```
#importing libraries

import matplotlib
import matplotlib.pyplot as plt
import random

import pandas as pd
import numpy as np

from tqdm import tqdm

from sklearn.decomposition import PCA
from sklearn.manifold import TSNE

from sklearn.model_selection import train_test_split

import pickle
```

```
!curl --header 'Host: doc-14-ak-docs.googleusercontent.com' --user-agent 'Mozilla/5.0 (X11; Linux x86_64; rv:81.0) Gecko/20100101 Firefox/81.0' --header 'Accept: text/html,appli
!curl --header 'Host: doc-08-ak-docs.googleusercontent.com' --user-agent 'Mozilla/5.0 (X11; Linux x86_64; rv:81.0) Gecko/20100101 Firefox/81.0' --header 'Accept: text/html,appli
!curl --header 'Host: doc-14-ak-docs.googleusercontent.com' --user-agent 'Mozilla/5.0 (X11; Linux x86_64; rv:81.0) Gecko/20100101 Firefox/81.0' --header 'Accept: text/html,appli

!unzip /content/falls.zip
!pip install seaborn --upgrade

import seaborn as sns

print(sns.__version__)
```

Loading scaler

```
#Loading Scaler

filename = '/content/scalar.pkl'


with open(filename, 'rb') as f:
    scaler = pickle.load(f)

print(scaler)
```

```
StandardScaler(copy=True, with_mean=True, with_std=True)
```

Loading varriables

```
#Loading varriables

filename = '/content/varriables.pickle'

with open(filename, 'rb') as f:
    high_nan_features, median, time_based_sensor, bottom_n_features, useless_features = pickle.load(f)

print("high_nan_features = ",high_nan_features)
print("median = ",median)
print("time_based_sensor = ",time_based_sensor)
print("bottom_n_features = ",bottom_n_features)
print("useless_features = ",useless_features)
```

```
high_nan_features =  ['sensor2_measure', 'sensor38_measure', 'sensor39_measure', 'sensor40_measure', 'sensor41_measure', 'sensor42_measure', 'sensor43_measure', 'sensor68_r
median =  sensor1_measure                 30755.0
sensor3_measure                  152.0
sensor4_measure                  126.0
sensor5_measure                    0.0
sensor6_measure                    0.0
                                 ...
sensor105_histogram_bin7_nan       0.0
sensor105_histogram_bin8_nan       0.0
sensor105_histogram_bin9_nan       0.0
sensor106_measure_nan              0.0
sensor107_measure_nan              0.0
Length: 332, dtype: float64
time_based_sensor =  [['sensor7_histogram_bin0', 'sensor7_histogram_bin1', 'sensor7_histogram_bin2', 'sensor7_histogram_bin3', 'sensor7_histogram_bin4', 'sensor7_histogram_
bottom_n_features =  {'sensor25_histogram_bin9': 0.000404517327265069, 'sensor4_measure': -0.0005747918610703464, 'sensor56_measure': -0.0005748712717671971, 'sensor5_measu
useless_features =  ['sensor7_histogram_bin5', 'sensor7_histogram_bin6', 'sensor8_measure', 'sensor12_measure', 'sensor14_measure', 'sensor15_measure', 'sensor16_measure',
```

Loading dataframe

```
#Loading dataframe
df = pd.read_csv("/content/falls/equip_failures_training_set.csv")

df.head()
```

	id	target	sensor1_measure	sensor2_measure	sensor3_measure	sensor4_measure	sensor5_measure	sensor6_measure	sensor7_histogram_bin0	sensor7_histogram_bin1	sensor7_h
0	1	0	76698	na	2130706438	280	0	0	0	0	
1	2	0	33058	na	0	na	0	0	0	0	
2	3	0	41040	na	228	100	0	0	0	0	
3	4	0	12	0	70	66	0	10	0	0	
4	5	0	60874	na	1368	458	0	0	0	0	

5 rows × 172 columns

Preprocessing for modelling

Replace na with np.nan

```
"""Instead of nan value we have na, so we will replace na with np.nan"""
```

```
df = df.replace('na', np.NaN)
df.head()
```

	id	target	sensor1_measure	sensor2_measure	sensor3_measure	sensor4_measure	sensor5_measure	sensor6_measure	sensor7_histogram_bin0	sensor7_histogram_bin1	sensor7_h
0	1	0	76698	NaN	2130706438	280	0	0	0	0	
1	2	0	33058	NaN	0	NaN	0	0	0	0	
2	3	0	41040	NaN	228	100	0	0	0	0	
3	4	0	12	0	70	66	0	10	0	0	
4	5	0	60874	NaN	1368	458	0	0	0	0	

5 rows × 172 columns

Change data-type of dataframe

```
df.dtypes
```

```
id                          int64
target                      int64
sensor1_measure             int64
sensor2_measure            object
sensor3_measure            object
                            ...
sensor105_histogram_bin7   object
sensor105_histogram_bin8   object
sensor105_histogram_bin9   object
sensor106_measure          object
sensor107_measure          object
Length: 172, dtype: object
```

```
"We could see that few coloumns are of int type, and other are of object type,So for using data we need to make them float data type"

df = df.astype("float32")
df.dtypes
```

```
id                         float32
target                     float32
sensor1_measure            float32
sensor2_measure            float32
sensor3_measure            float32
                            ...
sensor105_histogram_bin7   float32
sensor105_histogram_bin8   float32
sensor105_histogram_bin9   float32
sensor106_measure          float32
sensor107_measure          float32
Length: 172, dtype: object
```

Drop useless coloumn from feature

```
"""id coloumn is just index, we don't need it , so we will drop it"""
df = df.drop(["id"],axis=1)
df.head()
```

	target	sensor1_measure	sensor2_measure	sensor3_measure	sensor4_measure	sensor5_measure	sensor6_measure	sensor7_histogram_bin0	sensor7_histogram_bin1	sensor7_hist
0	0.0	76698.0	NaN	2.130706e+09	280.0	0.0	0.0	0.0	0.0	
1	0.0	33058.0	NaN	0.000000e+00	NaN	0.0	0.0	0.0	0.0	
2	0.0	41040.0	NaN	2.280000e+02	100.0	0.0	0.0	0.0	0.0	
3	0.0	12.0	0.0	7.000000e+01	66.0	0.0	10.0	0.0	0.0	
4	0.0	60874.0	NaN	1.368000e+03	458.0	0.0	0.0	0.0	0.0	

5 rows × 171 columns

Train test split

Here we are creating 4 dataset

- df_train = it donot contain target
- df_test = it donot contain target

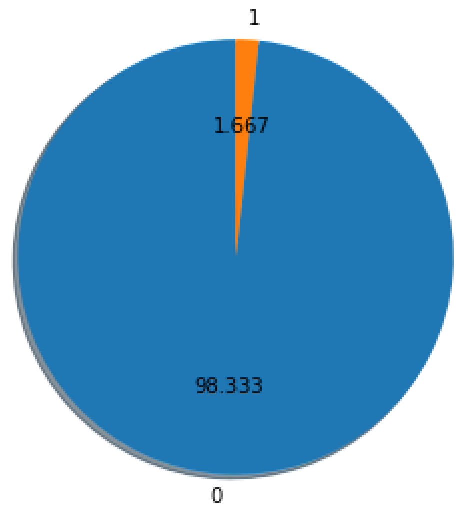
- df_train_t = it contain target for purpose EDA
- df_test_t = it contain target for purpose EDA

```
#We are not dropping target because, target will be used for EDA in next cells

y = df["target"].tolist()
df_ = df.drop(["target"],axis=1)

#For feature engineering
df_train , df_test , y_train , y_test = train_test_split( df_ , y , test_size=0.15, stratify = y ,  random_state=42)


#For EDA
df_train_t , df_test_t , y_train_t , y_test_t = train_test_split( df , y , test_size=0.15, stratify = y ,  random_state=42)


print("train = ",df_train.shape)
print("test = ",df_test.shape)
```

```
train =  (51000, 170)
test =  (9000, 170)
```

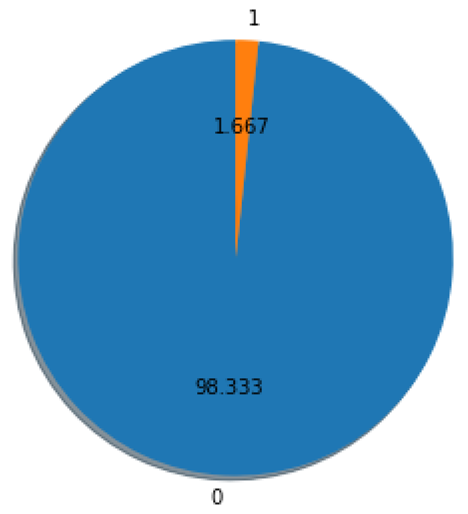
```
#train Percentage view of data distribution

plt.figure(figsize=(5,5))
plt.pie(df_train_t['target'].value_counts(),startangle=90,autopct="%.3f",labels=[0,1],shadow=True)
```

```
([<matplotlib.patches.Wedge at 0x7f315b9ec550>,
  <matplotlib.patches.Wedge at 0x7f315b9ecfd0>],
 [Text(-0.05756949701481714, -1.0984924911047236, '0'),
  Text(0.05756943916265415, 1.0984924941366225, '1')],
 [Text(-0.03140154382626389, -0.5991777224207583, '98.333'),
  Text(0.03140151227053862, 0.5991777240745213, '1.667')])
```




```
#test Percentage view of data distribution

plt.figure(figsize=(5,5))
plt.pie(df_test_t['target'].value_counts(),startangle=90,autopct="%.3f",labels=[0,1],shadow=True)
```

```
([<matplotlib.patches.Wedge at 0x7f315b515080>,
  <matplotlib.patches.Wedge at 0x7f315b515b38>],
 [Text(-0.05756949701481714, -1.0984924911047236, '0'),
  Text(0.05756943916265415, 1.0984924941366225, '1')],
 [Text(-0.03140154382626389, -0.5991777224207583, '98.333'),
  Text(0.03140151227053862, 0.5991777240745213, '1.667')])
```



For each feature create new feature, that tells presence of nan, because nan values also contains some information

```
coloumns = df_train.columns

#Train
for coloumn in tqdm(coloumns):
    df_train[coloumn + "_nan"] = [1.0 if np.isnan(x) else 0.0 for x in df_train[coloumn]]

#Test
for coloumn in tqdm(coloumns):
    df_test[coloumn + "_nan"] = [1.0 if np.isnan(x) else 0.0 for x in df_test[coloumn]]
```

Drop features with more than 50% nan values

```
#Train
df_train = df_train.drop(high_nan_features,axis=1)

#Test
df_test = df_test.drop(high_nan_features,axis=1)
```

```
df_train.head()
```

	sensor1_measure	sensor3_measure	sensor4_measure	sensor5_measure	sensor6_measure	sensor7_histogram_bin0	sensor7_histogram_bin1	sensor7_histogram_bin2	sensor7_h
54001	36.0	1.000000e+01	10.0	0.0	0.0	0.0	0.0	0.0	
47399	41968.0	2.130706e+09	504.0	0.0	0.0	0.0	0.0	0.0	
49418	7230.0	2.130706e+09	86.0	0.0	0.0	0.0	0.0	0.0	
57927	236940.0	2.130706e+09	496.0	0.0	0.0	0.0	0.0	0.0	
29123	20.0	2.200000e+01	4.0	12.0	14.0	0.0	0.0	0.0	

5 rows × 332 columns

Replace nan with median of that coloumn , because values of each feature is either very low or very high, replacing nan with mean is not sensible at all

```
#Train
df_train = df_train.fillna(median)

#Test
df_test = df_test.fillna(median)                                      #Here we are filling test nan values with, train median
```

```
df_test.head()
```

	sensor1_measure	sensor3_measure	sensor4_measure	sensor5_measure	sensor6_measure	sensor7_histogram_bin0	sensor7_histogram_bin1	sensor7_histogram_bin2	sensor7_h
19886	346.0	36.0	28.0	0.0	0.0	0.0	0.0	0.0	

14400	39642.0	352.0	288.0	0.0	0.0	0.0	0.0	0.0
13932	1142.0	84.0	72.0	0.0	0.0	0.0	0.0	0.0
49050	78342.0	1132.0	970.0	0.0	0.0	0.0	0.0	0.0
52585	2172.0	38.0	38.0	0.0	0.0	0.0	0.0	0.0

5 rows × 332 columns

We have 100 simple sensor, and 7 time based sensor. Here we will extract min, max and mean from those time based sensors

```
def mean(a,b,c,d,e,f,g,h,i,j):
    list_ = [a,b,c,d,e,f,g,h,i,j]
    return np.mean(list_)


def min_(a,b,c,d,e,f,g,h,i,j):
    list_ = [a,b,c,d,e,f,g,h,i,j]
    return min(list_)


def max_(a,b,c,d,e,f,g,h,i,j):
    list_ = [a,b,c,d,e,f,g,h,i,j]
    return max(list_)



#Train
for i in tqdm(range(0,len(time_based_sensor))):
    df_train[time_based_sensor[i][0].split("_")[0] + "_mean"] = df_train.apply(lambda row : mean(row[time_based_sensor[i][0]] , row[time_based_sensor[i][1]] , row[time_based_ser
                                                                                 row[time_based_sensor[i][3]] , row[time_based_sensor[i][4]] , row[time_based_sensor[i][5]] ,
                                                                                 row[time_based_sensor[i][6]] , row[time_based_sensor[i][7]] , row[time_based_sensor[i][8]] ,
                                                                                 row[time_based_sensor[i][9]] ) , axis = 1)


    df_train[time_based_sensor[i][0].split("_")[0] + "_min"] = df_train.apply(lambda row : min_(row[time_based_sensor[i][0]] , row[time_based_sensor[i][1]] , row[time_based_sens
                                                                                 row[time_based_sensor[i][3]] , row[time_based_sensor[i][4]] , row[time_based_sensor[i][5]] ,
                                                                                 row[time_based_sensor[i][6]] , row[time_based_sensor[i][7]] , row[time_based_sensor[i][8]] ,
                                                                                 row[time_based_sensor[i][9]] ) , axis = 1)

    df_train[time_based_sensor[i][0].split("_")[0] + "_max"] = df_train.apply(lambda row : max_(row[time_based_sensor[i][0]] , row[time_based_sensor[i][1]] , row[time_based_sens
                                                                                 row[time_based_sensor[i][3]] , row[time_based_sensor[i][4]] , row[time_based_sensor[i][5]] ,
                                                                                 row[time_based_sensor[i][6]] , row[time_based_sensor[i][7]] , row[time_based_sensor[i][8]] ,
                                                                                 row[time_based_sensor[i][9]] ) , axis = 1)




#Test
for i in tqdm(range(0,len(time_based_sensor))):
    df_test[time_based_sensor[i][0].split("_")[0] + "_mean"] = df_test.apply(lambda row : mean(row[time_based_sensor[i][0]] , row[time_based_sensor[i][1]] , row[time_based_senso
                                                                                 row[time_based_sensor[i][3]] , row[time_based_sensor[i][4]] , row[time_based_sensor[i][5]] ,
                                                                                 row[time_based_sensor[i][6]] , row[time_based_sensor[i][7]] , row[time_based_sensor[i][8]] ,
                                                                                 row[time_based_sensor[i][9]] ) , axis = 1)


    df_test[time_based_sensor[i][0].split("_")[0] + "_min"] = df_test.apply(lambda row : min_(row[time_based_sensor[i][0]] , row[time_based_sensor[i][1]] , row[time_based_sensor
                                                                                 row[time_based_sensor[i][3]] , row[time_based_sensor[i][4]] , row[time_based_sensor[i][5]] ,
                                                                                 row[time_based_sensor[i][6]] , row[time_based_sensor[i][7]] , row[time_based_sensor[i][8]] ,
                                                                                 row[time_based_sensor[i][9]] ) , axis = 1)

    df_test[time_based_sensor[i][0].split("_")[0] + "_max"] = df_test.apply(lambda row : max_(row[time_based_sensor[i][0]] , row[time_based_sensor[i][1]] , row[time_based_sensor
                                                                                 row[time_based_sensor[i][3]] , row[time_based_sensor[i][4]] , row[time_based_sensor[i][5]] ,
                                                                                 row[time_based_sensor[i][6]] , row[time_based_sensor[i][7]] , row[time_based_sensor[i][8]] ,
                                                                                 row[time_based_sensor[i][9]] ) , axis = 1)


df_train.head()
```

```
100%|██████████| 7/7 [00:50<00:00,  7.18s/it]
100%|██████████| 7/7 [00:08<00:00,  1.26s/it]
```

	sensor1_measure	sensor3_measure	sensor4_measure	sensor5_measure	sensor6_measure	sensor7_histogram_bin0	sensor7_histogram_bin1	sensor7_histogram_bin2	sensor7_h
54001	36.0	1.000000e+01	10.0	0.0	0.0	0.0	0.0	0.0	
47399	41968.0	2.130706e+09	504.0	0.0	0.0	0.0	0.0	0.0	
49418	7230.0	2.130706e+09	86.0	0.0	0.0	0.0	0.0	0.0	
57927	236940.0	2.130706e+09	496.0	0.0	0.0	0.0	0.0	0.0	
29123	20.0	2.200000e+01	4.0	12.0	14.0	0.0	0.0	0.0	

5 rows × 353 columns

Removing all the features which are least correlated to our target

```
#train
df_train = df_train.drop(bottom_n_features.keys(),axis=1)

#test
df_test = df_test.drop(bottom_n_features.keys(),axis=1)
```

Removing all the intercorrelated features

```
#Train
df_train = df_train.drop(useless_features , axis=1)

#Test
df_test = df_test.drop(useless_features , axis=1)


print("train_size = ",df_train.shape)
print("test_size = ",df_test.shape)
```

```
train_size =  (51000, 232)
test_size =  (9000, 232)
```

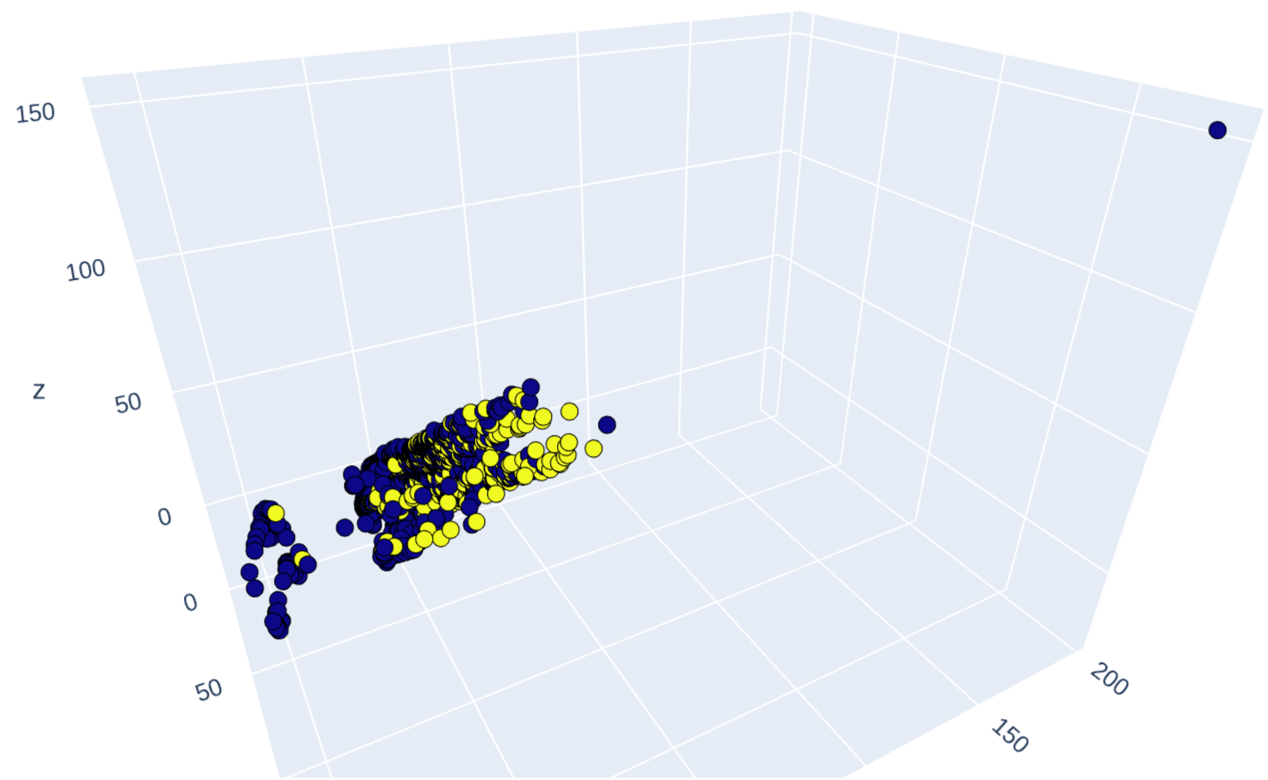
Feature Scaling

```
#Train
df_train = scaler.transform(df_train)

#Test
df_test = scaler.transform(df_test)
```

PCA 3d plot

```
pca = PCA(n_components=3)
pca_result = pca.fit_transform(df_train)

x = pca_result[:,0]
y = pca_result[:,1]
z = pca_result[:,2]
```

```
import plotly.express as px

pca_df = pd.DataFrame(list(zip(x, y, z, y_train)), columns =['x', 'y', 'z', 'target'])

fig = px.scatter_3d(pca_df, x='x', y='y', z='z',
              color='target')

fig.update_traces(marker=dict(size=5,
                              line=dict(width=0.5,
                                        color='DarkSlateGrey')),
                  selector=dict(mode='markers'))
fig.show()
```




```
y_test = np.array(y_test)
X_test = df_test
```

Modelling

We will over sample our minority(down hole equip fail) using RandomOverSampler

```
from imblearn.over_sampling import RandomOverSampler
from collections import Counter
```

```
oversample = RandomOverSampler(sampling_strategy='minority')

# fit and apply the transform
X_random, y_random = oversample.fit_resample(df_train, y_train)
```

```
# summarize class distribution
print("distribution before oversampling = ",Counter(y_train))
print("distribution after  oversampling = ",Counter(y_random))
print("-"*50)
print("shape of X_train = ", df_train.shape)
print("shape of y_train = ", len(y_train))
print("-"*50)
print("shape of X_train_over = ", X_random.shape)
print("shape of y_train_over = ", y_random.shape)
```

```
distribution before oversampling =  Counter({0.0: 50150, 1.0: 850})
distribution after  oversampling =  Counter({0.0: 50150, 1.0: 50150})
--------------------------------------------------
```

We will over sample our minority(down hole equip fail) using SMOTE(Synthetic minority over sampling technique)

```
shape of X train over =  (100300, 232)
```

```
from imblearn.over_sampling import SMOTE

oversample = SMOTE()

# fit and apply the transform
X_smote, y_smote = oversample.fit_resample(df_train, y_train)
```

```
# summarize class distribution
print("distribution before oversampling = ",Counter(y_train))
print("distribution after  oversampling = ",Counter(y_smote))
print("-"*50)
print("shape of X_train = ", df_train.shape)
print("shape of y_train = ", len(y_train))
print("-"*50)
print("shape of X_train_smote_over = ", X_smote.shape)
print("shape of y_train_smote_over = ", y_smote.shape)
```

```
distribution before oversampling =  Counter({0.0: 50150, 1.0: 850})
distribution after  oversampling =  Counter({0.0: 50150, 1.0: 50150})
--------------------------------------------------
shape of X_train =  (51000, 232)
shape of y_train =  51000
--------------------------------------------------
shape of X_train_smote_over =  (100300, 232)
shape of y_train_smote_over =  (100300,)
```

We will be using f1 score, AUC ,Precison,Recall and Confusion Matrix

```
from sklearn.metrics import f1_score
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
```

```
from sklearn.metrics import confusion_matrix
import seaborn as sns

def plot_confusion_matrix(test_y, predict_y,lables):
    C = confusion_matrix(test_y, predict_y)
    print("Number of misclassified points ",(len(test_y)-np.trace(C))/len(test_y)*100)
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i are predicted class j

    A =(((C.T)/(C.sum(axis=1))).T)
    #divid each element of the confusion matrix with the sum of elements in that column

    # C = [[1, 2],
    #     [3, 4]]
    # C.T = [[1, 3],
    #        [2, 4]]
    # C.sum(axis = 1)  axis=0 corresonds to columns and axis=1 corresponds to rows in two diamensional array
    # C.sum(axix =1) = [[3, 7]]
    # ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
    #                            [2/3, 4/7]]

    # ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
    #                            [3/7, 4/7]]
    # sum of row elements = 1

    B =(C/C.sum(axis=0))
    #divid each element of the confusion matrix with the sum of elements in that row
    # C = [[1, 2],
    #     [3, 4]]
    # C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to rows in two diamensional array
    # C.sum(axix =0) = [[4, 6]]
    # (C/C.sum(axis=0)) = [[1/4, 2/6],
    #                       [3/4, 4/6]]

    labels = lables
    cmap=sns.light_palette("green")
    # representing A in heatmap format
    print("-"*50, "Confusion matrix", "-"*50)
    plt.figure(figsize=(10,5))
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    print("-"*50, "Precision matrix", "-"*50)
    plt.figure(figsize=(10,5))
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
    print("Sum of columns in precision matrix",B.sum(axis=0))

    # representing B in heatmap format
    print("-"*50, "Recall matrix"    , "-"*50)
    plt.figure(figsize=(10,5))
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
    print("Sum of rows in precision matrix",A.sum(axis=1))
```

GaussianNB

On random over sampled

```
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import GridSearchCV

NB = GaussianNB()

parameters = {"var_smoothing":np.logspace(0,-9,num = 10) }

clf = GridSearchCV( NB , parameters , verbose=4 , cv=3 , scoring = "f1" , return_train_score = True)

clf.fit(X_random,y_random)
```

```
#Creating dataframe for grid search cv results

results_df = pd.concat([pd.DataFrame(clf.cv_results_["params"]),pd.DataFrame(clf.cv_results_["mean_train_score"], columns=["train_f1_score"]),pd.DataFrame(clf.cv_results_["mean_

train_cv_diffrence = abs(np.array(results_df['train_f1_score'].tolist()) - np.array(results_df['cv_f1_score'].tolist()))

results_df = pd.concat([results_df,pd.DataFrame(train_cv_diffrence, columns=["train_cv_diffrence"])],axis=1)

results_df
```

	var_smoothing	train_f1_score	cv_f1_score	train_cv_diffrence
0	1.000000e+00	0.534218	0.533758	0.000461
1	1.000000e-01	0.804726	0.804868	0.000141
2	1.000000e-02	0.881484	0.881719	0.000235
3	1.000000e-03	0.897259	0.897110	0.000149
4	1.000000e-04	0.901760	0.901814	0.000054
5	1.000000e-05	0.904298	0.904180	0.000119
6	1.000000e-06	0.905480	0.905384	0.000097
7	1.000000e-07	0.907217	0.906935	0.000281
8	1.000000e-08	0.908076	0.907724	0.000352
9	1.000000e-09	0.908969	0.908701	0.000268

```
clf.best_params_
```

```
{'var_smoothing': 1e-09}
```

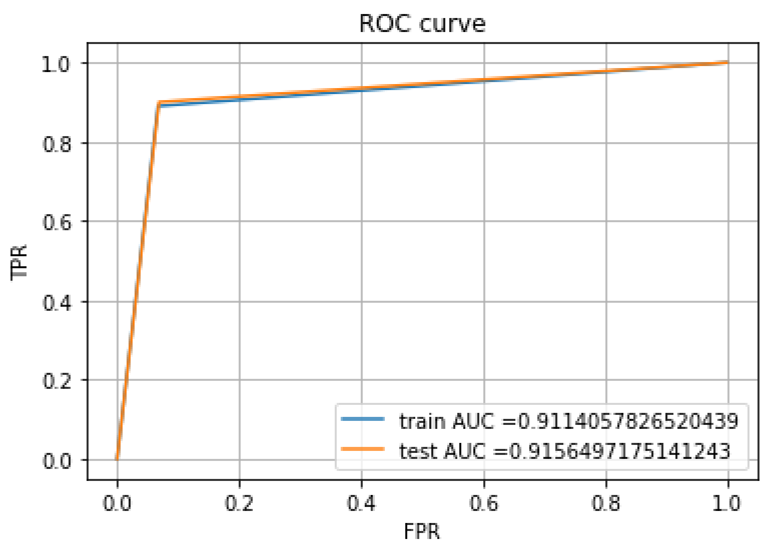
f1 score

```
NB_best = GaussianNB(var_smoothing=1e-09)
NB_best.fit(X_random,y_random)

print("Train F1 Score = ",f1_score(y_random , NB_best.predict(X_random)))
print("Test F1 Score = ",f1_score(y_test , NB_best.predict(X_test)))
```

```
Train F1 Score =  0.9094540341152254
Test F1 Score =  0.3023516237402016
```

AUC Score

```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_random, NB_best.predict(X_random))
test_fpr, test_tpr, te_thresholds = roc_curve(y_test , NB_best.predict(X_test))

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC curve")
plt.grid()
plt.show()
```



Precision

```
print("Train precision Score = ",precision_score(y_random , NB_best.predict(X_random)))
print("Test precision Score = ",precision_score(y_test , NB_best.predict(X_test)))
```

```
Train precision Score =  0.9299408185379678
Test precision Score =  0.1816958277254374
```

Recall

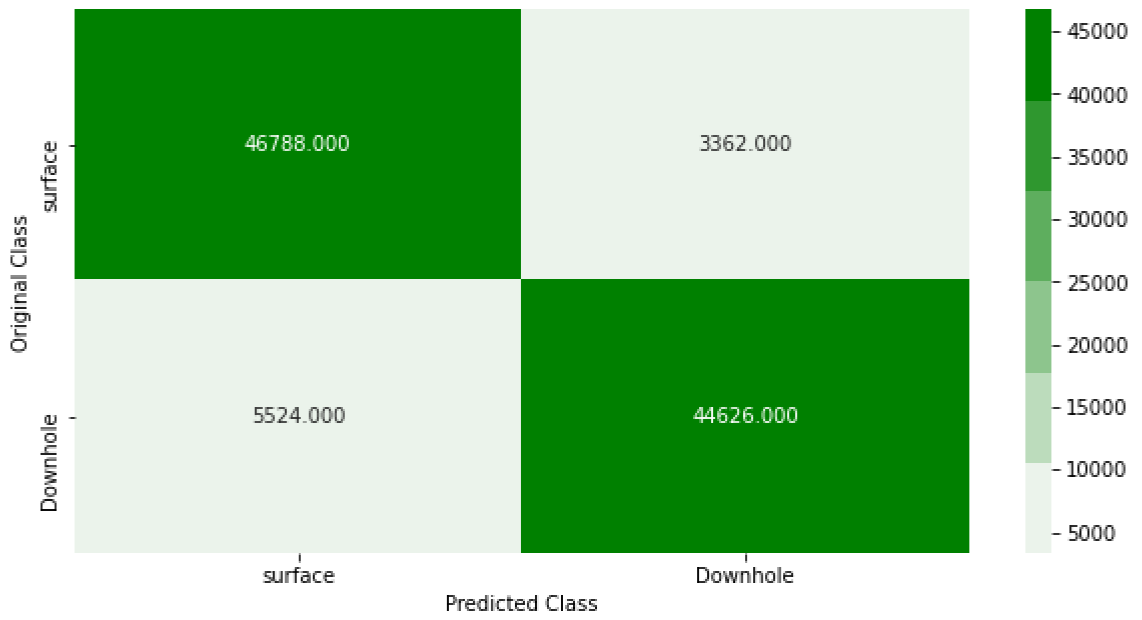
```
print("Train recall Score = ",recall_score(y_random , NB_best.predict(X_random)))
print("Test recall Score = ",recall_score(y_test , NB_best.predict(X_test)))
```

```
Train recall Score =  0.8898504486540378
Test recall Score =  0.9
```

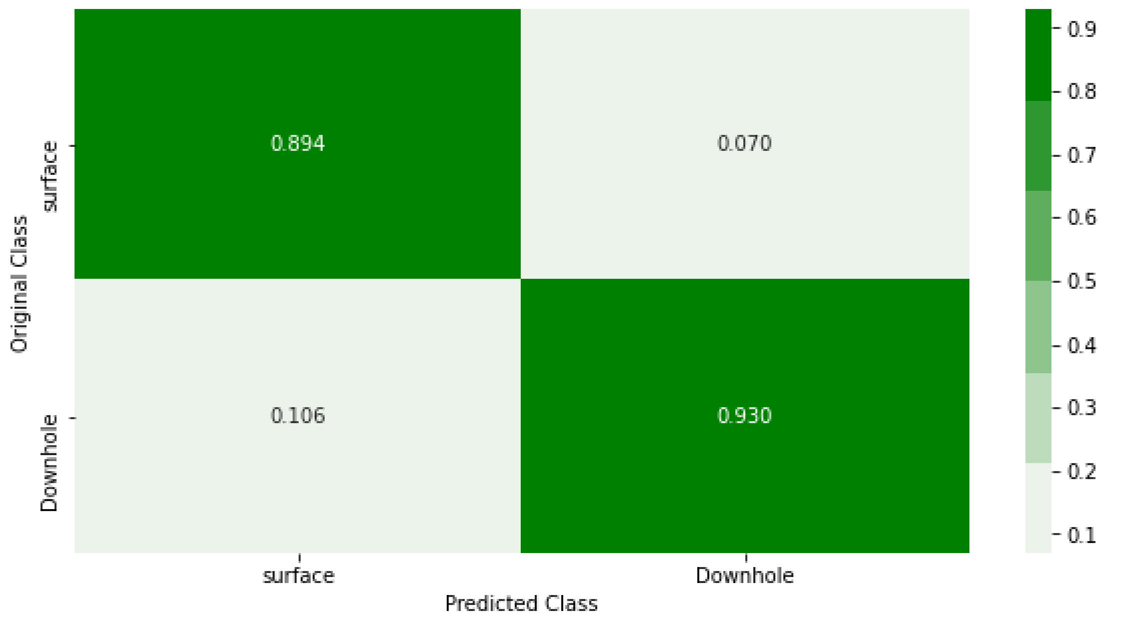
Confusion matrix train

```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_random, NB_best.predict(X_random) , lables)
```

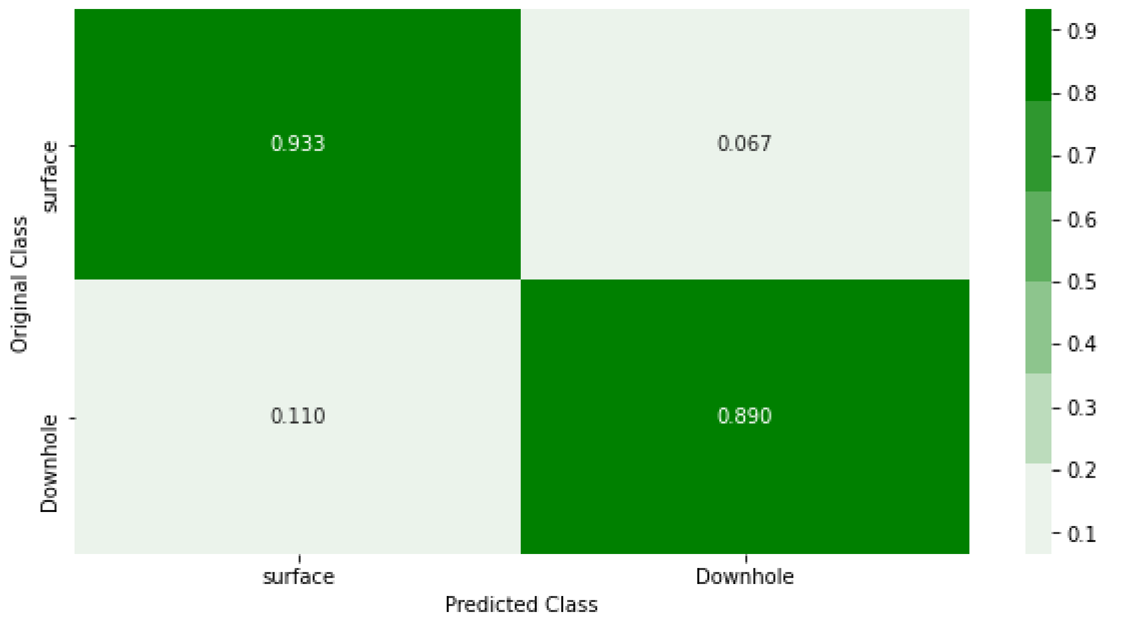
```
Number of misclassified points  8.859421734795612
------------------------------------------------ Confusion matrix ------------------------------------------------
```




```
------------------------------------------------ Precision matrix ------------------------------------------------
```




```
Sum of columns in precision matrix [1. 1.]
------------------------------------------------ Recall matrix ------------------------------------------------
```

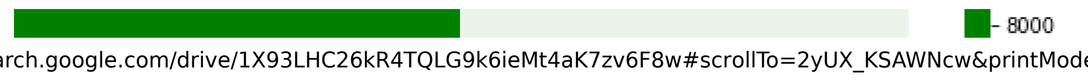


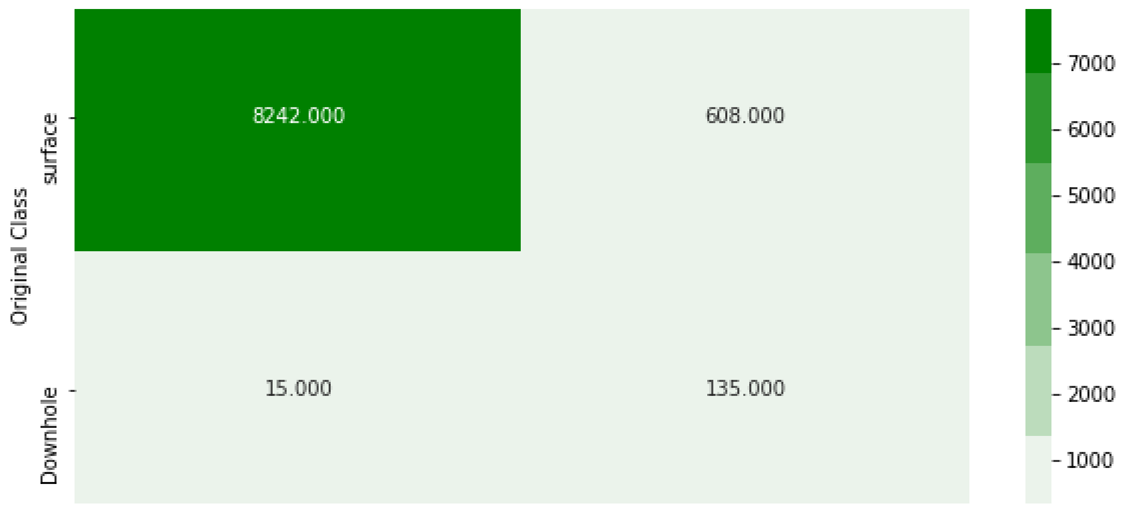

```
Sum of rows in precision matrix [1. 1.]
```

Confusion matrix test

```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_test, NB_best.predict(X_test) , lables)
```

```
Number of misclassified points  6.9222222222222225
------------------------------------------------ Confusion matrix ------------------------------------------------
```





On SMOTE over sampled

```
NB = GaussianNB()

parameters = {"var_smoothing":np.logspace(0,-9,num = 10) }

clf = GridSearchCV( NB , parameters , verbose=4 , cv=3 , scoring = "f1" , return_train_score = True)

clf.fit(X_smote,y_smote)
```

```
#Creating dataframe for grid search cv results

results_df = pd.concat([pd.DataFrame(clf.cv_results_["params"]),pd.DataFrame(clf.cv_results_["mean_train_score"], columns=["train_f1_score"]),pd.DataFrame(clf.cv_results_["mean_

train_cv_diffrence = abs(np.array(results_df['train_f1_score'].tolist()) - np.array(results_df['cv_f1_score'].tolist()))

results_df = pd.concat([results_df,pd.DataFrame(train_cv_diffrence, columns=["train_cv_diffrence"])],axis=1)

results_df
```

	var_smoothing	train_f1_score	cv_f1_score	train_cv_diffrence
0	1.000000e+00	0.588850	0.588867	0.000017
1	1.000000e-01	0.808038	0.808284	0.000246
2	1.000000e-02	0.872936	0.872959	0.000022
3	1.000000e-03	0.894204	0.894017	0.000187
4	1.000000e-04	0.898592	0.898717	0.000125
5	1.000000e-05	0.901115	0.901095	0.000020
6	1.000000e-06	0.903607	0.903520	0.000087
7	1.000000e-07	0.905600	0.905686	0.000085
8	1.000000e-08	0.906947	0.906952	0.000005
9	1.000000e-09	0.908073	0.908129	0.000057

```
clf.best_params_
```

```
{'var_smoothing': 1e-09}
```

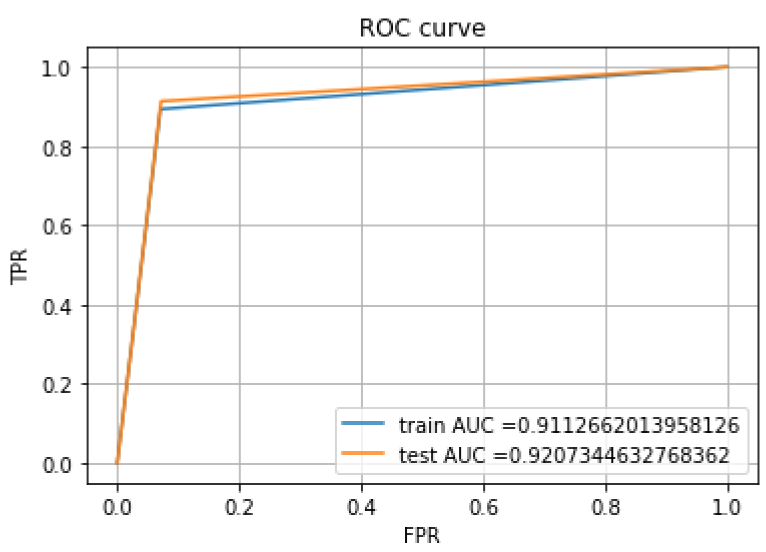
f1 score

```
NB_best = GaussianNB(var_smoothing=1e-09)
NB_best.fit(X_smote,y_smote)

print("Train F1 Score = ",f1_score(y_smote , NB_best.predict(X_smote)))
print("Test F1 Score = ",f1_score(y_test , NB_best.predict(X_test)))
```

```
Train F1 Score =  0.90965933446749767
Test F1 Score =  0.29685807150595883
```

AUC Score

```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_smote, NB_best.predict(X_smote))
test_fpr, test_tpr, te_thresholds = roc_curve(y_test , NB_best.predict(X_test))

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC curve")
plt.grid()
plt.show()
```



Precision

```
print("Train precision Score = ",precision_score(y_smote , NB_best.predict(X_smote)))

print("Test precision Score = ",precision_score(y_test , NB_best.predict(X_test)))
```

```
Train precision Score =  0.9264359260637638
Test precision Score =  0.17723156532988357
```

Recall

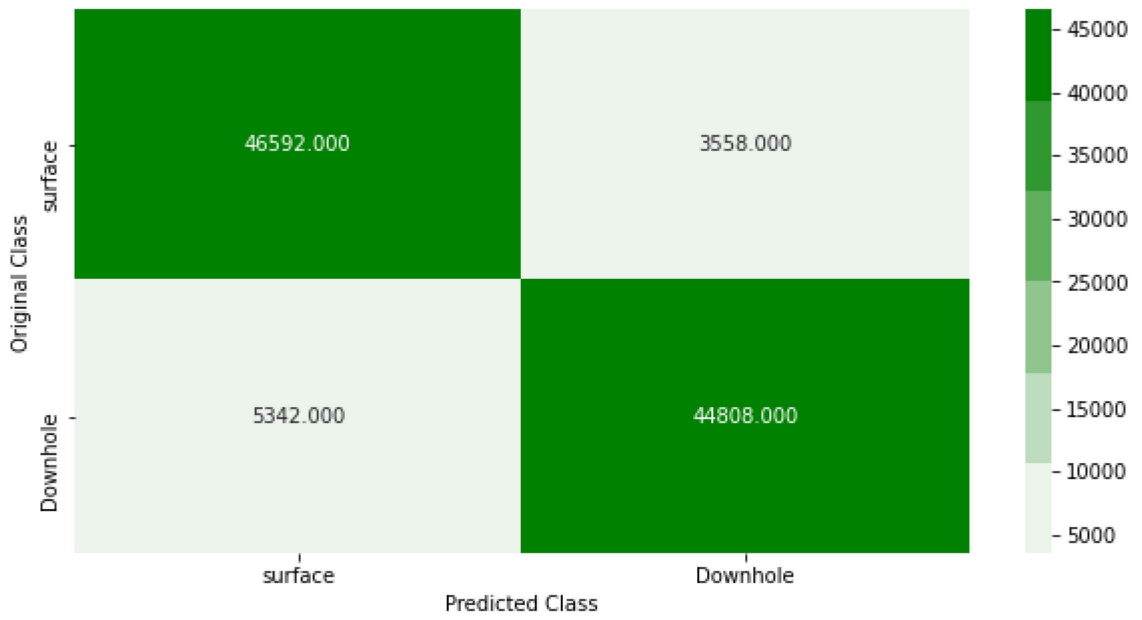
```
print("Train recall Score = ",recall_score(y_smote , NB_best.predict(X_smote)))
print("Test recall Score = ",recall_score(y_test , NB_best.predict(X_test)))
```

```
Train recall Score =  0.8934795613160519
Test recall Score =  0.9133333333333333
```

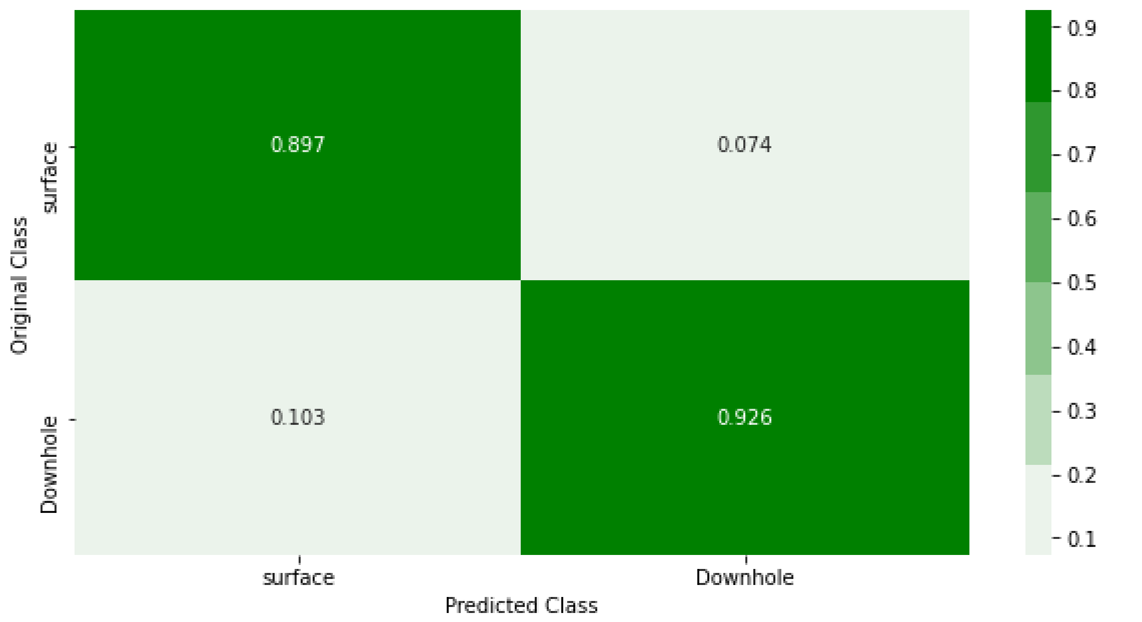
Confusion matrix train

```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_smote, NB_best.predict(X_smote) , lables)
```

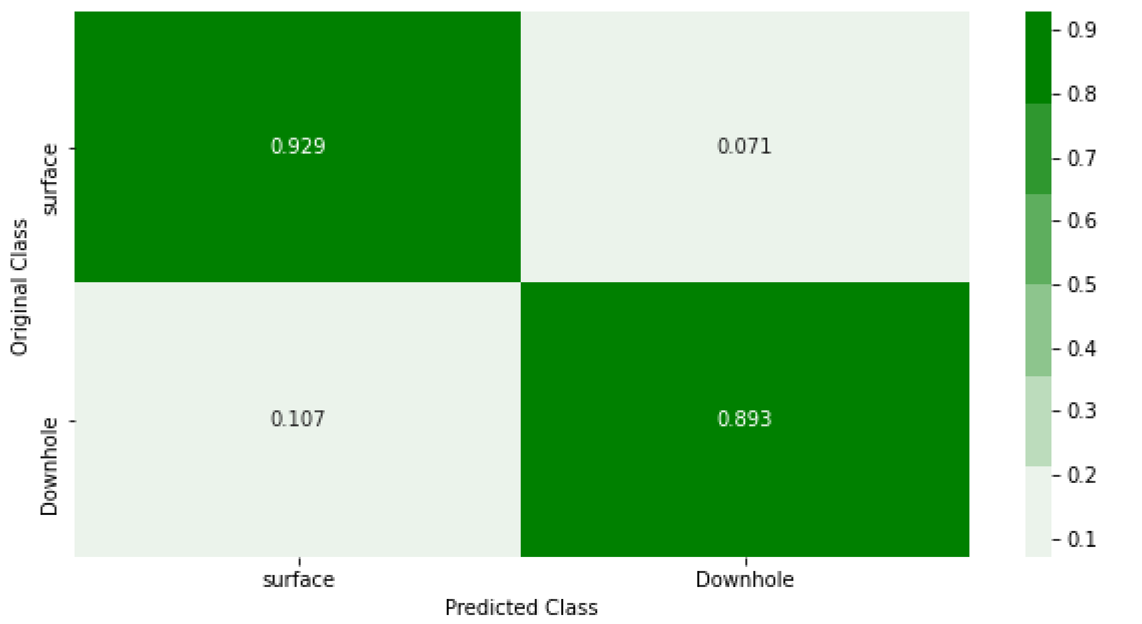
```
Number of misclassified points  8.873379860418744
-------------------------------------------------- Confusion matrix --------------------------------------------------
```




```
-------------------------------------------------- Precision matrix --------------------------------------------------
```




```
Sum of columns in precision matrix [1. 1.]
-------------------------------------------------- Recall matrix --------------------------------------------------
```

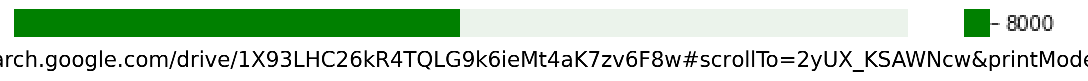


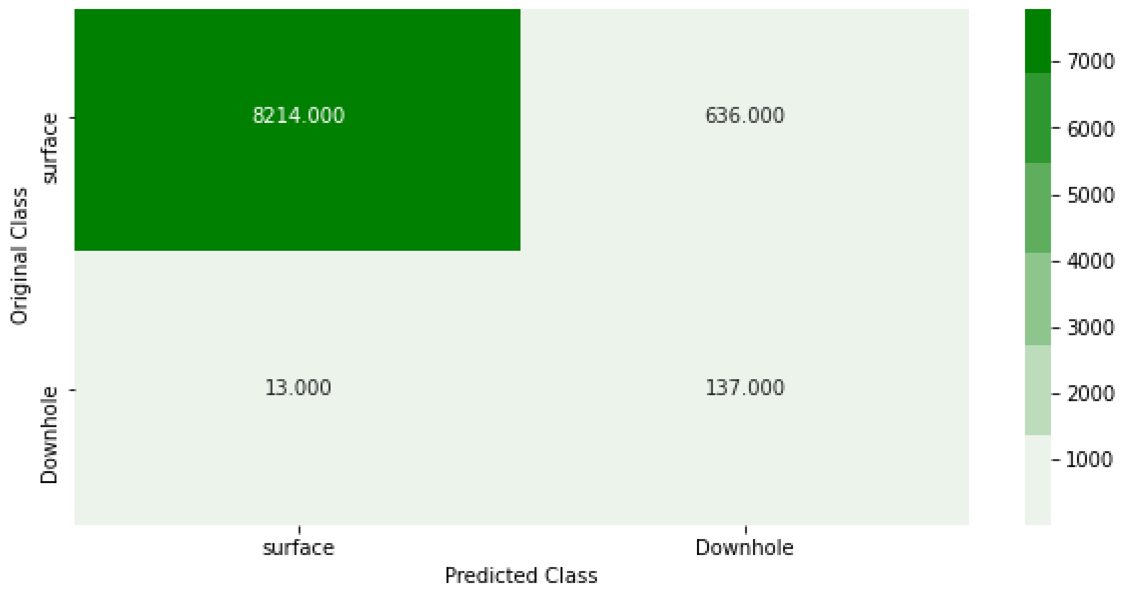

```
Sum of rows in precision matrix [1. 1.]
```

Confusion matrix test

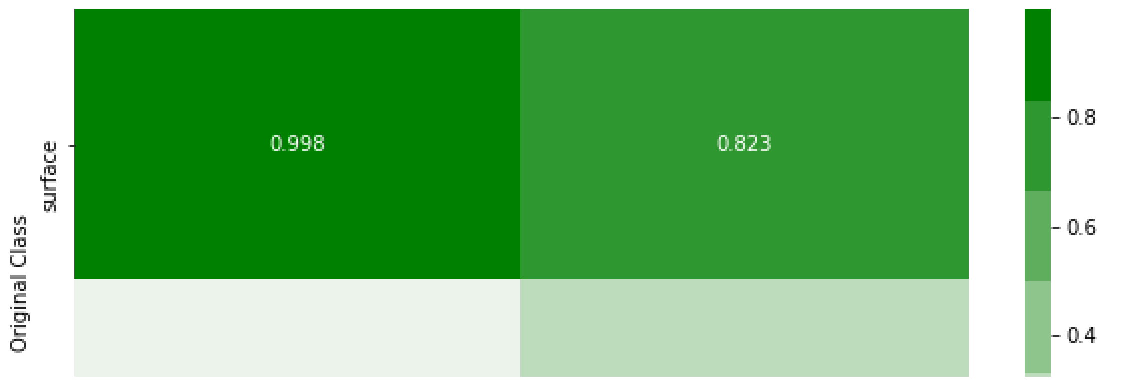
```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_test, NB_best.predict(X_test) , lables)
```

```
Number of misclassified points  7.211111111111111
-------------------------------------------------- Confusion matrix --------------------------------------------------
```






```
------------------------------------------------- Precision matrix -------------------------------------------------
```



Logistic regression

On random over sampled

```
------------------------------------------------- Recall matrix -------------------------------------------------
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

LR = LogisticRegression(class_weight="balanced" , max_iter = 1000)

parameters = {"C": [100 , 10 , 1.0 , 0.1 , 0.01] }

clf = GridSearchCV( LR , parameters , verbose=4 , cv=3 , scoring = "f1" , return_train_score = True)

clf.fit(X_random,y_random)
```



```
#Creating dataframe for grid search cv results

results_df = pd.concat([pd.DataFrame(clf.cv_results_["params"]),pd.DataFrame(clf.cv_results_["mean_train_score"], columns=["train_f1_score"]),pd.DataFrame(clf.cv_results_["mean_

train_cv_diffrence = abs(np.array(results_df['train_f1_score'].tolist()) - np.array(results_df['cv_f1_score'].tolist()))

results_df = pd.concat([results_df,pd.DataFrame(train_cv_diffrence, columns=["train_cv_diffrence"])],axis=1)

results_df
```

	C	train_f1_score	cv_f1_score	train_cv_diffrence
0	100.00	0.961981	0.961401	0.000580
1	10.00	0.961774	0.961169	0.000605
2	1.00	0.960894	0.960344	0.000551
3	0.10	0.960813	0.960188	0.000625
4	0.01	0.959489	0.958855	0.000633

```
clf.best_params_
```

```
{'C': 100}
```

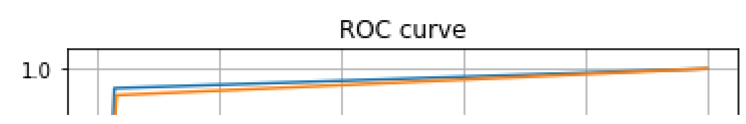
f1 score

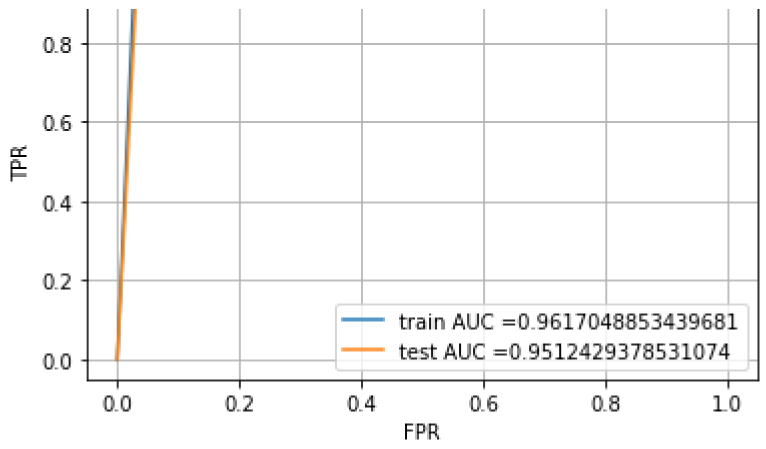
```
LR_best = LogisticRegression(class_weight="balanced" , max_iter = 1000 , C = 100)
LR_best.fit(X_random,y_random)

print("Train F1 Score = ",f1_score(y_random , LR_best.predict(X_random)))
print("Test F1 Score = ",f1_score(y_test , LR_best.predict(X_test)))
```

```
Train F1 Score =  0.9612876565980305
Test F1 Score =  0.497335701598579
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
```

AUC Score

```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_random, LR_best.predict(X_random))
test_fpr, test_tpr, te_thresholds = roc_curve(y_test , LR_best.predict(X_test))

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC curve")
plt.grid()
plt.show()
```





Precision

```
print("Train precision Score = ",precision_score(y_random , LR_best.predict(X_random)))
print("Test precision Score = ",precision_score(y_test , LR_best.predict(X_test)))
```

```
Train precision Score =  0.9718763374024333
Test precision Score =  0.3389830508474576
```

Recall

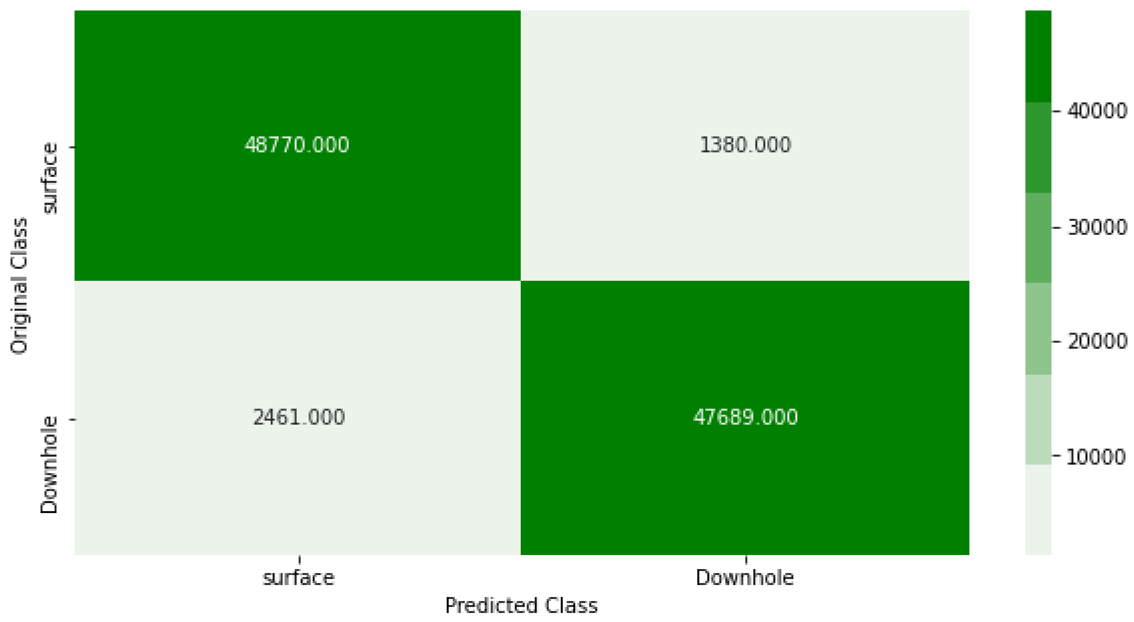
```
print("Train recall Score = ",recall_score(y_random , LR_best.predict(X_random)))
print("Test recall Score = ",recall_score(y_test , LR_best.predict(X_test)))
```

```
Train recall Score =  0.9509272183449651
Test recall Score =  0.9333333333333333
```

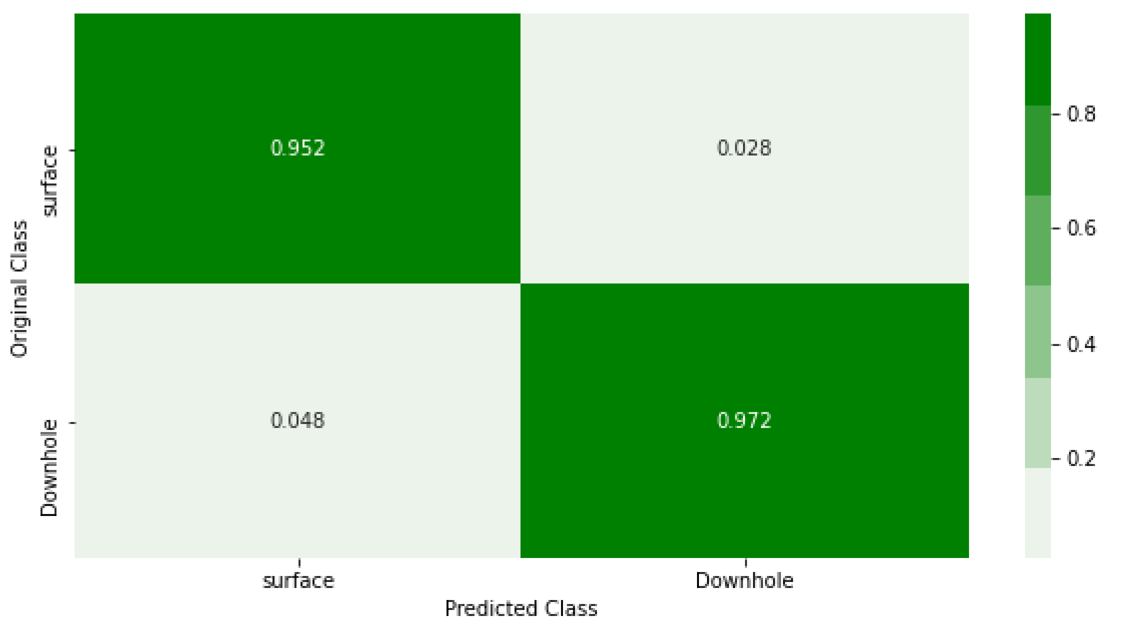
Confusion matrix train

```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_random, LR_best.predict(X_random) , lables)
```

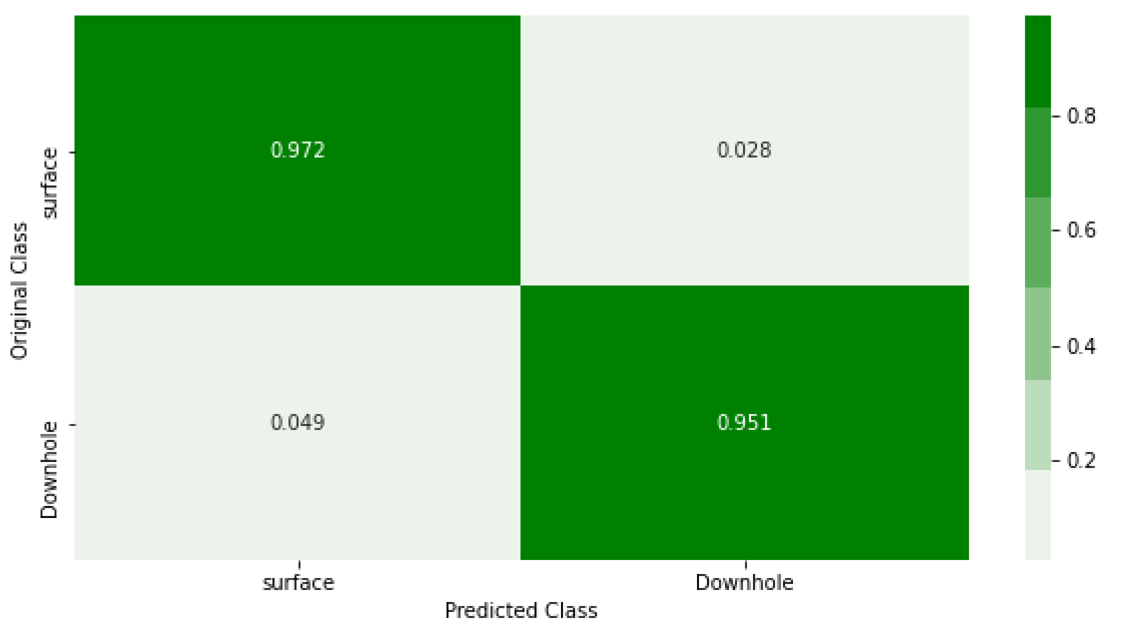
```
Number of misclassified points  3.829511465603191
-------------------------------------------------- Confusion matrix --------------------------------------------------
```




```
-------------------------------------------------- Precision matrix --------------------------------------------------
```




```
Sum of columns in precision matrix [1. 1.]
-------------------------------------------------- Recall matrix --------------------------------------------------
```

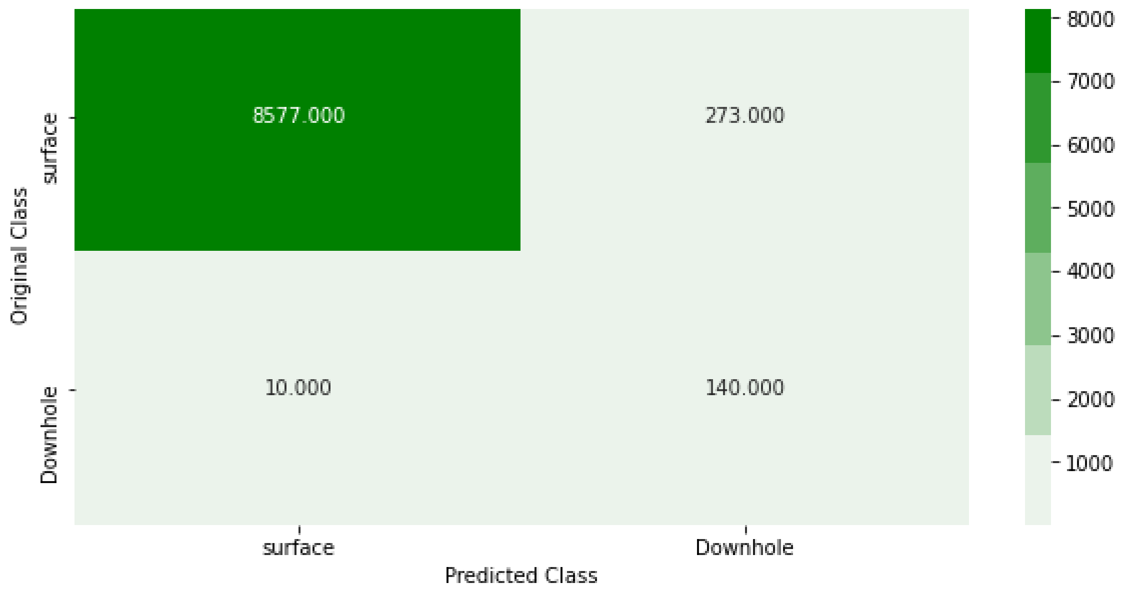



```
Sum of rows in precision matrix [1. 1.]
```

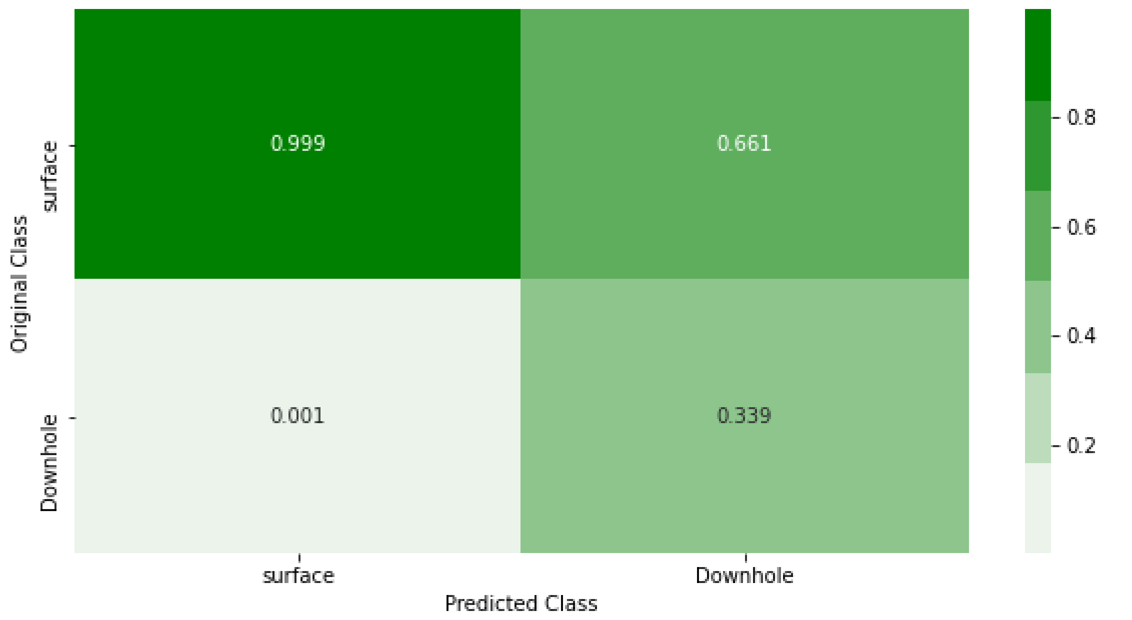
Confusion matrix test

```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_test, LR_best.predict(X_test) , lables)
```

```
Number of misclassified points  3.144444444444444
-------------------------------------------------- Confusion matrix --------------------------------------------------
```




```
------------------------------------------------- Precision matrix -------------------------------------------------
```




```
Sum of columns in precision matrix [1. 1.]
------------------------------------------------- Recall matrix -------------------------------------------------
```

On SMOTE over sampled

```
Sum of rows in precision matrix [1. 1.]
```

```
LR = LogisticRegression(class_weight="balanced" , max_iter = 1000)

parameters = {"C": [100 , 10 , 1.0 , 0.1 , 0.01] }

clf = GridSearchCV( LR , parameters , verbose=4 , cv=3 , scoring = "f1" , return_train_score = True)

clf.fit(X_smote,y_smote)


#Creating dataframe for grid search cv results

results_df = pd.concat([pd.DataFrame(clf.cv_results_["params"]),pd.DataFrame(clf.cv_results_["mean_train_score"], columns=["train_f1_score"]),pd.DataFrame(clf.cv_results_["mean_

train_cv_diffrence = abs(np.array(results_df['train_f1_score'].tolist()) - np.array(results_df['cv_f1_score'].tolist()))

results_df = pd.concat([results_df,pd.DataFrame(train_cv_diffrence, columns=["train_cv_diffrence"])],axis=1)

results_df
```

	C	train_f1_score	cv_f1_score	train_cv_diffrence
0	100.00	0.959768	0.959468	0.000300
1	10.00	0.959827	0.959425	0.000402
2	1.00	0.959694	0.959191	0.000503
3	0.10	0.959052	0.958655	0.000397
4	0.01	0.957316	0.956985	0.000331

```
clf.best_params_
```

```
{'C': 100}
```

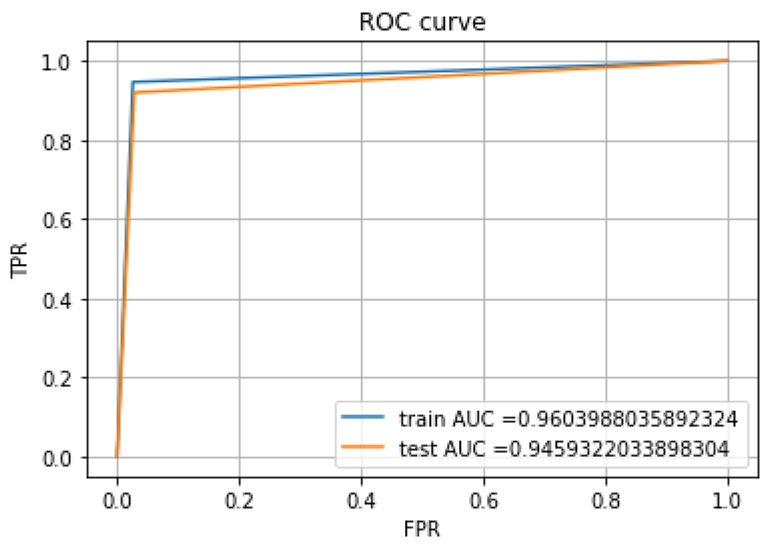
f1 score

```
LR_best = LogisticRegression(class_weight="balanced" , max_iter = 1000 , C = 100)
LR_best.fit(X_smote,y_smote)

print("Train F1 Score = ",f1_score(y_smote , LR_best.predict(X_smote)))
print("Test F1 Score = ",f1_score(y_test , LR_best.predict(X_test)))
```

```
Train F1 Score =  0.959844716729346
Test F1 Score =  0.5139664804469274
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
```

AUC Score

```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_smote, LR_best.predict(X_smote))
test_fpr, test_tpr, te_thresholds = roc_curve(y_test , LR_best.predict(X_test))

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC curve")
plt.grid()
plt.show()
```



Precision

```
print("Train precision Score = ",precision_score(y_smote , LR_best.predict(X_smote)))
print("Test precision Score = ",precision_score(y_test , LR_best.predict(X_test)))
```

```
Train precision Score =  0.9734651191403847
Test precision Score =  0.35658914728682173
```

Recall

```
print("Train recall Score = ",recall_score(y_smote , LR_best.predict(X_smote)))
print("Test recall Score = ",recall_score(y_test , LR_best.predict(X_test)))
```

```
Train recall Score =  0.9466001994017946
Test recall Score =  0.92
```

Confusion matrix train

```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_smote, LR_best.predict(X_smote) , lables)
```

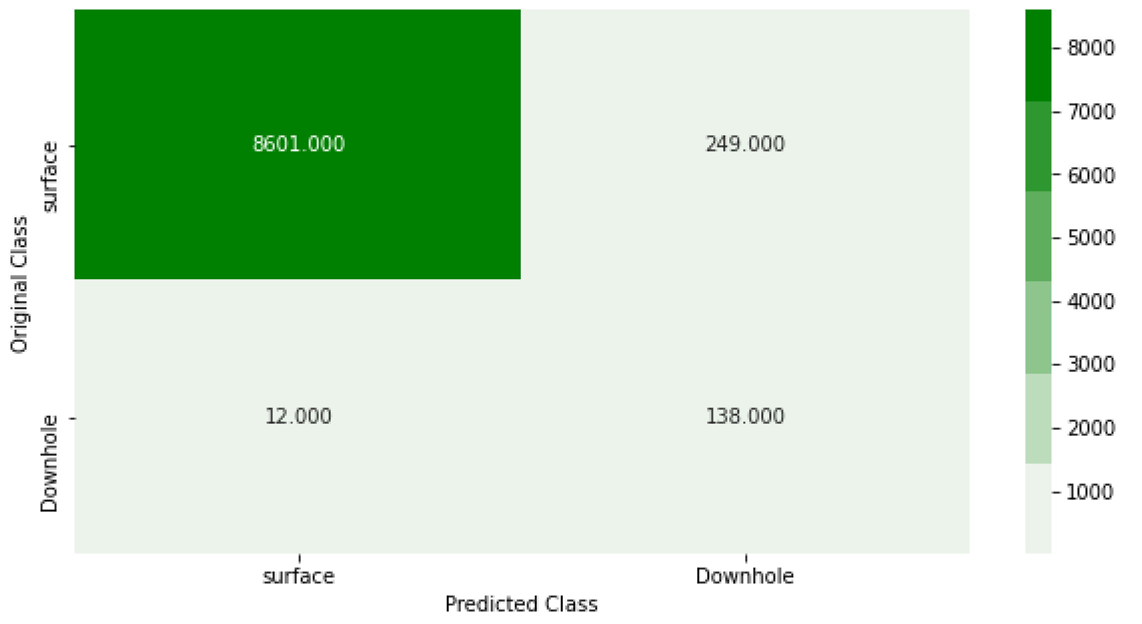
```
Number of misclassified points  3.9601196410767696
-------------------------------------------------- Confusion matrix --------------------------------------------------
```

Confusion matrix test

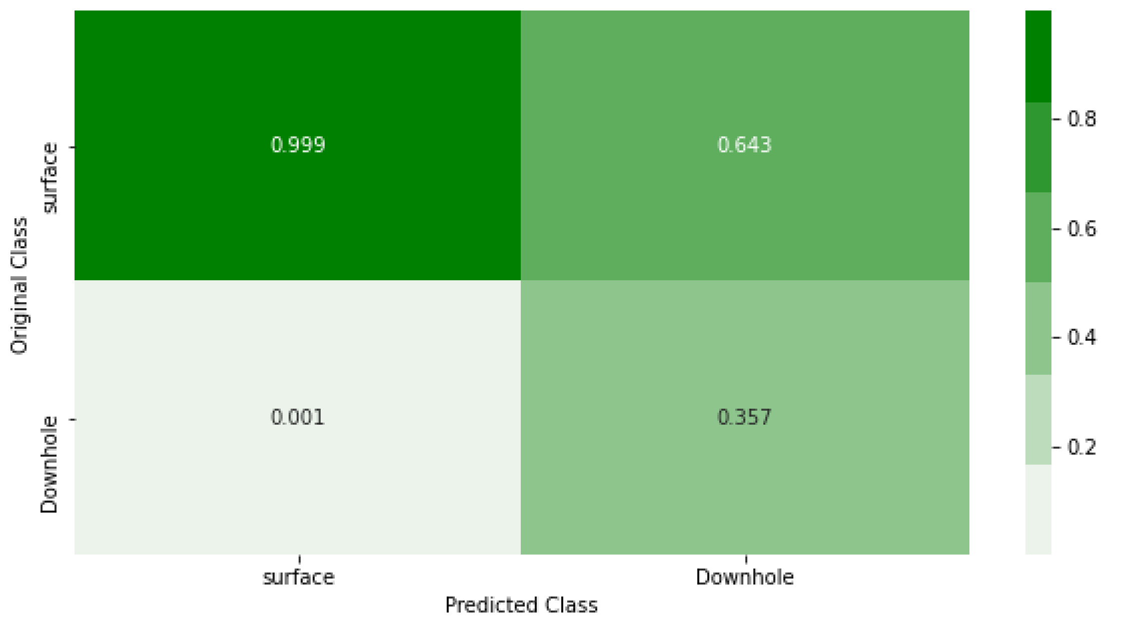
Confusion matrix test


```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_test, LR_best.predict(X_test) , lables)
```

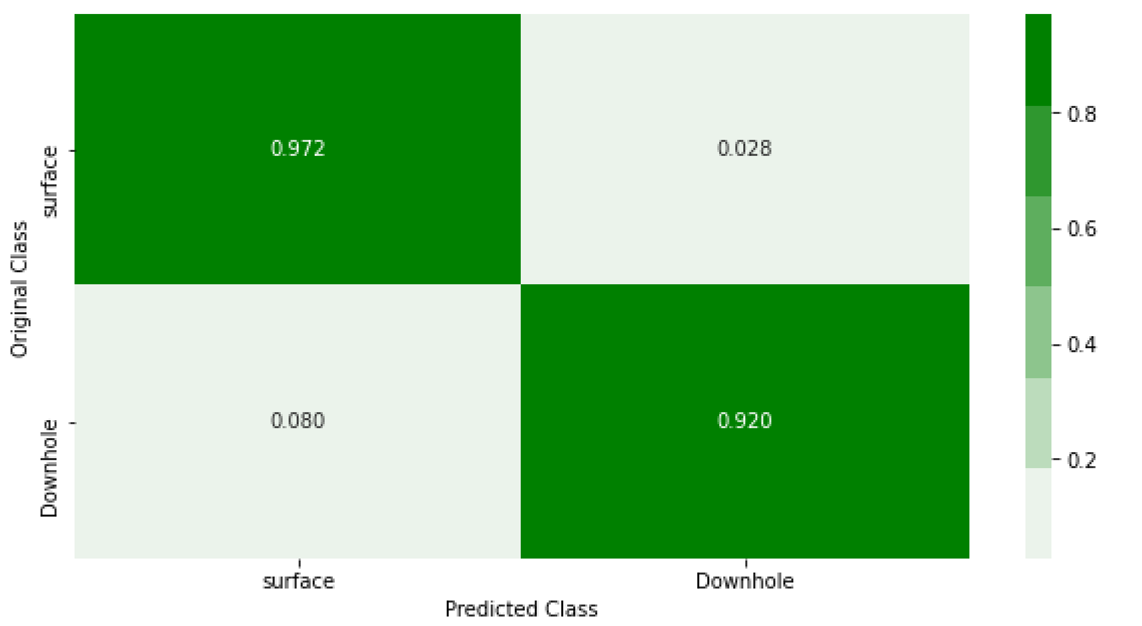
```
Number of misclassified points  2.9000000000000004
-------------------------------------------------- Confusion matrix --------------------------------------------------
```




```
-------------------------------------------------- Precision matrix --------------------------------------------------
```




```
Sum of columns in precision matrix [1. 1.]
-------------------------------------------------- Recall matrix --------------------------------------------------
```




```
Sum of rows in precision matrix [1. 1.]
```

Decision Tree

On random over sampled

```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier

DT = DecisionTreeClassifier(class_weight = "balanced")

parameters = { "max_depth":[1,5,10,50,100,500] , "min_samples_split":[2,10,100,500]}

clf = GridSearchCV( DT , parameters , verbose=4 , cv=3 , scoring = "f1" , return_train_score = True)

clf.fit(X_random,y_random)


#Creating dataframe for grid search cv results

results_df = pd.concat([pd.DataFrame(clf.cv_results_["params"]),pd.DataFrame(clf.cv_results_["mean_train_score"], columns=["train_f1_score"]),pd.DataFrame(clf.cv_results_["mean_

train_cv_diffrence = abs(np.array(results_df['train_f1_score'].tolist()) - np.array(results_df['cv_f1_score'].tolist()))

results_df = pd.concat([results_df,pd.DataFrame(train_cv_diffrence, columns=["train_cv_diffrence"])],axis=1)

results_df
```

	max_depth	min_samples_split	train_f1_score	cv_f1_score	train_cv_diffrence
0	1	2	0.934990	0.934990	5.750181e-09

1	1	10	0.934990	0.934990	5.750181e-09
2	1	100	0.934990	0.934990	5.750181e-09
3	1	500	0.934990	0.934990	5.750181e-09
4	5	2	0.967362	0.966712	6.495252e-04
5	5	10	0.967362	0.966817	5.449058e-04
6	5	100	0.967295	0.966665	6.304527e-04
7	5	500	0.964156	0.963533	6.224820e-04
8	10	2	0.982361	0.980647	1.713908e-03
9	10	10	0.982376	0.980618	1.757579e-03
10	10	100	0.980827	0.978974	1.852747e-03
11	10	500	0.971625	0.969871	1.753697e-03
12	50	2	0.999995	0.996048	3.947354e-03
13	50	10	0.999995	0.996245	3.749549e-03

```
clf.best_params_
```

```
{'max_depth': 50, 'min_samples_split': 10}
```

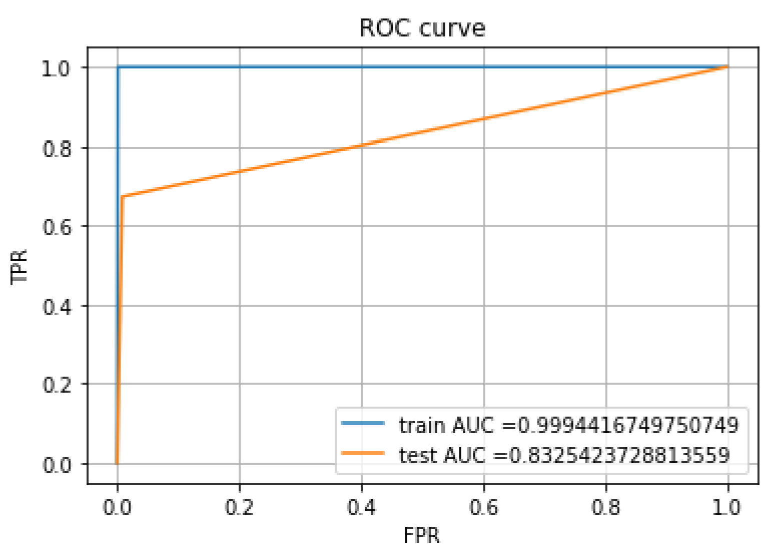
f1 score

```
DT_best = DecisionTreeClassifier(class_weight="balanced" , max_depth=50 , min_samples_split = 10)
DT_best.fit(X_random,y_random)

print("Train F1 Score = ",f1_score(y_random , DT_best.predict(X_random)))
print("Test F1 Score = ",f1_score(y_test , DT_best.predict(X_test)))
```

```
Train F1 Score =  0.9994419865279606
Test F1 Score =  0.6234567901234568
```

AUC Score

```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_random, DT_best.predict(X_random))
test_fpr, test_tpr, te_thresholds = roc_curve(y_test , DT_best.predict(X_test))

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC curve")
plt.grid()
plt.show()
```



Precision

```
print("Train precision Score = ",precision_score(y_random , DT_best.predict(X_random)))
print("Test precision Score = ",precision_score(y_test , DT_best.predict(X_test)))
```

```
Train precision Score =  0.9988845954666773
Test precision Score =  0.5804597701149425
```

Recall

```
print("Train recall Score = ",recall_score(y_random , DT_best.predict(X_random)))
print("Test recall Score = ",recall_score(y_test , DT_best.predict(X_test)))
```

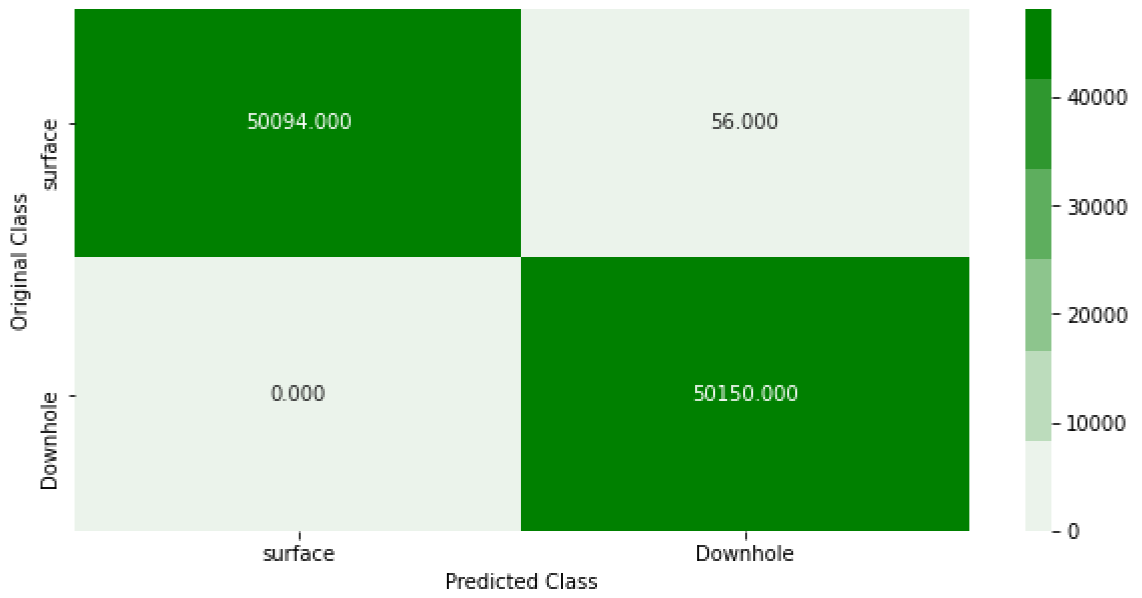
```
Train recall Score =  1.0
Test recall Score =  0.6733333333333333
```

Confusion matrix train

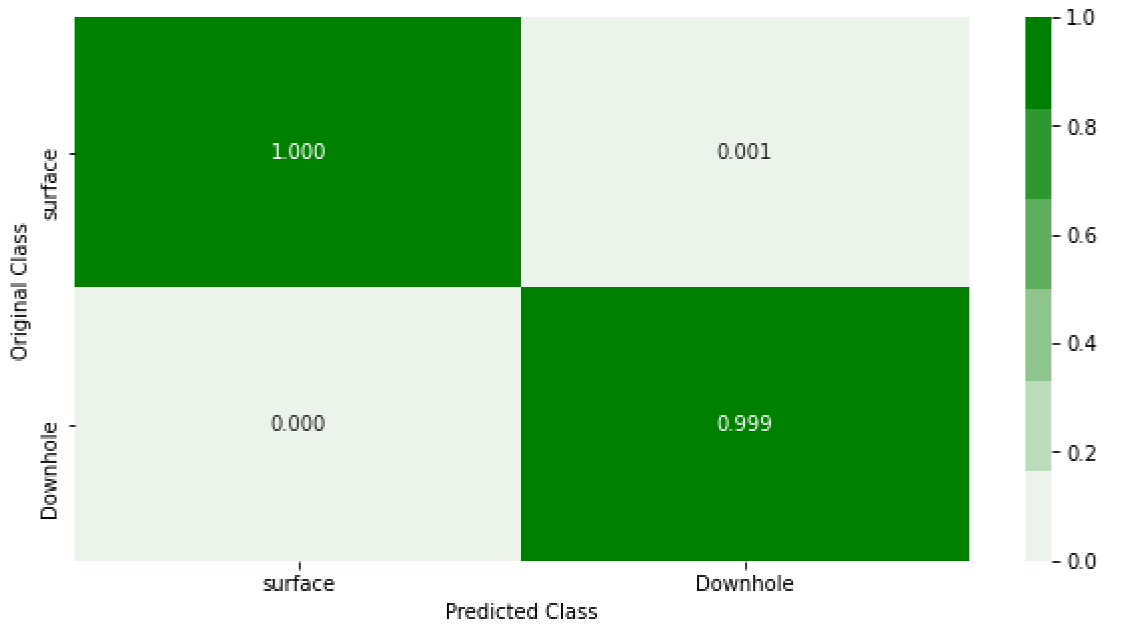
```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_random , DT_best.predict(X_random) , lables)
```

```
Number of misclassified points  0.05583250249252243
-------------------------------------------------- Confusion matrix --------------------------------------------------
```

50000




```
-------------------------------------------------- Precision matrix --------------------------------------------------
```

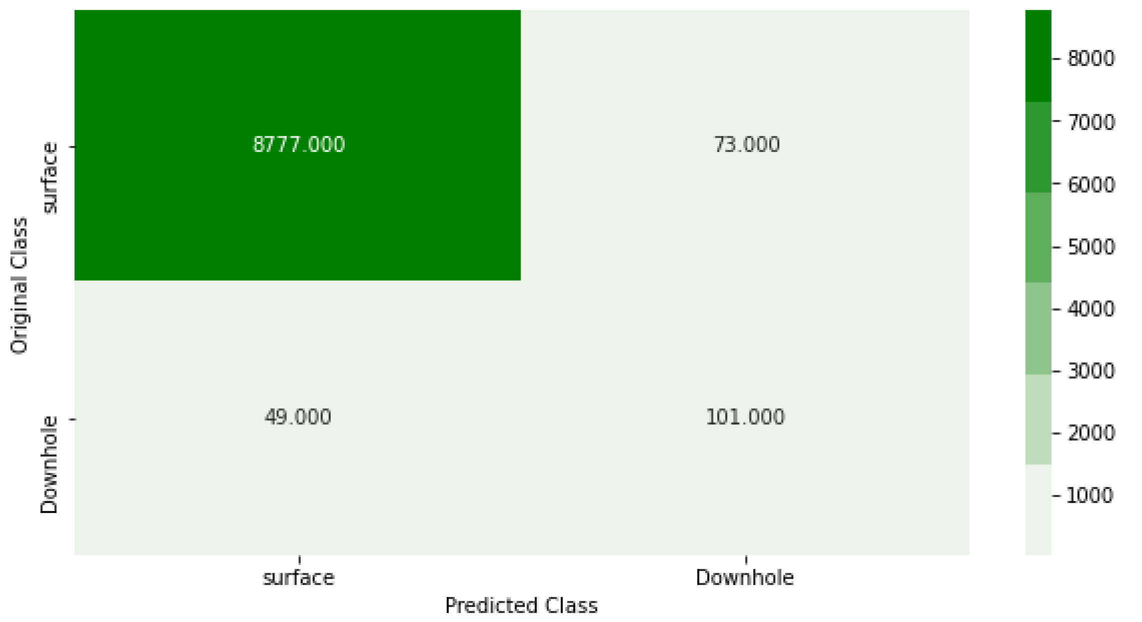



```
Sum of columns in precision matrix [1. 1.]
-------------------------------------------------- Recall matrix --------------------------------------------------
```

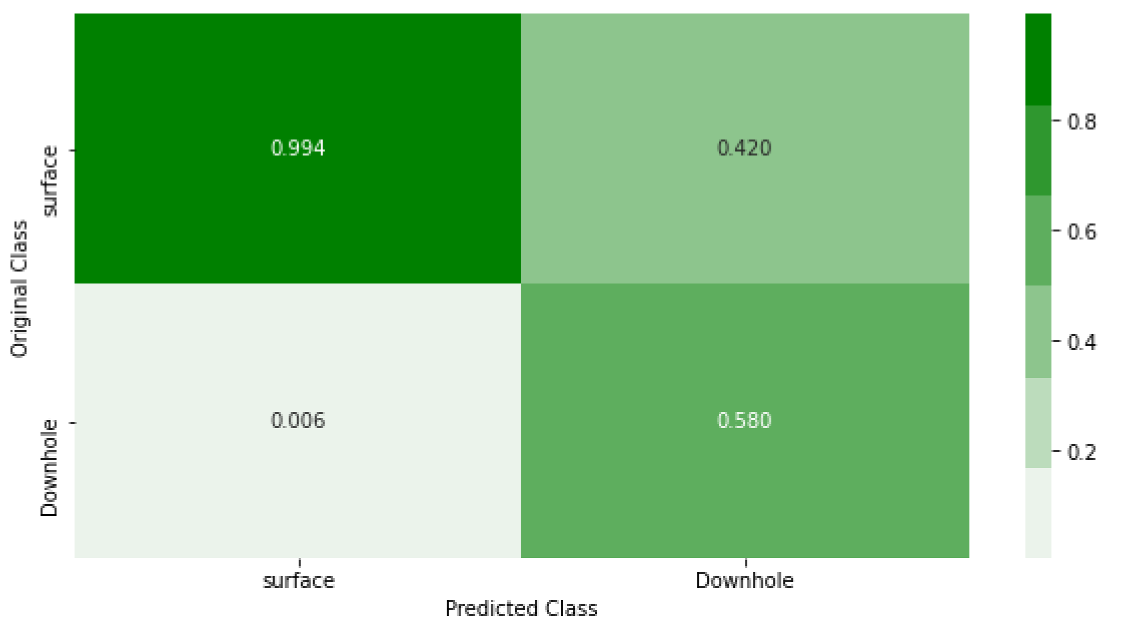
Confusion matrix test

```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_test , DT_best.predict(X_test) , lables)
```

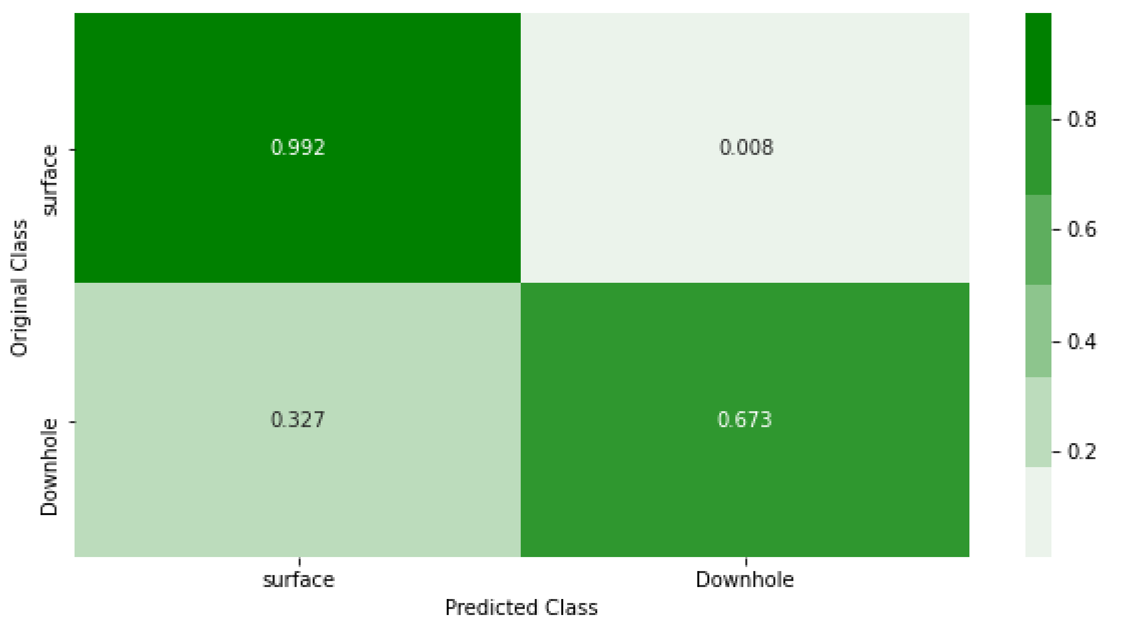
```
Number of misclassified points  1.3555555555555554
-------------------------------------------------- Confusion matrix --------------------------------------------------
```




```
-------------------------------------------------- Precision matrix --------------------------------------------------
```




```
Sum of columns in precision matrix [1. 1.]
-------------------------------------------------- Recall matrix --------------------------------------------------
```




```
Sum of rows in precision matrix [1. 1.]
```

On SMOTE over sampled

```
DT = DecisionTreeClassifier(class_weight = "balanced")
```

```
DT = DecisionTreeClassifier(class_weight = "balanced")

parameters = { "max_depth":[1,5,10,50,100,500] , "min_samples_split":[2,10,100,500]}

clf = GridSearchCV( DT , parameters , verbose=4 , cv=3 , scoring = "f1" , return_train_score = True)

clf.fit(X_smote,y_smote)


#Creating dataframe for grid search cv results

results_df = pd.concat([pd.DataFrame(clf.cv_results_["params"]),pd.DataFrame(clf.cv_results_["mean_train_score"], columns=["train_f1_score"]),pd.DataFrame(clf.cv_results_["mean_

train_cv_diffrence = abs(np.array(results_df['train_f1_score'].tolist()) - np.array(results_df['cv_f1_score'].tolist()))

results_df = pd.concat([results_df,pd.DataFrame(train_cv_diffrence, columns=["train_cv_diffrence"])],axis=1)

results_df
```

	max_depth	min_samples_split	train_f1_score	cv_f1_score	train_cv_diffrence
0	1	2	0.936229	0.936174	0.000055
1	1	10	0.936229	0.936174	0.000055
2	1	100	0.936229	0.936174	0.000055
3	1	500	0.936229	0.936174	0.000055
4	5	2	0.964676	0.962715	0.001961
5	5	10	0.964676	0.962716	0.001960
6	5	100	0.964105	0.962308	0.001797
7	5	500	0.960194	0.958425	0.001770
8	10	2	0.984617	0.979427	0.005190
9	10	10	0.984324	0.979323	0.005001
10	10	100	0.978547	0.974959	0.003587
11	10	500	0.964648	0.962264	0.002384
12	50	2	0.999930	0.987678	0.012252
13	50	10	0.998041	0.986695	0.011345
14	50	100	0.986371	0.978456	0.007915
15	50	500	0.967996	0.963371	0.004625
16	100	2	1.000000	0.987529	0.012471
17	100	10	0.998086	0.986369	0.011717
18	100	100	0.986366	0.978428	0.007938
19	100	500	0.967996	0.963401	0.004595
20	500	2	1.000000	0.987795	0.012205
21	500	10	0.998046	0.986793	0.011252
22	500	100	0.986351	0.978359	0.007992
23	500	500	0.968001	0.963403	0.004598

```
clf.best_params_
```

```
{'max_depth': 500, 'min_samples_split': 2}
```

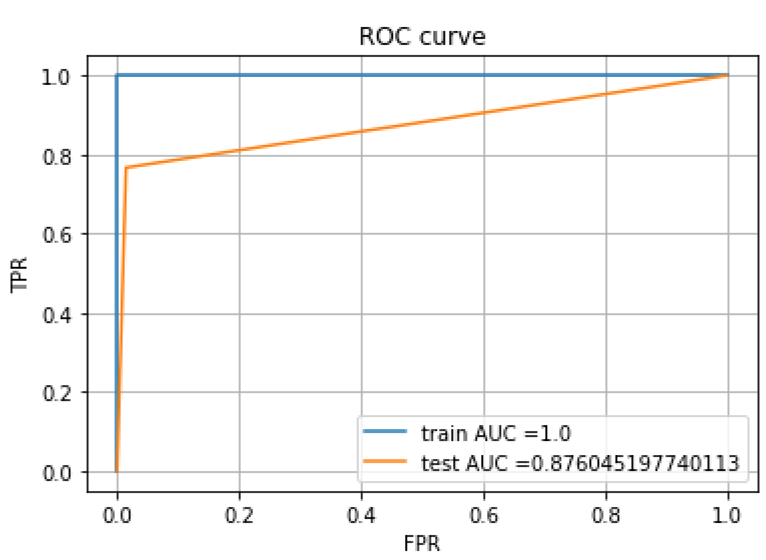
f1 score

```
DT_best = DecisionTreeClassifier(class_weight="balanced" , max_depth=500 , min_samples_split = 2)
DT_best.fit(X_smote,y_smote)

print("Train F1 Score = ",f1_score(y_smote , DT_best.predict(X_smote)))
print("Test F1 Score = ",f1_score(y_test , DT_best.predict(X_test)))
```

```
Train F1 Score =  1.0
Test F1 Score =  0.5837563451776651
```

AUC Score

```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_smote, DT_best.predict(X_smote))
test_fpr, test_tpr, te_thresholds = roc_curve(y_test , DT_best.predict(X_test))

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC curve")
plt.grid()
plt.show()
```



Precision

```
print("Train precision Score = ",precision_score(y_smote , DT_best.predict(X_smote)))
```

```
print("Test precision Score = ",precision_score(y_test , DT_best.predict(X_test)))
```

```
Train precision Score =  1.0
Test precision Score =  0.4713114754098361
```

Recall

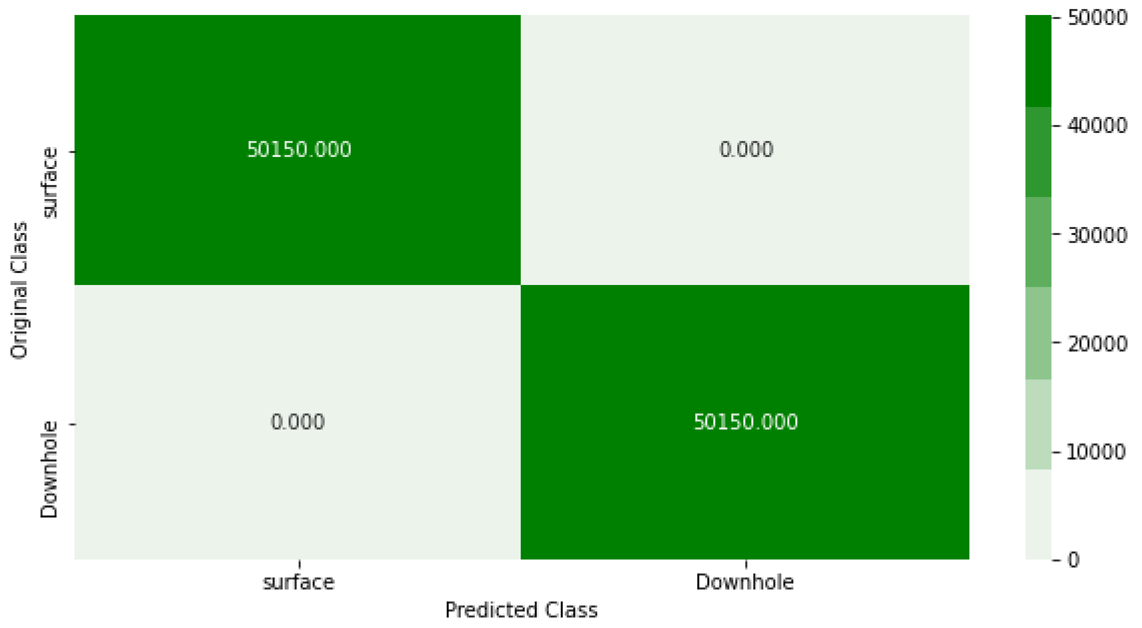
```
print("Train recall Score = ",recall_score(y_smote , DT_best.predict(X_smote)))
print("Test recall Score = ",recall_score(y_test , DT_best.predict(X_test)))
```

```
Train recall Score =  1.0
Test recall Score =  0.7666666666666667
```

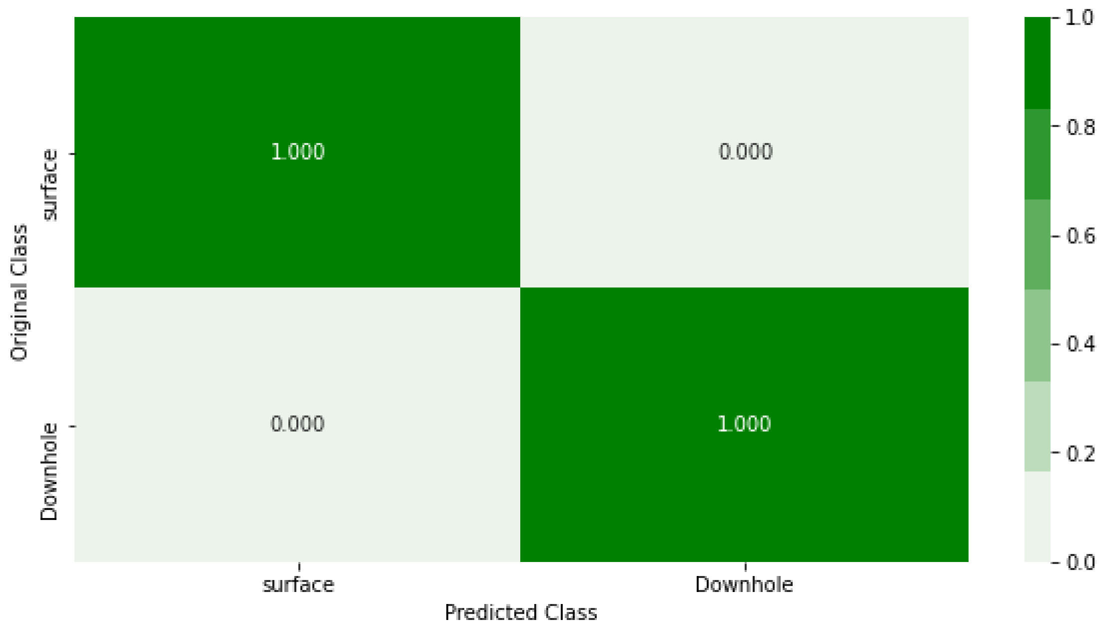
Confusion matrix train

```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_smote , DT_best.predict(X_smote) , lables)
```

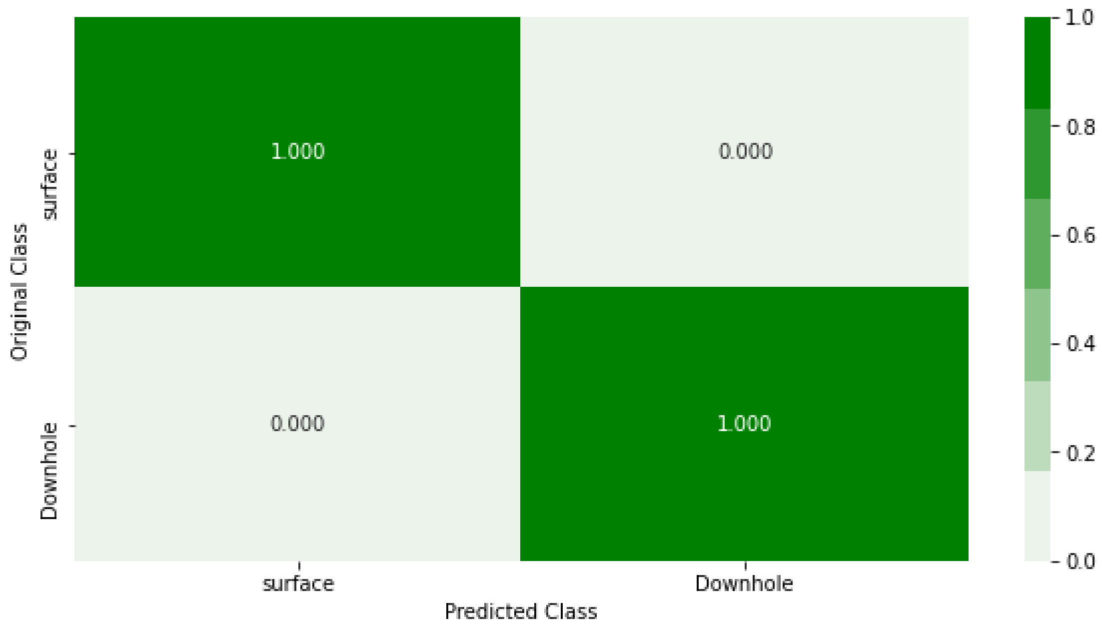
```
Number of misclassified points  0.0
-------------------------------------------------- Confusion matrix --------------------------------------------------
```




```
-------------------------------------------------- Precision matrix --------------------------------------------------
```




```
Sum of columns in precision matrix [1. 1.]
-------------------------------------------------- Recall matrix --------------------------------------------------
```

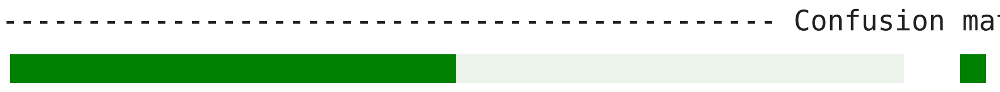


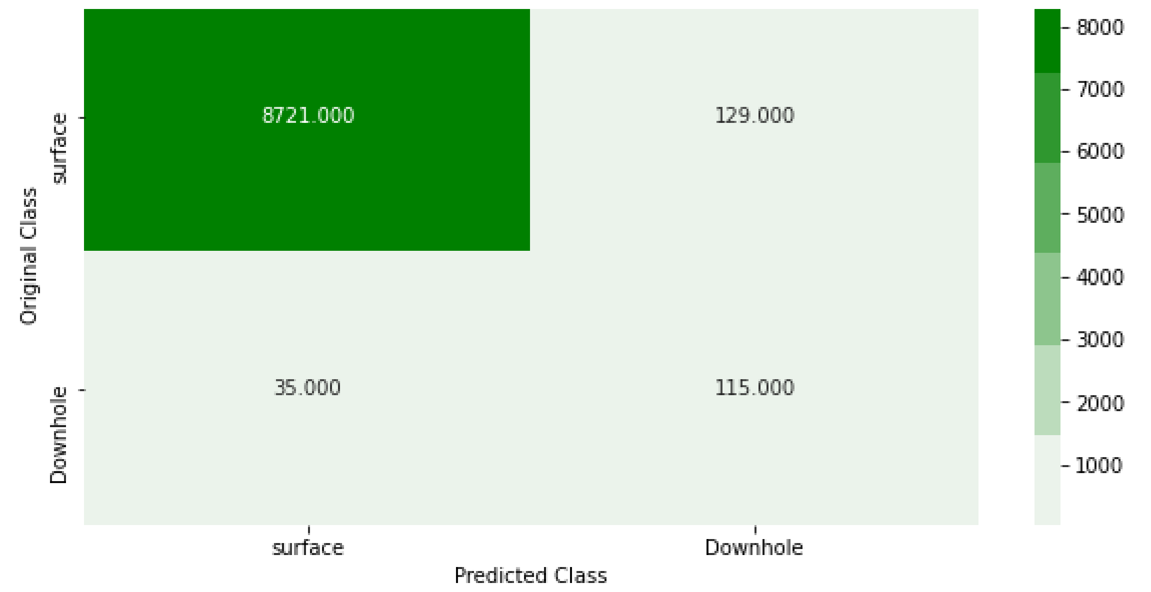

```
Sum of rows in precision matrix [1. 1.]
```

Confusion matrix test

```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_test , DT_best.predict(X_test) , lables)
```

```
Number of misclassified points  1.8222222222222224
-------------------------------------------------- Confusion matrix --------------------------------------------------
```





--- Precision matrix ---

Gradient Boosting

```
import xgboost as xgb

GB = xgb.XGBClassifier(max_depth=100,learning_rate=0.12,n_estimators=2000,colsample_bytree=0.4,subsample=0.4)
```

On random over sampled

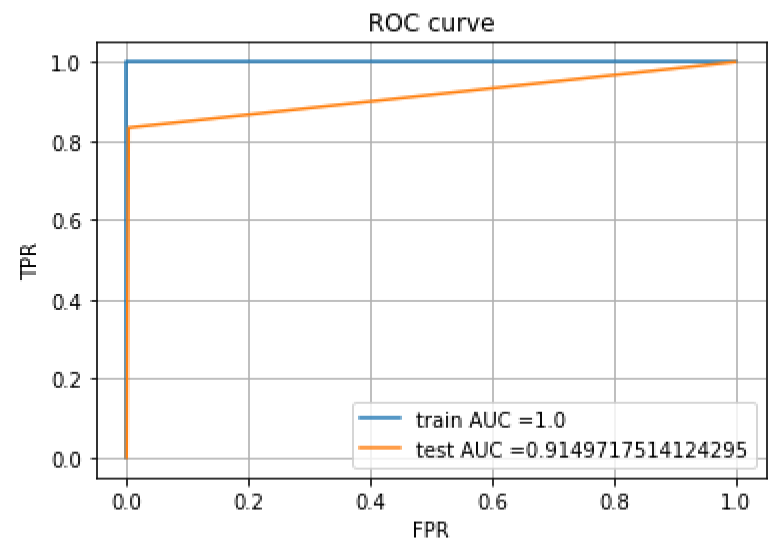
F1 score

```
GB.fit(X_random,y_random)

print("Train F1 Score = ",f1_score(y_random , GB.predict(X_random)))
print("Test F1 Score = ",f1_score(y_test , GB.predict(X_test)))
```

```
Train F1 Score =  1.0
Test F1 Score =  0.819672131147541
```

AUC Score

```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_random, GB.predict(X_random))
test_fpr, test_tpr, te_thresholds = roc_curve(y_test , GB.predict(X_test))

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC curve")
plt.grid()
plt.show()
```



Precision

```
print("Train precision Score = ",precision_score(y_random , GB.predict(X_random)))
print("Test precision Score = ",precision_score(y_test , GB.predict(X_test)))
```

```
Train precision Score =  1.0
Test precision Score =  0.8064516129032258
```

Recall

```
print("Train recall Score = ",recall_score(y_random , GB.predict(X_random)))
print("Test recall Score = ",recall_score(y_test , GB.predict(X_test)))
```

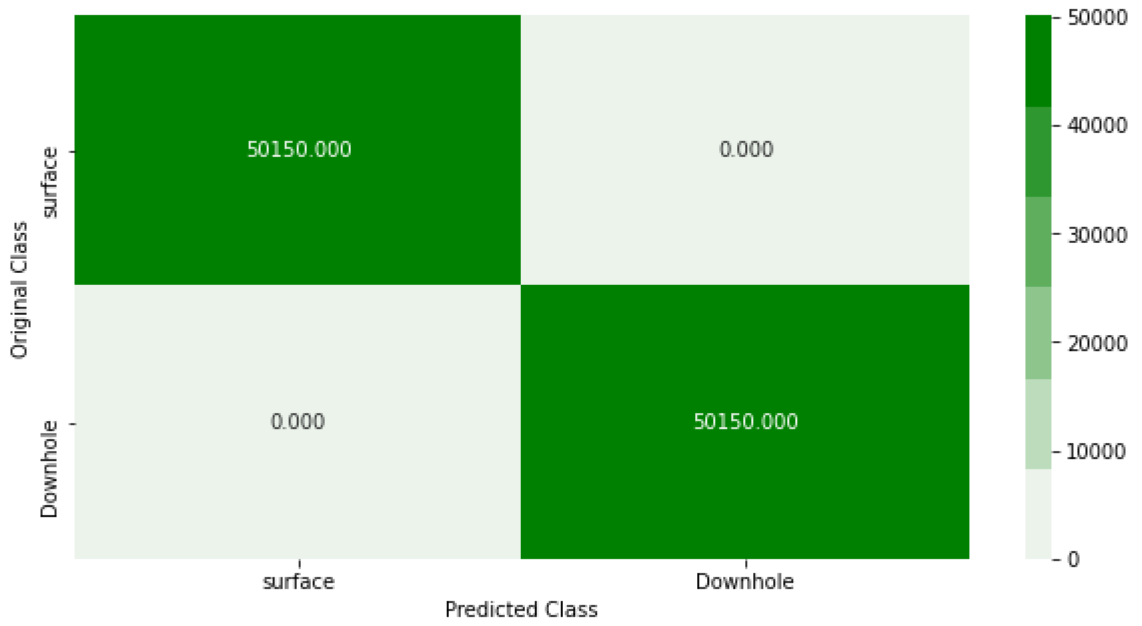
```
Train recall Score =  1.0
Test recall Score =  0.8333333333333334
```

Confusion matrix train

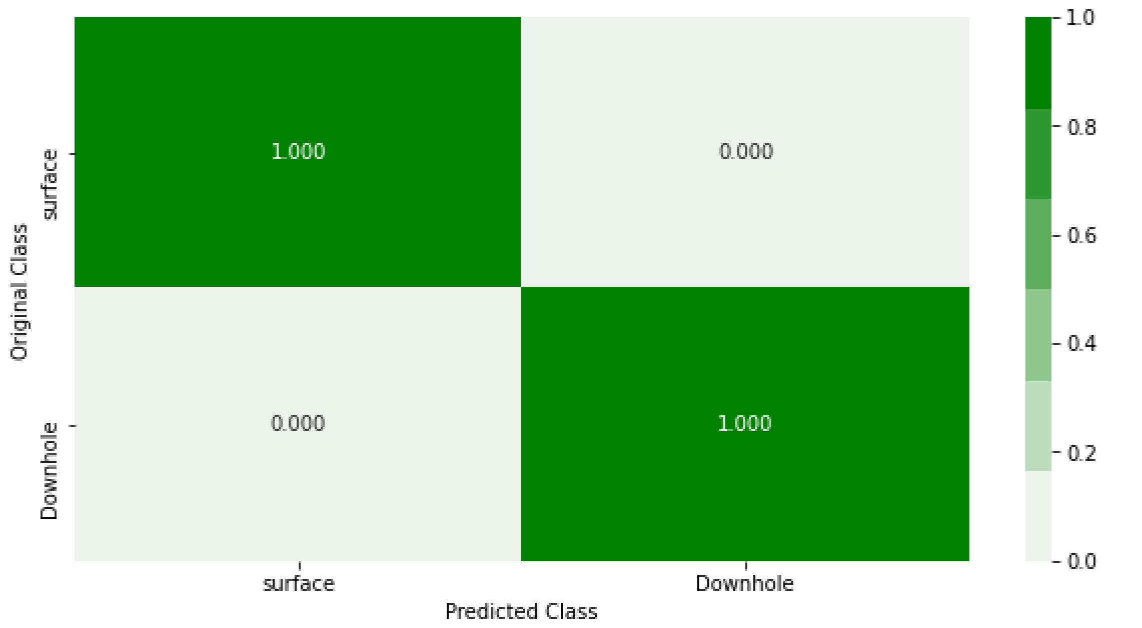
```
lables = ["surface" , "Downhole"]
```

```
plot_confusion_matrix(y_random , GB.predict(X_random) , lables)
```

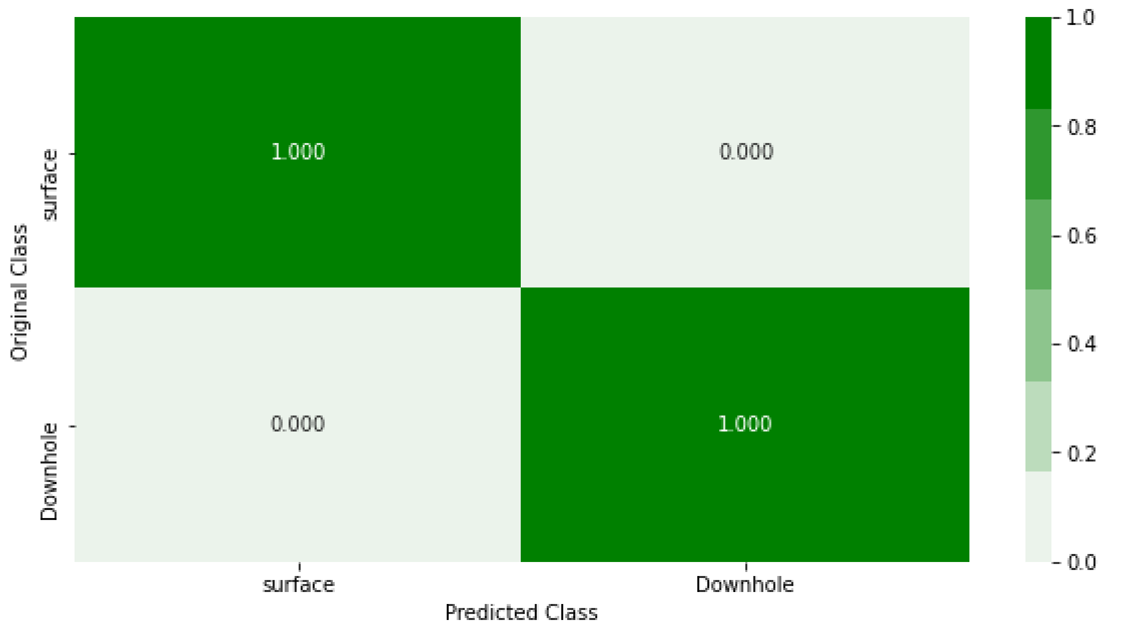
```
Number of misclassified points  0.0
-------------------------------------------------- Confusion matrix --------------------------------------------------
```




```
-------------------------------------------------- Precision matrix --------------------------------------------------
```




```
Sum of columns in precision matrix [1. 1.]
-------------------------------------------------- Recall matrix --------------------------------------------------
```



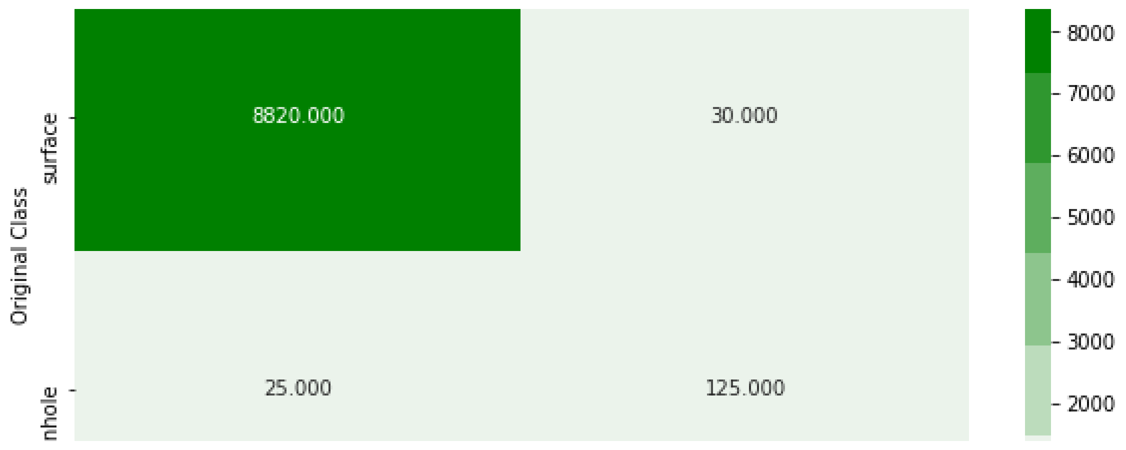

```
Sum of rows in precision matrix [1. 1.]
```

Confusion matrix test

```
lables = ["surface" , "Downhole"]
```

```
plot_confusion_matrix(y_test , GB.predict(X_test) , lables)
```

```
Number of misclassified points  0.6111111111111112
-------------------------------------------------- Confusion matrix --------------------------------------------------
```



On SMOTE over sampled

Predicted Class

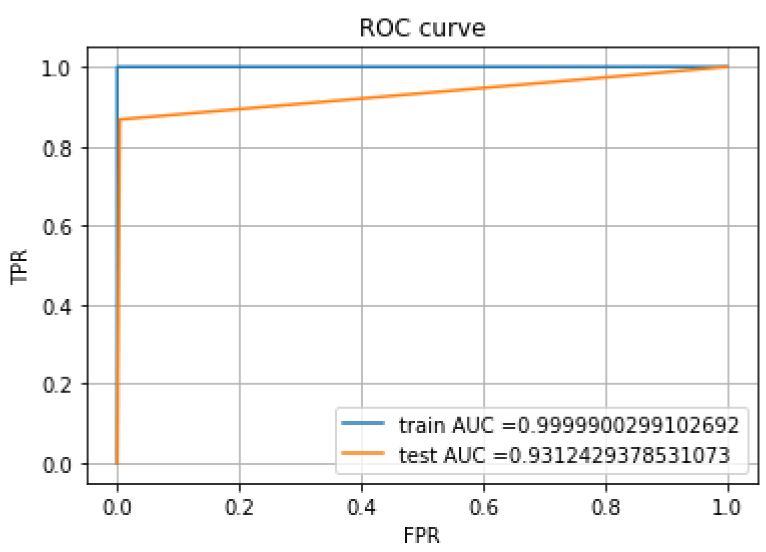
F1 score

```
GB.fit(X_smote,y_smote)

print("Train F1 Score = ",f1_score(y_smote , GB.predict(X_smote)))
print("Test F1 Score = ",f1_score(y_test , GB.predict(X_test)))
```

```
Train F1 Score =  0.9999900298108655
Test F1 Score =  0.8201892744479495
```

AUC Score

```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_smote, GB.predict(X_smote))
test_fpr, test_tpr, te_thresholds = roc_curve(y_test , GB.predict(X_test))

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC curve")
plt.grid()
plt.show()
```



Precision

```
print("Train precision Score = ",precision_score(y_smote , GB.predict(X_smote)))
print("Test precision Score = ",precision_score(y_test , GB.predict(X_test)))
```

```
Train precision Score =  1.0
Test precision Score =  0.7784431137724551
```

Recall

```
print("Train recall Score = ",recall_score(y_smote , GB.predict(X_smote)))
print("Test recall Score = ",recall_score(y_test , GB.predict(X_test)))
```

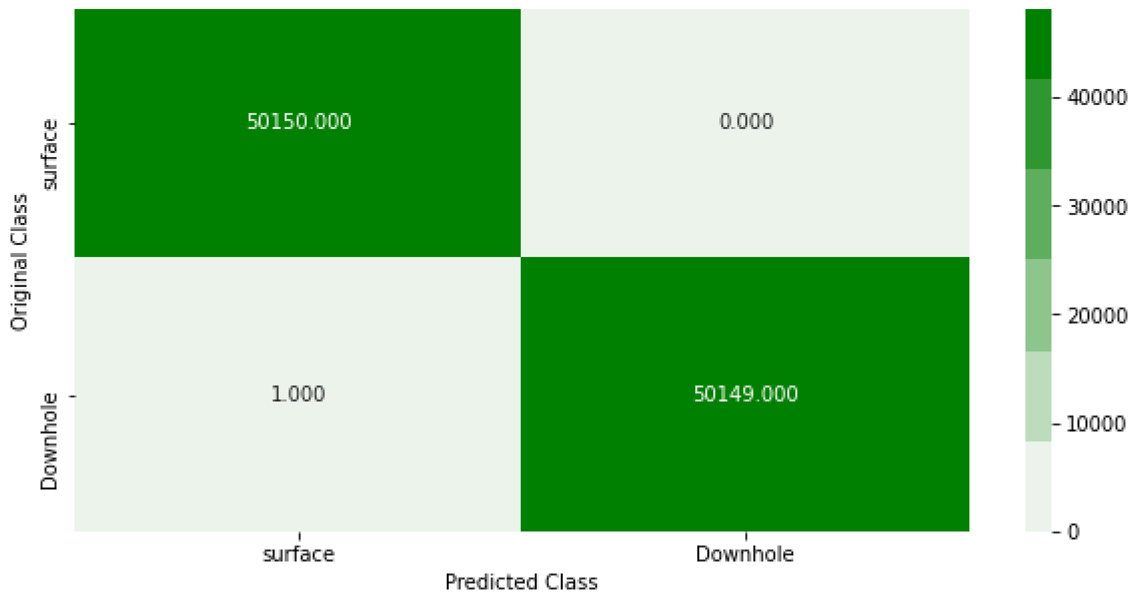
```
Train recall Score =  0.9999800598205384
Test recall Score =  0.8666666666666667
```

Confusion matrix train

```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_smote , GB.predict(X_smote) , lables)
```

```
Number of misclassified points  0.0009970089730807576
-------------------------------------------------- Confusion matrix --------------------------------------------------
```

50000



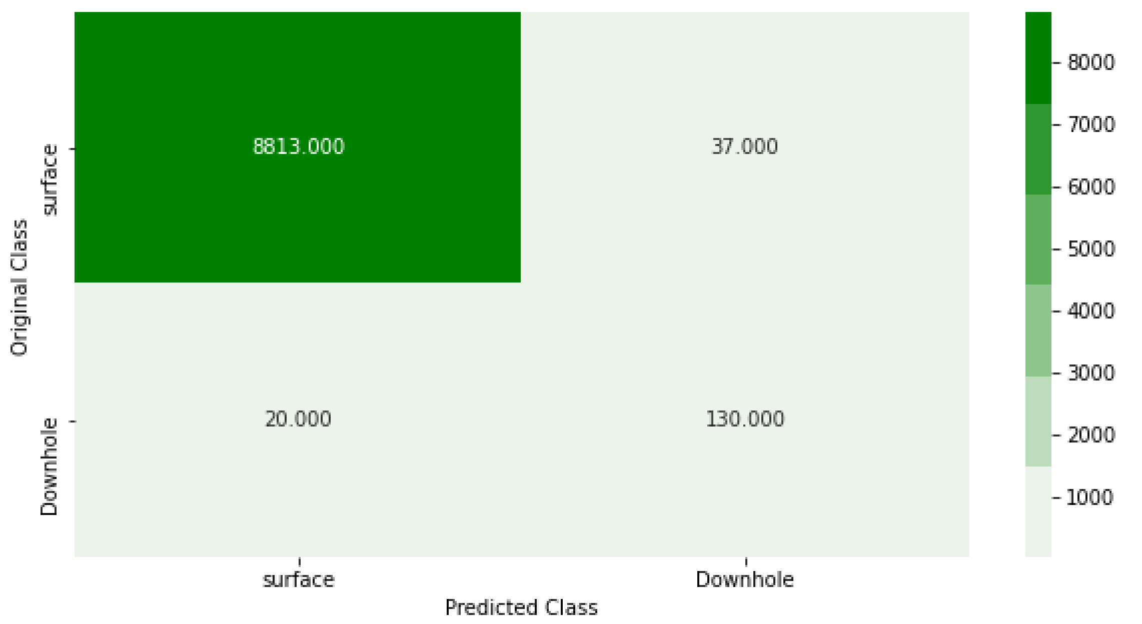

```
------------------------------------------------- Precision matrix ------------------------------------------------
```

Confusion matrix test

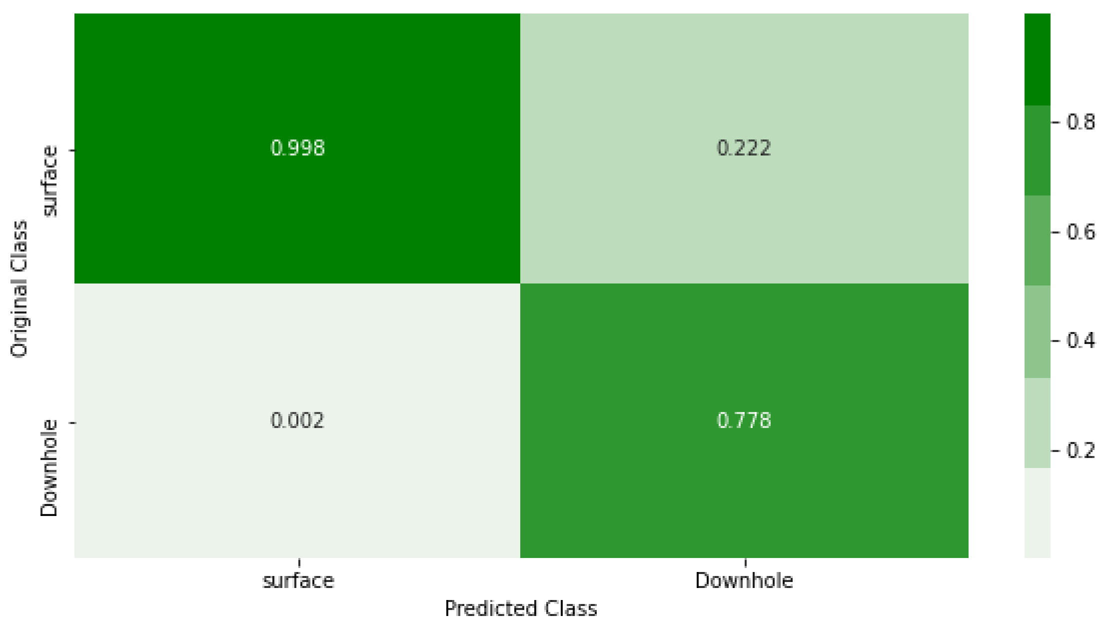
```
Sum of columns in precision matrix [1. 1.]
```

```
lables = ["surface" , "Downhole"]

plot_confusion_matrix(y_test , GB.predict(X_test) , lables)
```

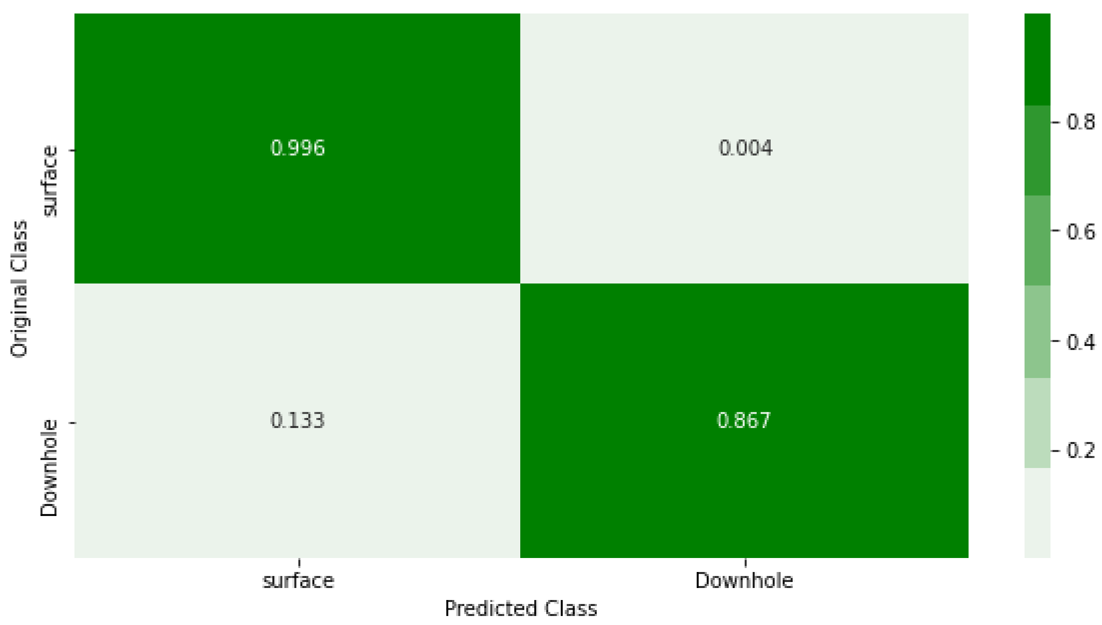
```
Number of misclassified points  0.6333333333333333
------------------------------------------------- Confusion matrix ------------------------------------------------
```




```
------------------------------------------------- Precision matrix ------------------------------------------------
```




```
Sum of columns in precision matrix [1. 1.]
------------------------------------------------- Recall matrix ------------------------------------------------
```




```
Sum of rows in precision matrix [1. 1.]
```

Results

```
from prettytable import PrettyTable
x = PrettyTable()

x.field_names = ["model", "dataset", "train f1","test f1", "test AUC","test precision","test recall"]
x.add_row(["Naive Bayes","Random over", 0.91, 0.3 ,0.915,0.18,0.9])
x.add_row(["Naive Bayes","SMOTE over", 0.91, 0.29 ,0.92,0.17,0.91])
x.add_row(["Logistic Regression","Random over", 0.96, 0.5 ,0.95,0.34,0.93])
x.add_row(["Logistic Regression","SMOTE over", 0.96, 0.51 ,0.94,0.35,0.92])
x.add_row(["Decision Tree","Random over", 0.99, 0.62 ,0.83,0.58,0.67])
x.add_row(["Decision Tree","SMOTE over", 1, 0.58 ,0.87,0.47,0.76])
x.add_row(["Gradient Boosting","Random over", 1, 0.82 ,0.91,0.8,0.83])
x.add_row(["Gradient Boosting","SMOTE over", 0.99, 0.82 ,0.93,0.78,0.866])

print(x)
```

```
print(x)
```

model	dataset	train f1	test f1	test AUC	test precision	test recall
Naive Bayes	Random over	0.91	0.3	0.915	0.18	0.9
Naive Bayes	SMOTE over	0.91	0.29	0.92	0.17	0.91
Logistic Regression	Random over	0.96	0.5	0.95	0.34	0.93
Logistic Regression	SMOTE over	0.96	0.51	0.94	0.35	0.92
Decision Tree	Random over	0.99	0.62	0.83	0.58	0.67
Decision Tree	SMOTE over	1	0.58	0.87	0.47	0.76
Gradient Boosting	Random over	1	0.82	0.91	0.8	0.83
Gradient Boosting	SMOTE over	0.99	0.82	0.93	0.78	0.866