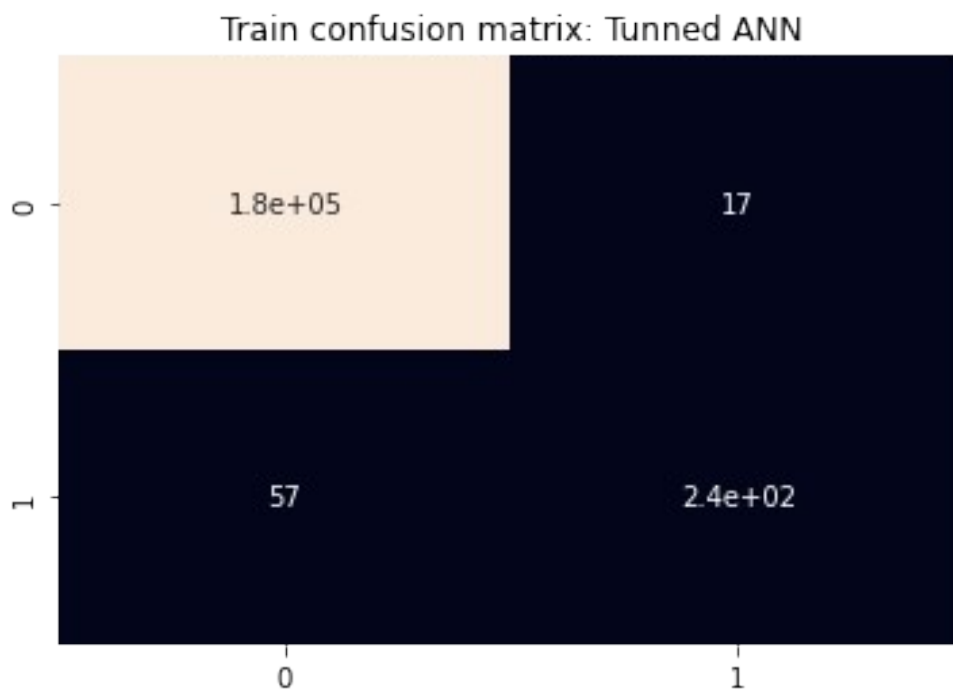
```
accuracy score train 0.9995913904871288
accuracy score test 0.9993594840533616
```

Train classification report: Tunned ANN

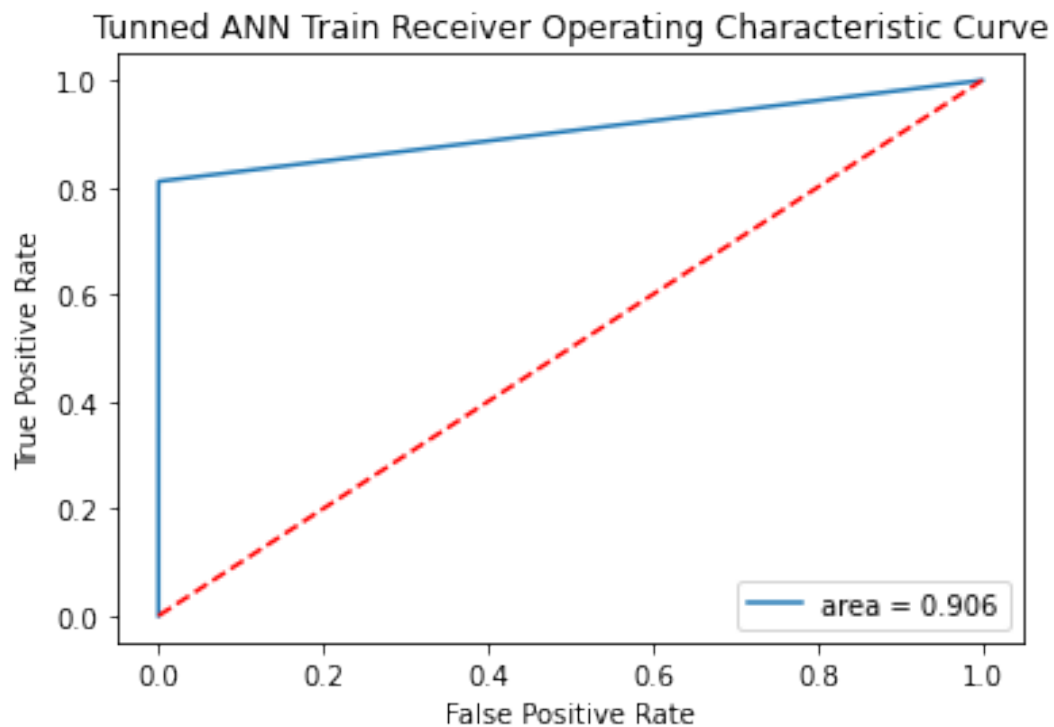
	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	0.94	0.81	0.87	302
accuracy			1.00	181102
macro avg	0.97	0.91	0.93	181102
weighted avg	1.00	1.00	1.00	181102

Test classification report: Tunned ANN

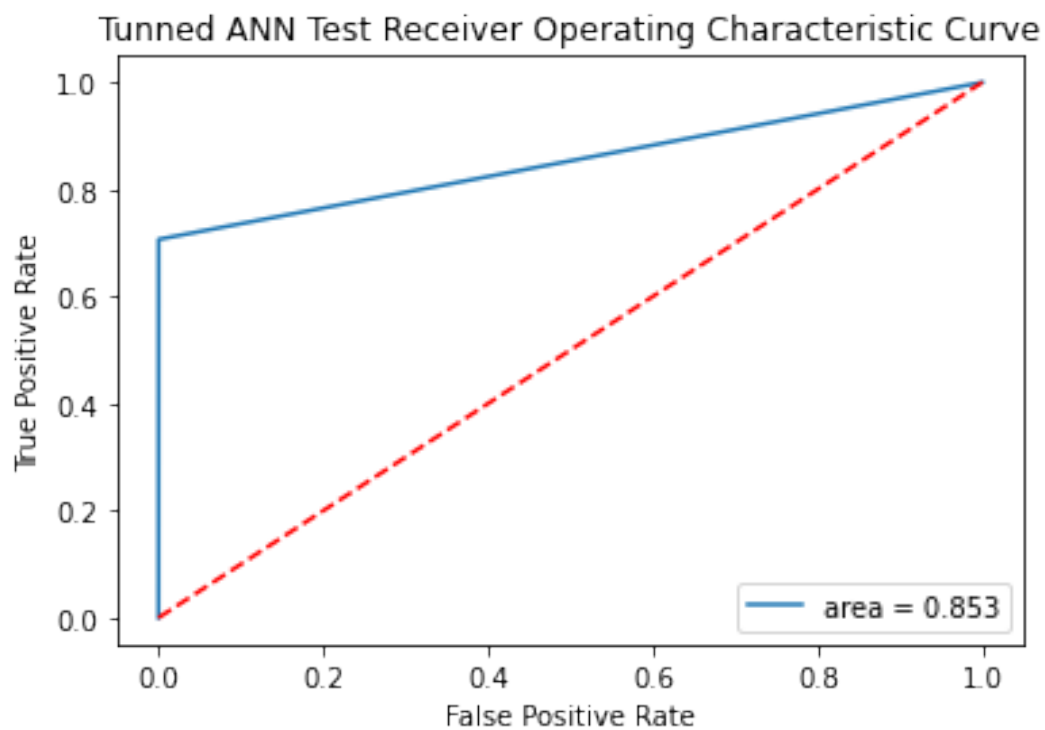
	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	0.88	0.71	0.79	75
accuracy			1.00	45276
macro avg	0.94	0.85	0.89	45276
weighted avg	1.00	1.00	1.00	45276



roc auc score train 0.9055821257985115



roc auc score test 0.8532559014181101



1781/1781 [=====] - 4s 2ms/step

Test accuracy score 0.9994382219725431

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.93	0.72	0.82	98
accuracy			1.00	56962
macro avg	0.97	0.86	0.91	56962
weighted avg	1.00	1.00	1.00	56962

Completed and saved for model Tunned ANN

As we can see the latest model gave the highest performance now among all the ANN models (f1-score macro= 0.91 with test data).

But again we can use other models as well giving top results.

If we consider both ML and DL models, still random forest classifier gae the highest score of 0.92.

Anomaly Detection

All the records we have, there is a possibility that we can have anomaly/outliers which lies with large separation as compared to other records. Based on the selected features, we can decide whether a point in feature space is anomaly or not. We can also assign scores to the points implying the chances of being a anomaly.

We can use IsolationForest model to provide anomaly label prediction and scores to the data points.

```
print(train_X.shape)
print(train_y.shape)
```

```
(226378, 30)
(226378, 1)
```

```
model = IsolationForest(n_estimators=50, max_samples=500,
contamination=.05, max_features=10,
                        bootstrap=False, n_jobs=1, random_state=1,
verbose=0, warm_start=False).fit(train_X)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451:
UserWarning: X does not have valid feature names, but IsolationForest
was fitted with feature names
  "X does not have valid feature names, but"
```



```

anomaly_score = model.decision_function(train_X)
predictions = model.predict(train_X)

anomaly_score[:5]

array([0.12114711, 0.01284614, 0.06780871, 0.11218362, 0.09971792])

print(np.unique(predictions, return_counts=True))

(array([-1, 1]), array([ 11318, 215060]))

anomaly_score_test = model.decision_function(test_X)

```

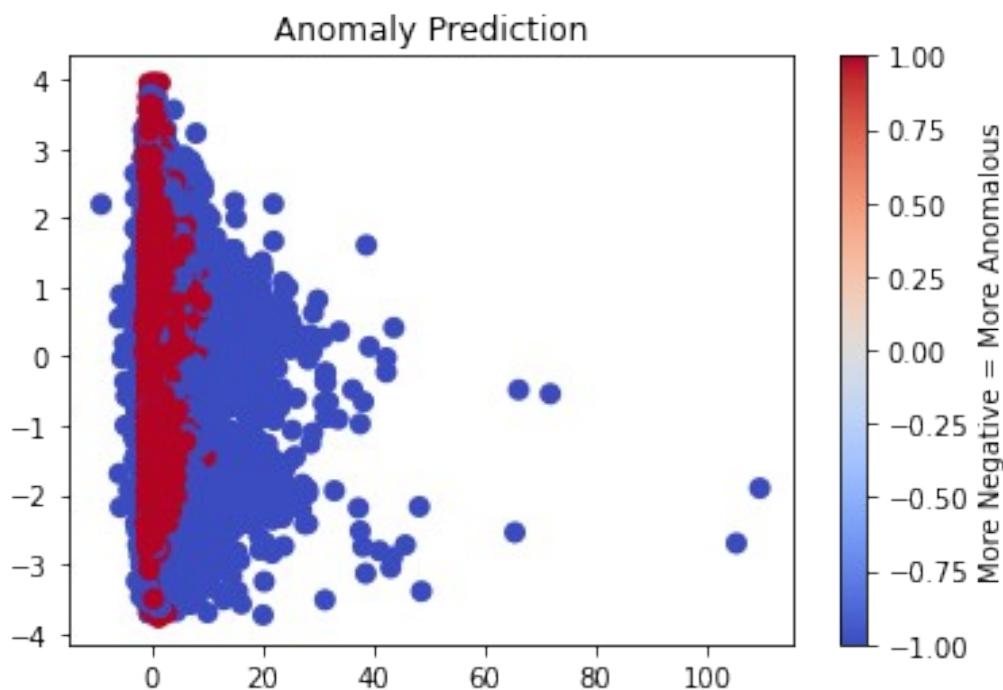
The finance data got fit with the model for anomaly detection. Here we got the scores and the labels of anomaly (-1,1)

Now we can visualize the data points with the score values and the predictions.

```

X_pca = PCA(n_components=2,
random_state=42).fit_transform(train_X.values)
s = plt.scatter(X_pca[:,0], X_pca[:,1], c=predictions,
cmap='coolwarm', linewidths=2)
plt.colorbar(s, label = 'More Negative = More Anomalous')
plt.title('Anomaly Prediction')
plt.show()

```

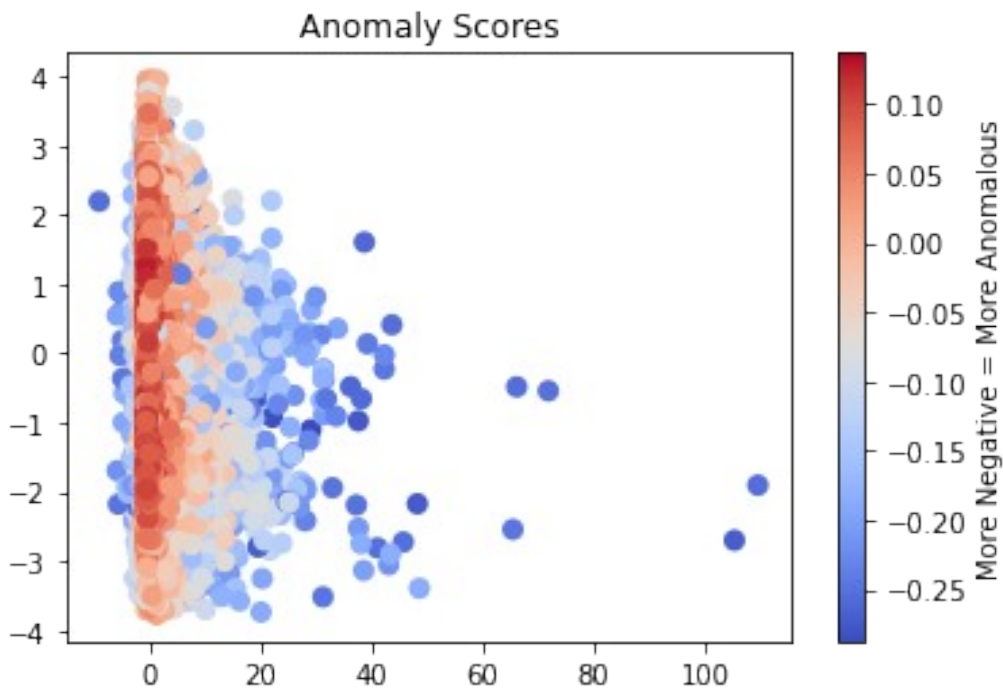


```

X_pca = PCA(n_components=2,
random_state=42).fit_transform(train_X.values)
s = plt.scatter(X_pca[:,0], X_pca[:,1], c=anomaly_score,
cmap='coolwarm', linewidths=2)

```

```
plt.colorbar(s, label = 'More Negative = More Anomalous')
plt.title('Anomaly Scores')
plt.show()
```



Now lets try to add this anomaly scores to our input data as a feature and check the performance.

Before that, we need to fit a model (Random Forest) with the original data.

```
x_train, x_test, y_train, y_test = train_test_split(train_X, train_y,
stratify= train_y,

test_size= 0.2, random_state= 0)

rf = RandomForestClassifier(class_weight='balanced')

rf.fit(x_train, y_train)
y_train_pred = rf.predict(x_train)
y_test_pred = rf.predict(x_test)
getPerformance(y_train, y_train_pred, y_test, y_test_pred, 'RF with
original data')
test_y_pred = rf.predict(test_X)
print('\nTest accuracy score {} \n'.format(accuracy_score(test_y,
test_y_pred)))
print('Classification report\n')
print(classification_report(test_y, test_y_pred))
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1:
DataConversionWarning: A column-vector y was passed when a 1d array
was expected. Please change the shape of y to (n_samples,), for
example using ravel().
```

```
"""Entry point for launching an IPython kernel.
```

Model performance RF with original data

```
accuracy score train 1.0
accuracy score test 0.9993594840533616
```

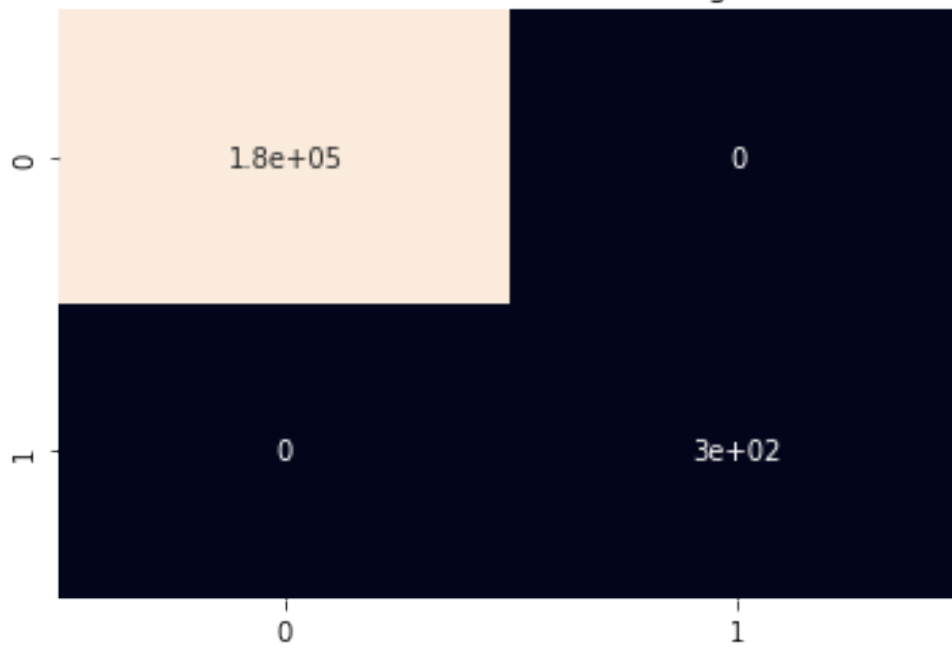
Train classification report: RF with original data

	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	1.00	1.00	1.00	302
accuracy			1.00	181102
macro avg	1.00	1.00	1.00	181102
weighted avg	1.00	1.00	1.00	181102

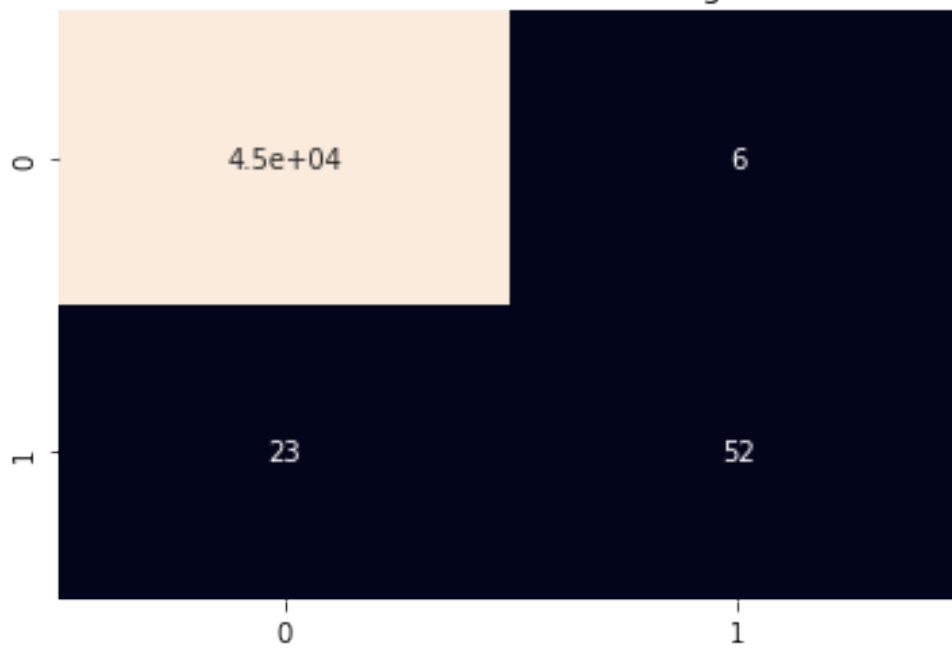
Test classification report: RF with original data

	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	0.90	0.69	0.78	75
accuracy			1.00	45276
macro avg	0.95	0.85	0.89	45276
weighted avg	1.00	1.00	1.00	45276

Train confusion matrix: RF with original data

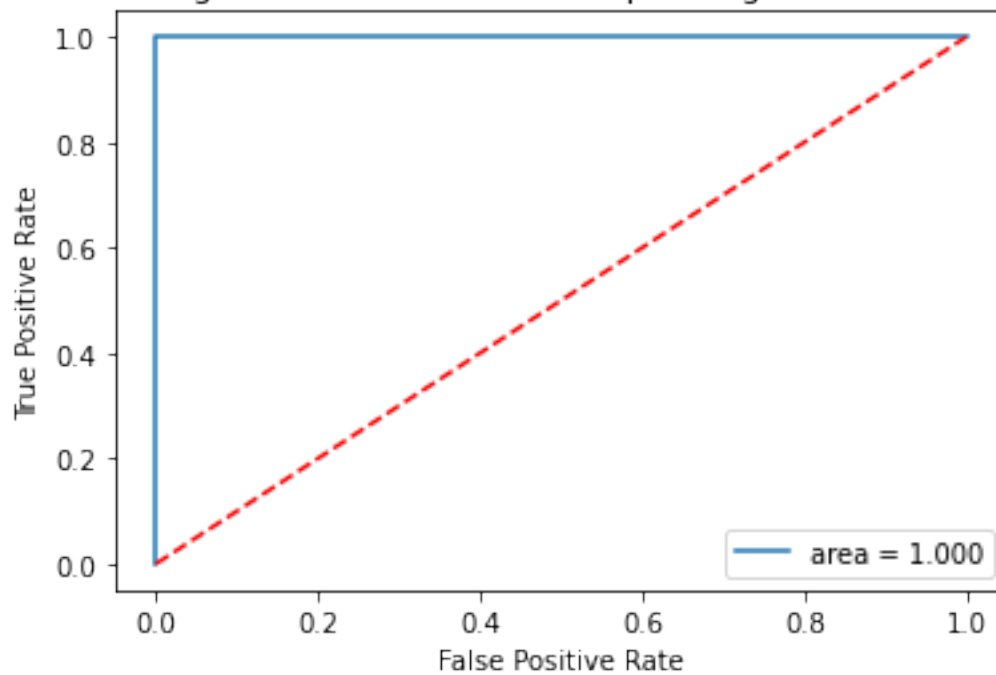


Test confusion matrix: RF with original data



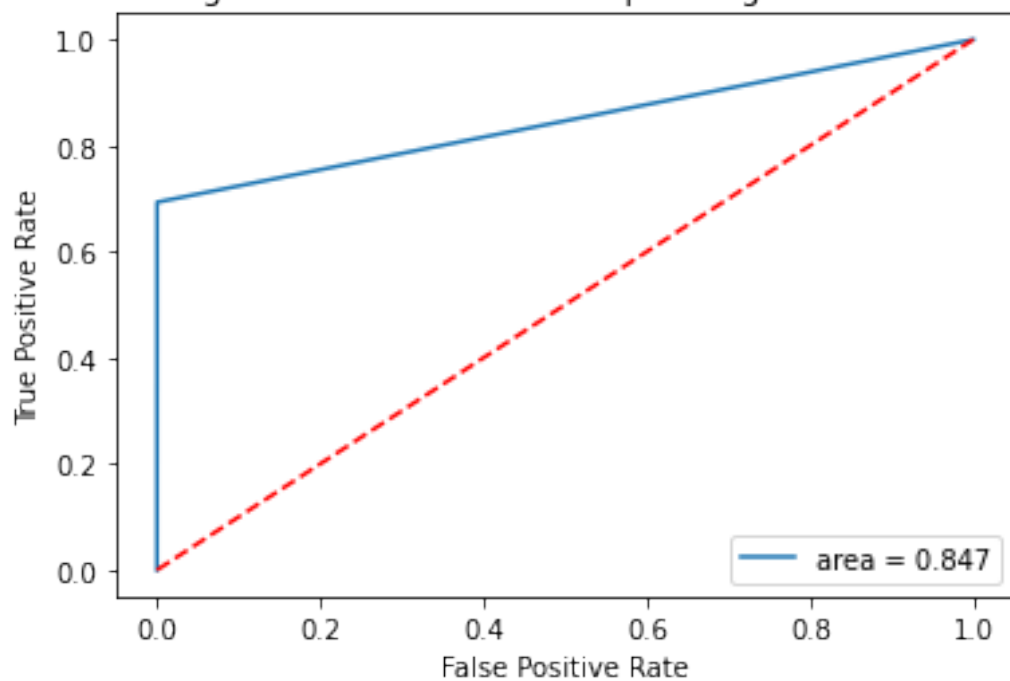
roc auc score train 1.0

RF with original data Train Receiver Operating Characteristic Curve



roc auc score test 0.8466002964536182

RF with original data Test Receiver Operating Characteristic Curve



Test accuracy score 0.9994557775359011

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.95	0.72	0.82	98
accuracy			1.00	56962
macro avg	0.97	0.86	0.91	56962
weighted avg	1.00	1.00	1.00	56962

Random forest with original data gave a good performance with f-score macro as 0.91.

Now we can add the anomaly scores to the input and fit a new model.

```
train_X['Anomaly Score'] = anomaly_score
test_X['Anomaly Score'] = anomaly_score_test

x_train, x_test, y_train, y_test = train_test_split(train_X, train_y,
                                                    stratify= train_y,

                                                    test_size= 0.2, random_state= 0)

print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
print(test_X.shape)
print(test_y.shape)

(181102, 31)
(181102, 1)
(45276, 31)
(45276, 1)
(56962, 31)
(56962, 1)

rf_anmly = RandomForestClassifier(class_weight='balanced')

rf_anmly.fit(x_train, y_train)
y_train_pred = rf_anmly.predict(x_train)
y_test_pred = rf_anmly.predict(x_test)
getPerformance(y_train, y_train_pred, y_test, y_test_pred, 'RF with
original data and anomaly score')
test_y_pred = rf_anmly.predict(test_X)
print('\nTest accuracy score {} \n'.format(accuracy_score(test_y,
test_y_pred)))
```

```

print('Classification report\n')
print(classification_report(test_y, test_y_pred))

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1:
DataConversionWarning: A column-vector y was passed when a 1d array
was expected. Please change the shape of y to (n_samples,), for
example using ravel().
  """Entry point for launching an IPython kernel.

```

Model performance RF with original data and anomaly score

```

accuracy score train 1.0
accuracy score test 0.9993594840533616

```

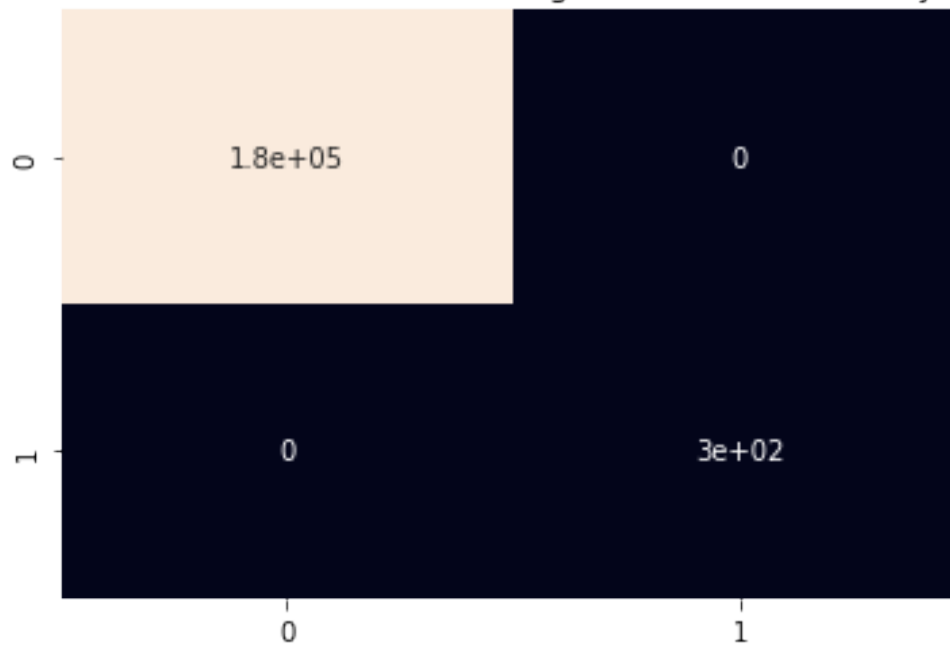
Train classification report: RF with original data and anomaly score

	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	1.00	1.00	1.00	302
accuracy			1.00	181102
macro avg	1.00	1.00	1.00	181102
weighted avg	1.00	1.00	1.00	181102

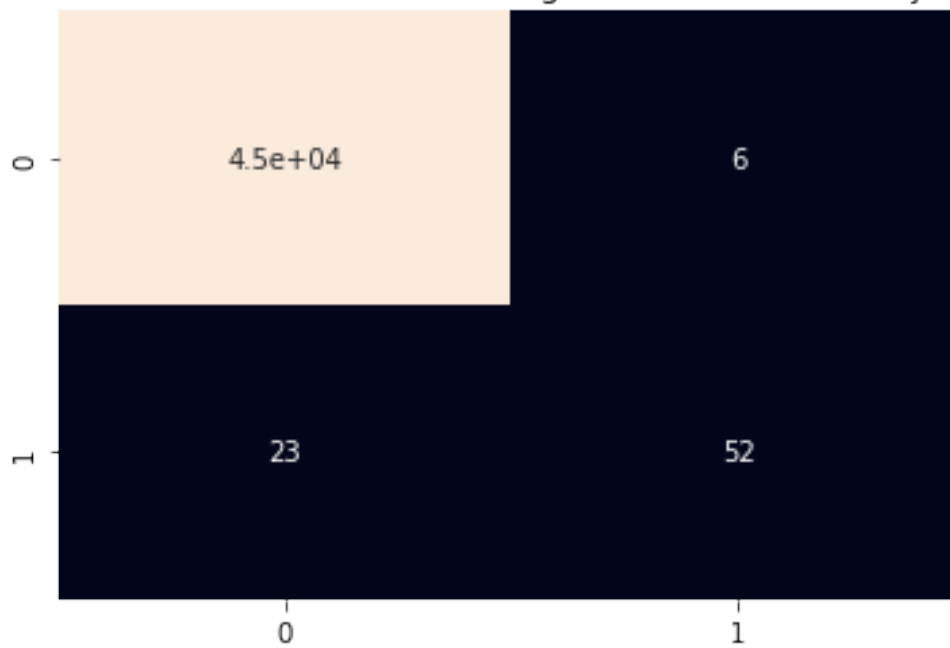
Test classification report: RF with original data and anomaly score

	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	0.90	0.69	0.78	75
accuracy			1.00	45276
macro avg	0.95	0.85	0.89	45276
weighted avg	1.00	1.00	1.00	45276

Train confusion matrix: RF with original data and anomaly score

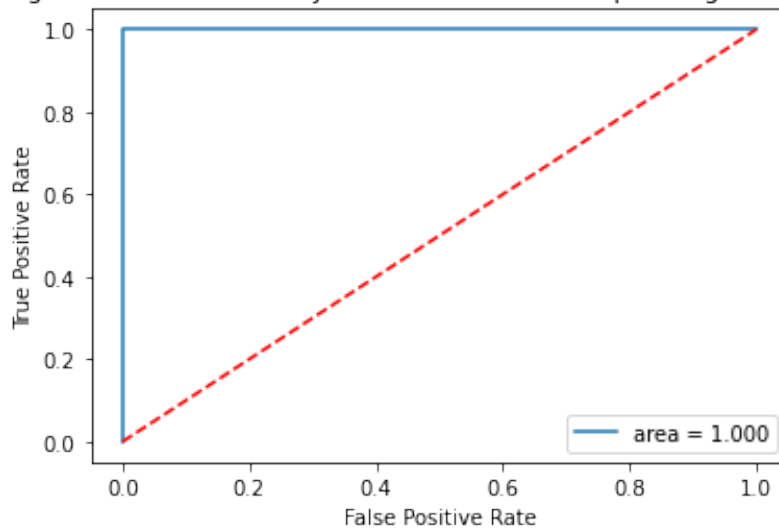


Test confusion matrix: RF with original data and anomaly score



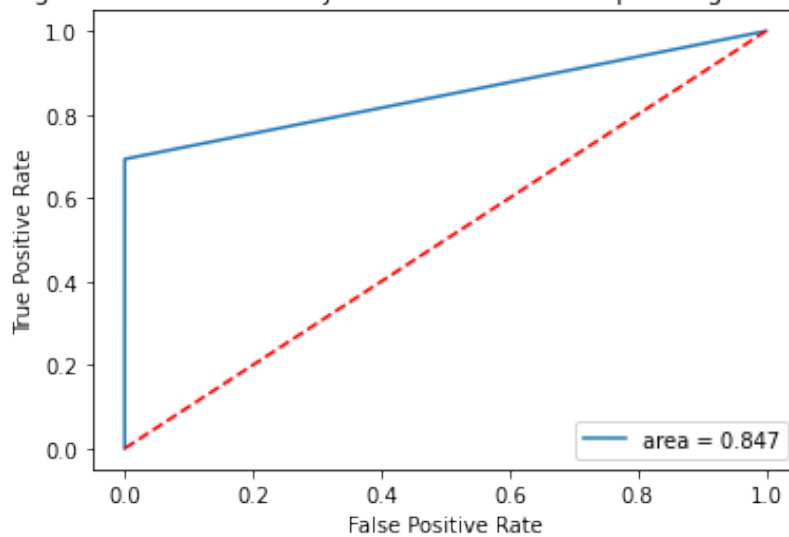
roc auc score train 1.0

RF with original data and anomaly score Train Receiver Operating Characteristic Curve



roc auc score test 0.8466002964536182

RF with original data and anomaly score Test Receiver Operating Characteristic Curve



Test accuracy score 0.9994557775359011

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.96	0.71	0.82	98
accuracy			1.00	56962

macro avg	0.98	0.86	0.91	56962
weighted avg	1.00	1.00	1.00	56962

Random forest model trained with original data and the anomaly score gave very good performance (f1-score macro= 0.91) same as the previous model.

So yes, we can use the anomaly score as a new feature, but it would be optional as we didnt see much difference in the two performances.

We didnt see much difference in f1-score is may be because the score we got is not a useful feature to detect froudulent transacations, as the anolamaly model detects the anomaly based on selected features, so there is guarentee that the anomaly data points will be the froud transaction.

Threshold for label prediction

From all the ML model we have, we got the highest score (f-score macro= 0.92) in random forest with oversampled.

Now we can consider the random forest model with oversampled data as final model.

But for thresholding, we can use the random forest model with original data.

```
finance_train = pd.read_pickle('finance_train.pkl')
finance_test = pd.read_pickle('finance_test.pkl')

train_X = finance_train.drop(['Class'], axis=1)
train_y = finance_train[['Class']]

test_X = finance_test.drop(['Class'], axis=1)
test_y = finance_test[['Class']]

x_train, x_test, y_train, y_test = train_test_split(train_X, train_y,
stratify= train_y,

test_size= 0.2, random_state= 0)

print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
print(test_X.shape)
print(test_y.shape)

(181102, 30)
(181102, 1)
(45276, 30)
(45276, 1)
(56962, 30)
(56962, 1)
```

```

y_train_pred = rf.predict(x_train)
y_test_pred = rf.predict(x_test)
test_y_pred = rf.predict(test_X)
getPerformance(y_train, y_train_pred, y_test, y_test_pred, 'RF with
original data')
print('\nTest accuracy score {} \n'.format(accuracy_score(test_y,
test_y_pred)))
print('Classification report\n')
print(classification_report(test_y, test_y_pred))

```

Model performance RF with original data

```

accuracy score train 1.0
accuracy score test 0.9993594840533616

```

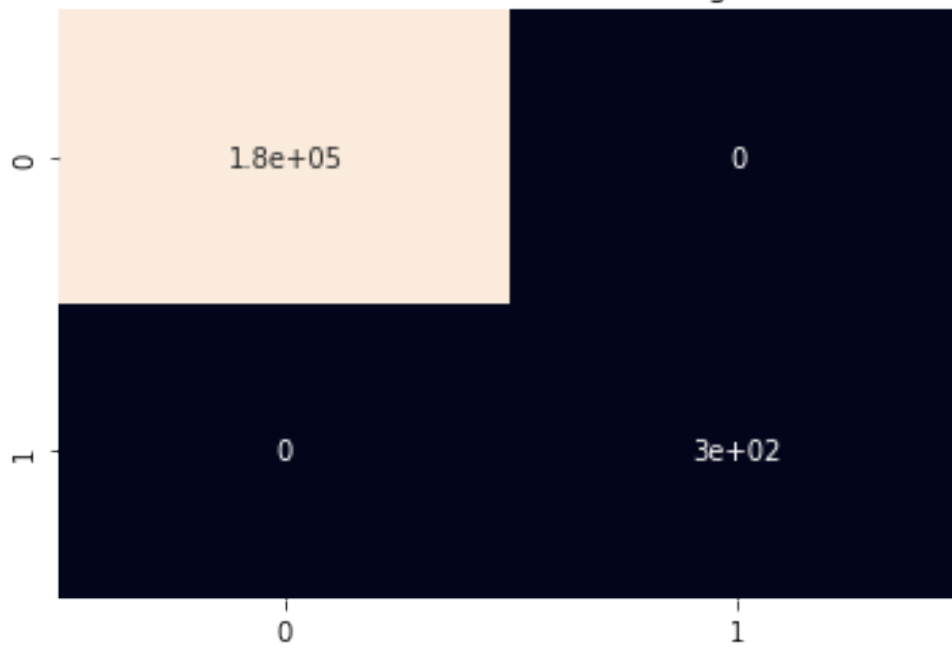
Train classification report: RF with original data

	precision	recall	f1-score	support
0	1.00	1.00	1.00	180800
1	1.00	1.00	1.00	302
accuracy			1.00	181102
macro avg	1.00	1.00	1.00	181102
weighted avg	1.00	1.00	1.00	181102

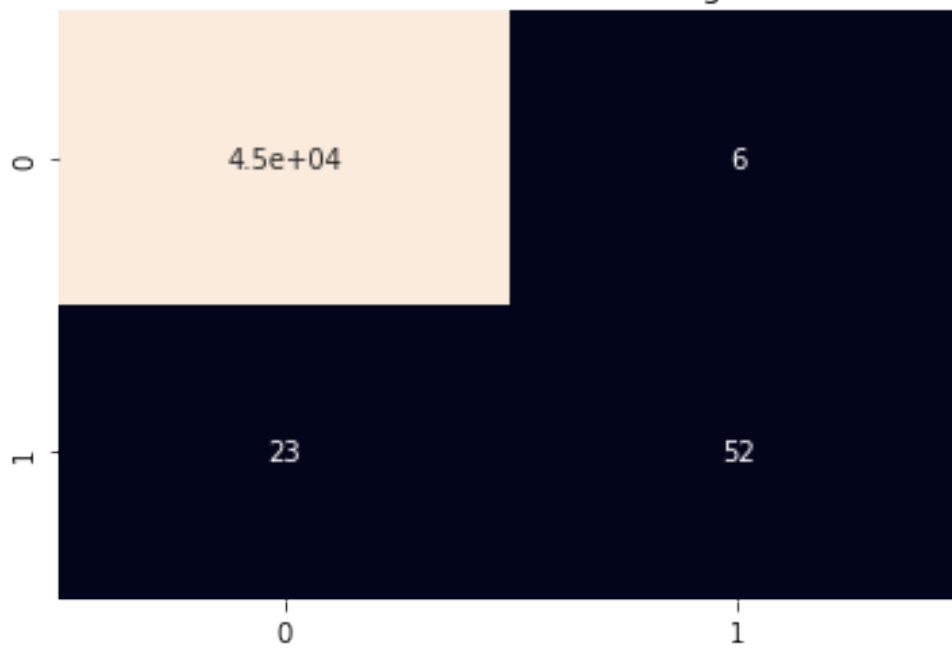
Test classification report: RF with original data

	precision	recall	f1-score	support
0	1.00	1.00	1.00	45201
1	0.90	0.69	0.78	75
accuracy			1.00	45276
macro avg	0.95	0.85	0.89	45276
weighted avg	1.00	1.00	1.00	45276

Train confusion matrix: RF with original data

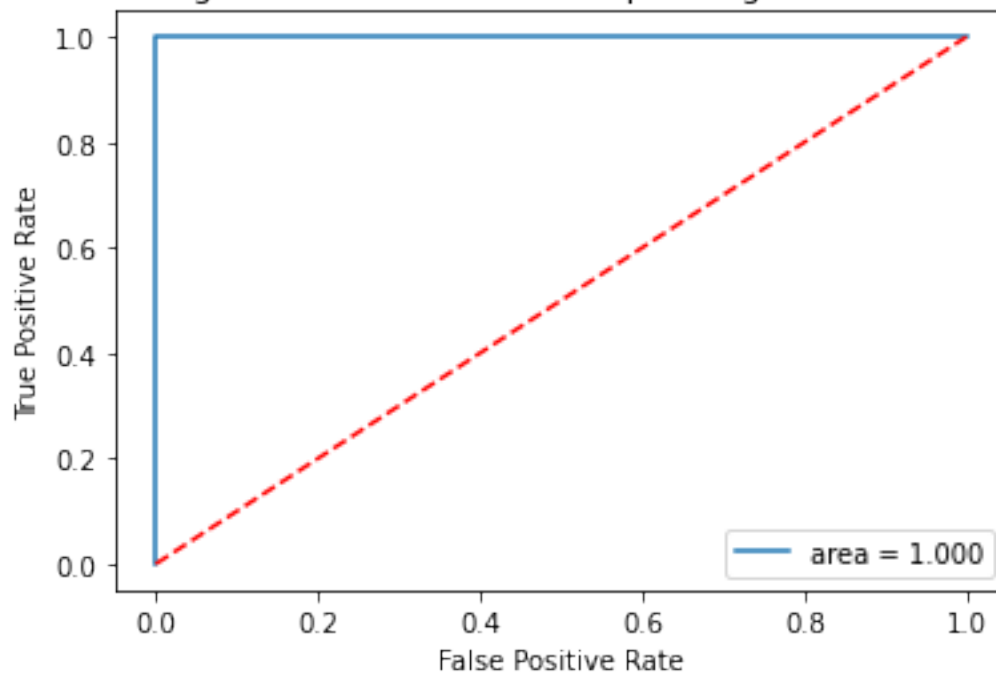


Test confusion matrix: RF with original data



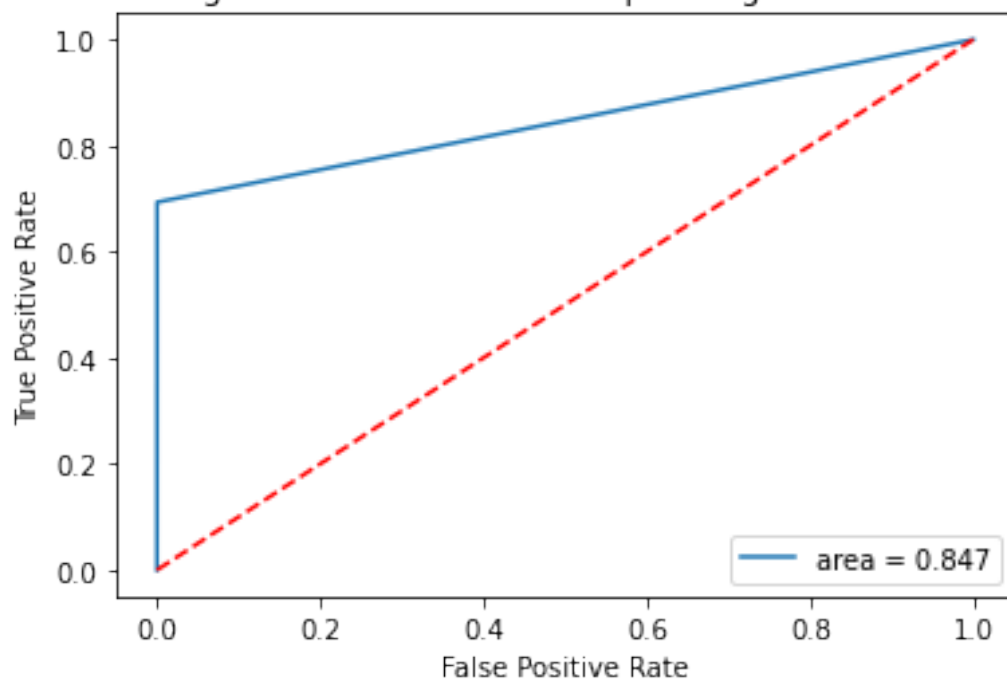
roc auc score train 1.0

RF with original data Train Receiver Operating Characteristic Curve



roc auc score test 0.8466002964536182

RF with original data Test Receiver Operating Characteristic Curve



Test accuracy score 0.9994557775359011

Classification report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56864
1	0.95	0.72	0.82	98
accuracy			1.00	56962
macro avg	0.97	0.86	0.91	56962
weighted avg	1.00	1.00	1.00	56962

```
y_train_pred_proba = rf.predict_proba(x_train)[: , 1]
y_test_pred_proba = rf.predict_proba(x_test)[: , 1]
test_y_pred_proba = rf.predict_proba(test_X)[: , 1]

fpr, tpr, th = roc_curve(y_train, y_train_pred)

f1_scores = []
cur_th = None
def setClass(val):
    if val > cur_th:
        return 1
    else:
        return 0

for t in th:
    cur_th = t
    y_train_pred = np.array(list(map(setClass, y_train_pred_proba)))
    score = f1_score(y_train, y_train_pred, average= 'macro')
    f1_scores.append(score)

f1_scores = np.array(f1_scores)
max_idx = np.argmax(f1_scores)
final_th = th[max_idx]
final_th

0

cur_th = final_th
y_train_pred = np.array(list(map(setClass, y_train_pred_proba)))
score = f1_score(y_train, y_train_pred, average= 'macro')
score

0.6474639191293603

test_y_pred = np.array(list(map(setClass, test_y_pred_proba)))
score = f1_score(test_y, test_y_pred, average= 'macro')
score

0.5646132750465037
```

We can take 0 as final threshold value to predict the class labels.

But still without doing thresholding manually, we get much higher f1-score (0.92) directly with the oversampled random forest model.