Section-III- Self Case Study-1_Pump it up-Data Mining the Water Table

5. Modeling

In this notebook, we will try various models and assess their performance to decide upon the best model.

5.1 Importing required libraries & reading data

In [2]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import re
import time
import warnings
warnings.filterwarnings("ignore")
import numpy as np
from nltk.corpus import stopwords
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.manifold import TSNE
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
import sys
from category_encoders import OneHotEncoder
from sklearn.preprocessing import MinMaxScaler
from category_encoders import TargetEncoder, LeaveOneOutEncoder, WOEEncoder
from sklearn.preprocessing import RobustScaler
from sklearn.metrics import accuracy_score, balanced_accuracy_score
from sklearn.metrics import confusion_matrix
```

In [7]:
```
df = pd.read_csv('clean_df.csv')
```

In [13]:
```
pd.set_option('display.max_columns', None)
df.head(2)
```

Out[13]:

	Unnamed: 0	id	amount_tsh	funder	gps_height	installer	longitude	latitude	basin	region	district_code	lga	population	public_meeting	per
0	0	69572	6000.0	other	1390	other	34.938093	-9.856322	Lake Nyasa	Iringa	5	Ludewa	109.0	True	Fa
1	1	8776	0.0	other	1399	other	34.698766	-2.147466	Lake Victoria	Mara	2	Serengeti	280.0	True	T

In previous notebook (section-II), we have checked the baseline model performance using above features. Baseline model was run with and without feature 'amount_tsh' which has nearly 70% values as zero. It was found that removal of 'amount_tsh' improved the performace.

In [14]:
```
df1 = df.copy() #creating copy of df
```

In [15]:
```
df1.drop(columns=['Unnamed: 0', 'amount_tsh', 'id' ],inplace=True ) # dropping unwanted columns
```

In [16]:
```
df1['permit'] = df1['permit'].astype(bool).astype(int) #converting True/Flse into 0/1
df1['public_meeting'] = df1['public_meeting'].astype(bool).astype(int) #converting True/Flse into 0/1
```

In [19]:
```
df1.head(1)
```

Out[19]:

	funder	gps_height	installer	longitude	latitude	basin	region	district_code	lga	population	public_meeting	permit	extraction_type_group	manag
0	other	1390	other	34.938093	-9.856322	Lake Nyasa	Iringa	5	Ludewa	109.0	1	0	gravity	

5.2 Encoding & Standardizaton of fearures using RobustScaler & TargetEncoder

In [17]:
```
#encoding target variables manualy
numeric_target_values = {'functional':1, 'non functional':0, 'functional needs repair':2}
df1['status_group'] = df1['status_group'].replace(numeric_target_values)
df1['status_group'].value_counts()
```

Out[17]:
```
1    32259
0    22824
2     4317
Name: status_group, dtype: int64
```

In [18]:
```
numerical_features = ['gps_height','longitude', 'latitude', 'district_code','population', 'public_meeting',
                      'permit','operational_year']
categorical_features = ['funder','installer','basin', 'region', 'lga', 'extraction_type_group','management',
                        'payment', 'water_quality', 'quantity', 'source','waterpoint_type']
```

In [20]:
```
y=df1['status_group']
X = df1.drop(columns = ['status_group'])
```

In [26]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=40)
```

In [27]:
```
import category_encoders as ce
scaler1 = RobustScaler()
encoder1 = ce.TargetEncoder()
```

In [28]:
```
transformer1 = scaler1.fit(X_train[numerical_features])

X_train[numerical_features] = transformer1.transform(X_train[numerical_features])
X_test[numerical_features] = transformer1.transform(X_test[numerical_features])
```

In [29]:
```
transformer_te_1 = encoder1.fit(X_train[categorical_features], y_train)

X_train[categorical_features] = transformer_te_1.transform(X_train[categorical_features])
X_test[categorical_features] = transformer_te_1.transform(X_test[categorical_features])
```

5.2.1 Applying Linear regression

In [30]:
```python
from sklearn.linear_model import LogisticRegression
clf_lr1 = LogisticRegression(class_weight = 'balanced', solver = 'lbfgs', random_state=30)
clf_lr1.fit(X_train, y_train)
```

Out[30]:
```
LogisticRegression(class_weight='balanced', random_state=30)
```

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In [31]:
```python
from sklearn.metrics import roc_auc_score
from sklearn.metrics import f1_score
```

In [32]:
```
# making predictions on test set
y_pred_train = clf_lr1.predict(X_train)
y_pred_train_proba = clf_lr1.predict_proba(X_train)
# making predictions on test set
y_pred_test = clf_lr1.predict(X_test)
y_pred_test_proba = clf_lr1.predict_proba(X_test)

# printing the result
print("Accuracy:")
print("*"*50)
print("Train:", accuracy_score(y_train, y_pred_train))
print("Test:", accuracy_score(y_test, y_pred_test))

print("\nBalanced Accuracy:")
print("*"*50)
print("Train:", balanced_accuracy_score(y_train, y_pred_train))
print("Test:", balanced_accuracy_score(y_test, y_pred_test))

print("\nF1_score:")
print("*"*50)
print("Train:",f1_score(y_train, y_pred_train, average="weighted"))
print("Test:",f1_score(y_test, y_pred_test, average="weighted"))

print("\nroc_auc_score:")
print("*"*50)
print("Train:", roc_auc_score(y_train, y_pred_train_proba, multi_class='ovr'))
print("Test:", roc_auc_score(y_test, y_pred_test_proba, multi_class='ovr'))
```

```
Accuracy:
**************************************************
Train: 0.6226430976430977
Test: 0.6239057239057239

Balanced Accuracy:
**************************************************
Train: 0.605188476871113
Test: 0.6032531418049696

F1_score:
**************************************************
Train: 0.6565152508234546
Test: 0.6556423940145812

roc_auc_score:
**************************************************
Train: 0.7912755897425586
Test: 0.7910068826308301
```

5.2.2 Applying KNN

In [33]:
```
from sklearn.neighbors import KNeighborsClassifier
clf_knn1 = KNeighborsClassifier()
clf_knn1.fit(X_train, y_train)
```

Out[33]:
```
KNeighborsClassifier()
```

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In [34]:

```python
# making predictions on test set
y_pred_train = clf_knn1.predict(X_train)
y_pred_train_proba = clf_knn1.predict_proba(X_train)
# making predictions on test set
y_pred_test = clf_knn1.predict(X_test)
y_pred_test_proba = clf_knn1.predict_proba(X_test)

# printing the result
print("Accuracy:")
print("*"*50)
print("Train:", accuracy_score(y_train, y_pred_train))
print("Test:", accuracy_score(y_test, y_pred_test))

print("\nBalanced Accuracy:")
print("*"*50)
print("Train:", balanced_accuracy_score(y_train, y_pred_train))
print("Test:", balanced_accuracy_score(y_test, y_pred_test))

print("\nF1_score:")
print("*"*50)
print("Train:",f1_score(y_train, y_pred_train, average="weighted"))
print("Test:",f1_score(y_test, y_pred_test, average="weighted"))

print("\nroc_auc_score:")
print("*"*50)
print("Train:", roc_auc_score(y_train, y_pred_train_proba, multi_class='ovr'))
print("Test:", roc_auc_score(y_test, y_pred_test_proba, multi_class='ovr'))
```

```
Accuracy:
**************************************************
Train: 0.8303872053872053
Test: 0.759006734006734

Balanced Accuracy:
**************************************************
Train: 0.6941365864165254
Test: 0.6108819497283525

F1_score:
**************************************************
Train: 0.8233388856686996
Test: 0.749075658784774

roc_auc_score:
**************************************************
Train: 0.9467684546711088
Test: 0.831141964503991
```

5.2.3 Applying Decision Tree

In [37]:

```
from sklearn.tree import DecisionTreeClassifier
clf_dt1 = DecisionTreeClassifier(criterion='gini', max_depth=4, min_samples_leaf=5,
                                 random_state=42, class_weight='balanced')
clf_dt1.fit(X_train, y_train)
```

Out[37]:

```
DecisionTreeClassifier(class_weight='balanced', max_depth=4, min_samples_leaf=5,
                       random_state=42)
```

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In [38]:
```python
# making predictions on test set
y_pred_train = clf_dt1.predict(X_train)
y_pred_train_proba = clf_dt1.predict_proba(X_train)
# making predictions on test set
y_pred_test = clf_dt1.predict(X_test)
y_pred_test_proba = clf_dt1.predict_proba(X_test)

# printing the result
print("Accuracy:")
print("*"*50)
print("Train:", accuracy_score(y_train, y_pred_train))
print("Test:", accuracy_score(y_test, y_pred_test))

print("\nBalanced Accuracy:")
print("*"*50)
print("Train:", balanced_accuracy_score(y_train, y_pred_train))
print("Test:", balanced_accuracy_score(y_test, y_pred_test))

print("\nF1_score:")
print("*"*50)
print("Train:",f1_score(y_train, y_pred_train, average="weighted"))
print("Test:",f1_score(y_test, y_pred_test, average="weighted"))

print("\nroc_auc_score:")
print("*"*50)
print("Train:", roc_auc_score(y_train, y_pred_train_proba, multi_class='ovr'))
print("Test:", roc_auc_score(y_test, y_pred_test_proba, multi_class='ovr'))
```

```
Accuracy:
**************************************************
Train: 0.6842803030303031
Test: 0.6867003367003367

Balanced Accuracy:
**************************************************
Train: 0.5519779283592047
Test: 0.552951823991462

F1_score:
**************************************************
Train: 0.6757230233643264
Test: 0.6768887886696735

roc_auc_score:
**************************************************
Train: 0.7304044669780986
Test: 0.7299602954040708
```

5.2.4 Applying Random Forrest

In [39]:
```
from sklearn.ensemble import RandomForestClassifier
clf_rf1 = RandomForestClassifier(n_estimators=150, random_state=42, n_jobs=-1, criterion= 'gini',min_samples_split= 5,
                                class_weight='balanced')
clf_rf1.fit(X_train, y_train)
```

Out[39]:
```
RandomForestClassifier(class_weight='balanced', min_samples_split=5,
                       n_estimators=150, n_jobs=-1, random_state=42)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [40]:
```
# making predictions on test set
y_pred_train = clf_rf1.predict(X_train)
y_pred_train_proba = clf_rf1.predict_proba(X_train)
# making predictions on test set
y_pred_test = clf_rf1.predict(X_test)
y_pred_test_proba = clf_rf1.predict_proba(X_test)

# printing the result
print("Accuracy:")
print("*"*50)
print("Train:", accuracy_score(y_train, y_pred_train))
print("Test:", accuracy_score(y_test, y_pred_test))

print("\nBalanced Accuracy:")
print("*"*50)
print("Train:", balanced_accuracy_score(y_train, y_pred_train))
print("Test:", balanced_accuracy_score(y_test, y_pred_test))

print("\nF1_score:")
print("*"*50)
print("Train:",f1_score(y_train, y_pred_train, average="weighted"))
print("Test:",f1_score(y_test, y_pred_test, average="weighted"))

print("\nroc_auc_score:")
print("*"*50)
print("Train:", roc_auc_score(y_train, y_pred_train_proba, multi_class='ovr'))
print("Test:", roc_auc_score(y_test, y_pred_test_proba, multi_class='ovr'))
```

```
Accuracy:
**************************************************
Train: 0.9664351851851852
Test: 0.8047979797979798

Balanced Accuracy:
**************************************************
Train: 0.9738089370693183
Test: 0.7031972425944858

F1_score:
**************************************************
Train: 0.9667777445145996
Test: 0.803432446536808

roc_auc_score:
**************************************************
Train: 0.9967192506096815
Test: 0.9032102237969853
```

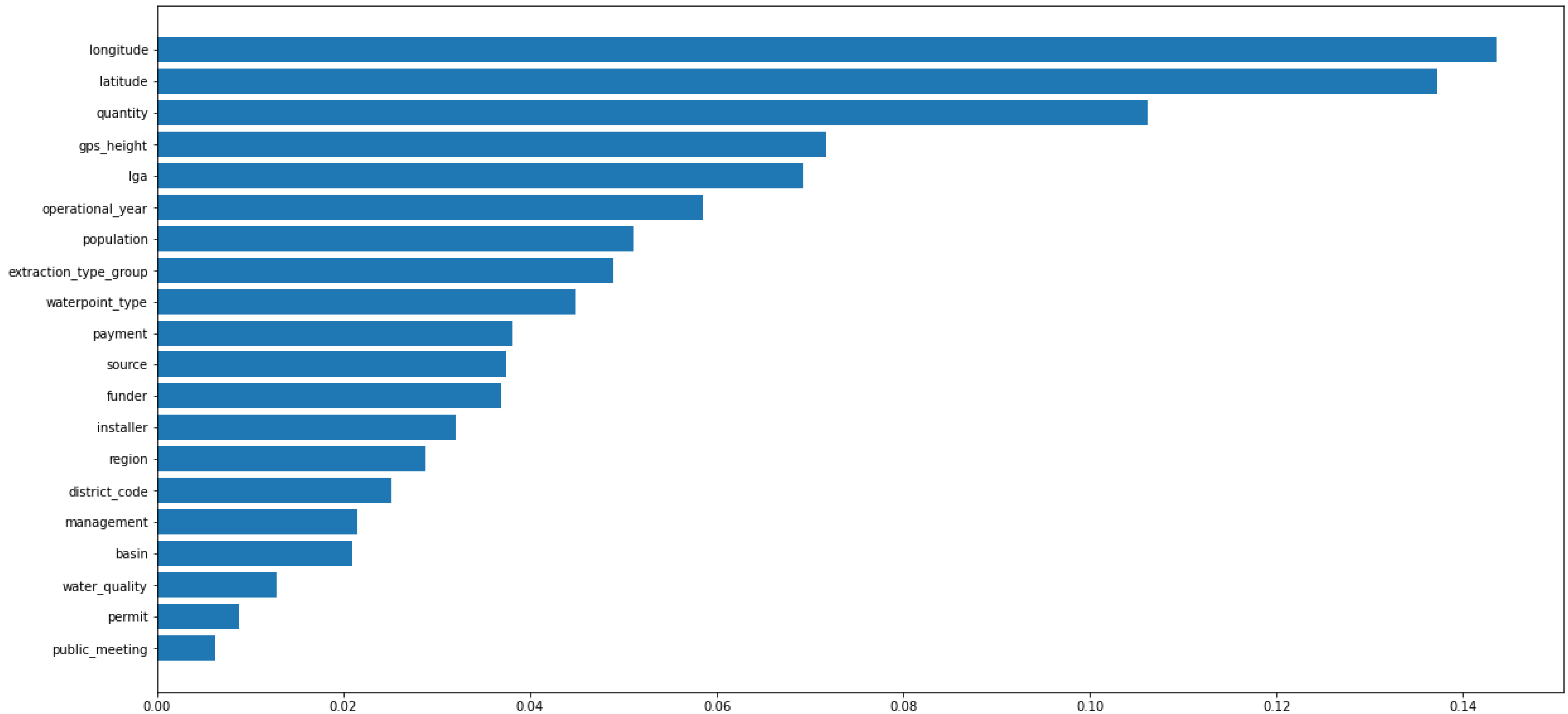
5.2.4.1 Feature importance in RandomForest

In [41]:
```
clf_rf1.feature_importances_
```

Out[41]:
```
array([0.03692044, 0.07177467, 0.03203825, 0.14354274, 0.13726511,
       0.02089314, 0.02884282, 0.02515766, 0.06935551, 0.051031  ,
       0.0062247 , 0.00877044, 0.04887417, 0.02143978, 0.03809518,
       0.01291049, 0.10614632, 0.03739319, 0.05849199, 0.04483239])
```

In [47]:
```
sorted_idx = clf_rf1.feature_importances_.argsort()
plt.figure(figsize=(20, 10))
plt.barh(X_train.columns[sorted_idx], clf_rf1.feature_importances_[sorted_idx])
```

Out[47]:
```
<BarContainer object of 20 artists>
```



From the above plot it is seen that the feaures such as 'permit' & 'public_meeting' are least important. lets remove them.

In [52]:
```
X_train.drop(columns=['permit', 'public_meeting'], inplace=True )
X_test.drop(columns=['permit', 'public_meeting'], inplace=True )
```

In [53]:
```
clf_rf2 = RandomForestClassifier(n_estimators=150, random_state=42, n_jobs=-1, criterion= 'gini',min_samples_split= 5,
                                class_weight='balanced')
clf_rf2.fit(X_train, y_train)
```

Out[53]:
```
RandomForestClassifier(class_weight='balanced', min_samples_split=5,
                       n_estimators=150, n_jobs=-1, random_state=42)
```

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5.2.4.2 Checking performance of RandomForest after removing least important features

In [54]:

```python
# making predictions on test set
y_pred_train = clf_rf2.predict(X_train)
y_pred_train_proba = clf_rf2.predict_proba(X_train)
# making predictions on test set
y_pred_test = clf_rf2.predict(X_test)
y_pred_test_proba = clf_rf2.predict_proba(X_test)

# printing the result
print("Accuracy:")
print("*"*50)
print("Train:", accuracy_score(y_train, y_pred_train))
print("Test:", accuracy_score(y_test, y_pred_test))

print("\nBalanced Accuracy:")
print("*"*50)
print("Train:", balanced_accuracy_score(y_train, y_pred_train))
print("Test:", balanced_accuracy_score(y_test, y_pred_test))

print("\nF1_score:")
print("*"*50)
print("Train:",f1_score(y_train, y_pred_train, average="weighted"))
print("Test:",f1_score(y_test, y_pred_test, average="weighted"))

print("\nroc_auc_score:")
print("*"*50)
print("Train:", roc_auc_score(y_train, y_pred_train_proba, multi_class='ovr'))
print("Test:", roc_auc_score(y_test, y_pred_test_proba, multi_class='ovr'))
```

```
Accuracy:
**************************************************
Train: 0.9678451178451178
Test: 0.8032828282828283

Balanced Accuracy:
**************************************************
Train: 0.9749178404127838
Test: 0.6967651220798095

F1_score:
**************************************************
Train: 0.9681619397959844
Test: 0.8014343733709647

roc_auc_score:
**************************************************
Train: 0.9967410532279221
Test: 0.9022438622306468
```

From some of the above results, its seen that the models are overfitting due to imbalance in data. Lets try an oversampling technique called 'SMOTE' to deal with imbalance.

5.2.4.3 SMOTE

In [56]:

```
from imblearn.over_sampling import SMOTE
smote1 = SMOTE(sampling_strategy = 'auto', n_jobs = -1)

X_smote_train, y_smote_train = smote1.fit_resample(X_train, y_train)
y_smote_train = pd.Series(y_smote_train)
print(y_train.value_counts())
print("\nAfter applying SMOTE")
print(y_smote_train.value_counts())
```

```
1    25790
0    18317
2     3413
Name: status_group, dtype: int64

After applying SMOTE
1    25790
0    25790
2    25790
Name: status_group, dtype: int64
```

In [57]:

```
smote2 = SMOTE(sampling_strategy = 'auto', n_jobs = -1)

X_smote_test, y_smote_test = smote2.fit_resample(X_test, y_test)
y_smote_test = pd.Series(y_smote_test)
print(y_test.value_counts())
print("\nAfter applying SMOTE")
print(y_smote_test.value_counts())
```

```
1    6469
0    4507
2     904
Name: status_group, dtype: int64

After applying SMOTE
1    6469
0    6469
2    6469
Name: status_group, dtype: int64
```

5.2.4.4 Recheckig performance after applying 'SMOTE' technique

In [58]:
```
clf_rf3 = RandomForestClassifier(n_estimators=150, random_state=42, n_jobs=-1, criterion= 'gini',min_samples_split= 5,
                                class_weight='balanced')
clf_rf3.fit(X_smote_train, y_smote_train)
```

Out[58]:
```
RandomForestClassifier(class_weight='balanced', min_samples_split=5,
                       n_estimators=150, n_jobs=-1, random_state=42)
```

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In [59]:
```python
# making predictions on test set
y_pred_train = clf_rf3.predict(X_smote_train)
y_pred_train_proba = clf_rf3.predict_proba(X_smote_train)
# making predictions on test set
y_pred_test = clf_rf3.predict(X_smote_test)
y_pred_test_proba = clf_rf3.predict_proba(X_smote_test)

# printing the result
print("Accuracy:")
print("*"*50)
print("Train:", accuracy_score(y_smote_train, y_pred_train))
print("Test:", accuracy_score(y_smote_test, y_pred_test))

print("\nBalanced Accuracy:")
print("*"*50)
print("Train:", balanced_accuracy_score(y_smote_train, y_pred_train))
print("Test:", balanced_accuracy_score(y_smote_test, y_pred_test))

print("\nF1_score:")
print("*"*50)
print("Train:",f1_score(y_smote_train, y_pred_train, average="weighted"))
print("Test:",f1_score(y_smote_test, y_pred_test, average="weighted"))

print("\nroc_auc_score:")
print("*"*50)
print("Train:", roc_auc_score(y_smote_train, y_pred_train_proba, multi_class='ovr'))
print("Test:", roc_auc_score(y_smote_test, y_pred_test_proba, multi_class='ovr'))
```

```
Accuracy:
**************************************************
Train: 0.9787643789582525
Test: 0.8071314474158808

Balanced Accuracy:
**************************************************
Train: 0.9787643789582526
Test: 0.8071314474158808

F1_score:
**************************************************
Train: 0.978774218498059
Test: 0.8074066807360177

roc_auc_score:
**************************************************
Train: 0.9988996783958562
Test: 0.9352664259237544
```

From above result after applying SMOTE, it is seen that the overfitting problem has been reduced to some extent

In [ ]:
```
# clf_xgb = XGBClassifier(booster='gbtree', colsample_bylevel=1,
#        colsample_bynode=1, colsample_bytree=1, learning_rate=0.1,
#        max_depth=10, min_child_weight=1,n_estimators=100, n_jobs=-1,
#        objective='multi:softprob', random_state=0,verbosity=1)
```

In [61]:
```
from xgboost import XGBClassifier
clf_xgb =XGBClassifier()
clf_xgb.fit(X_smote_train, y_smote_train)
```

```
[23:26:09] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.1/src/learner.cc:1115: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

Out[61]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
              gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=4,
              num_parallel_tree=1, objective='multi:softprob', predictor='auto',
              random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=None,
              subsample=1, tree_method='exact', validate_parameters=1,
              verbosity=None)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [62]:
```
# making predictions on test set
y_pred_train = clf_xgb.predict(X_smote_train)
y_pred_train_proba = clf_xgb.predict_proba(X_smote_train)
# making predictions on test set
y_pred_test = clf_xgb.predict(X_smote_test)
y_pred_test_proba = clf_xgb.predict_proba(X_smote_test)

# printing the result
print("Accuracy:")
print("*"*50)
print("Train:", accuracy_score(y_smote_train, y_pred_train))
print("Test:", accuracy_score(y_smote_test, y_pred_test))

print("\nBalanced Accuracy:")
print("*"*50)
print("Train:", balanced_accuracy_score(y_smote_train, y_pred_train))
print("Test:", balanced_accuracy_score(y_smote_test, y_pred_test))

print("\nF1_score:")
print("*"*50)
print("Train:",f1_score(y_smote_train, y_pred_train, average="weighted"))
print("Test:",f1_score(y_smote_test, y_pred_test, average="weighted"))

print("\nroc_auc_score:")
print("*"*50)
print("Train:", roc_auc_score(y_smote_train, y_pred_train_proba, multi_class='ovr'))
print("Test:", roc_auc_score(y_smote_test, y_pred_test_proba, multi_class='ovr'))
```

```
Accuracy:
**************************************************
Train: 0.8624272974020938
Test: 0.8114082547534395

Balanced Accuracy:
**************************************************
Train: 0.8624272974020938
Test: 0.8114082547534395

F1_score:
**************************************************
Train: 0.8621542054573937
Test: 0.8107848004014945

roc_auc_score:
**************************************************
```

```
Train: 0.9661977455284911
Test: 0.9390995537393089
```

5.3 Using Leave One Out Encoding Encoder for encoding categorical features

In [66]:
```
numerical_features1 = ['gps_height','longitude', 'latitude', 'district_code','population', 'operational_year']
categorical_features1 = ['funder','installer','basin', 'region', 'lga', 'extraction_type_group','management',
                         'payment', 'water_quality', 'quantity', 'source','waterpoint_type']
```

In [65]:
```
df1.drop(columns=['permit', 'public_meeting'], inplace=True )
```

In [67]:
```
y1=df1['status_group']
X1 = df1.drop(columns = ['status_group'])
```

In [68]:
```
from sklearn.model_selection import train_test_split
X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size=0.2, random_state=40)
```

In [72]:
```
scaler2 = RobustScaler()
encoder2 = ce.LeaveOneOutEncoder()
```

In [73]:
```
transformer2 = scaler2.fit(X_train1[numerical_features1])

X_train1[numerical_features1] = transformer2.transform(X_train1[numerical_features1])
X_test1[numerical_features1] = transformer2.transform(X_test1[numerical_features1])

transformer_loe_1 = encoder2.fit(X_train1[categorical_features1], y_train1)

X_train1[categorical_features1] = transformer_loe_1.transform(X_train1[categorical_features1])
X_test1[categorical_features1] = transformer_loe_1.transform(X_test1[categorical_features1])
```

In [75]:
```
smote1 = SMOTE(sampling_strategy = 'auto', n_jobs = -1)

X_smote_train, y_smote_train = smote1.fit_resample(X_train1, y_train1)
y_smote_train = pd.Series(y_smote_train)
print(y_train.value_counts())
print("\nAfter applying SMOTE")
print(y_smote_train.value_counts())
```

```
1    25790
0    18317
2     3413
Name: status_group, dtype: int64

After applying SMOTE
1    25790
0    25790
2    25790
Name: status_group, dtype: int64
```

In [76]:
```
smote2 = SMOTE(sampling_strategy = 'auto', n_jobs = -1)

X_smote_test, y_smote_test = smote2.fit_resample(X_test1, y_test1)
y_smote_test = pd.Series(y_smote_test)
print(y_test.value_counts())
print("\nAfter applying SMOTE")
print(y_smote_test.value_counts())
```

```
1    6469
0    4507
2     904
Name: status_group, dtype: int64

After applying SMOTE
1    6469
0    6469
2    6469
Name: status_group, dtype: int64
```

In [77]:
```
from xgboost import XGBClassifier
clf_xgb1 =XGBClassifier()
clf_xgb1.fit(X_smote_train, y_smote_train)
```

```
[01:02:59] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.1/src/learner.cc:1115: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

Out[77]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
              gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=4,
              num_parallel_tree=1, objective='multi:softprob', predictor='auto',
              random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=None,
              subsample=1, tree_method='exact', validate_parameters=1,
              verbosity=None)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [78]:

```
# making predictions on test set
y_pred_train = clf_xgb1.predict(X_smote_train)
y_pred_train_proba = clf_xgb1.predict_proba(X_smote_train)
# making predictions on test set
y_pred_test = clf_xgb1.predict(X_smote_test)
y_pred_test_proba = clf_xgb1.predict_proba(X_smote_test)

# printing the result
print("Accuracy:")
print("*"*50)
print("Train:", accuracy_score(y_smote_train, y_pred_train))
print("Test:", accuracy_score(y_smote_test, y_pred_test))

print("\nBalanced Accuracy:")
print("*"*50)
print("Train:", balanced_accuracy_score(y_smote_train, y_pred_train))
print("Test:", balanced_accuracy_score(y_smote_test, y_pred_test))

print("\nF1_score:")
print("*"*50)
print("Train:",f1_score(y_smote_train, y_pred_train, average="weighted"))
print("Test:",f1_score(y_smote_test, y_pred_test, average="weighted"))

print("\nroc_auc_score:")
print("*"*50)
print("Train:", roc_auc_score(y_smote_train, y_pred_train_proba, multi_class='ovr'))
print("Test:", roc_auc_score(y_smote_test, y_pred_test_proba, multi_class='ovr'))
```

```
Accuracy:
**************************************************
Train: 0.8592865451725475
Test: 0.8106353377647241

Balanced Accuracy:
**************************************************
Train: 0.8592865451725475
Test: 0.8106353377647241

F1_score:
**************************************************
Train: 0.8589568631252777
Test: 0.8099731365985003

roc_auc_score:
**************************************************
```

```
Train: 0.9655189116837996
Test: 0.9398856334561517
```

Summary of results

In [80]:
```
pip install prettytable
```

```
Collecting prettytableNote: you may need to restart the kernel to use updated packages.

  Downloading prettytable-3.3.0-py3-none-any.whl (26 kB)
Requirement already satisfied: wcwidth in c:\users\prafull mohite\anaconda3\lib\site-packages (from prettytable) (0.2.5)
Installing collected packages: prettytable
Successfully installed prettytable-3.3.0
```

In [90]:
```
from prettytable import PrettyTable
table = PrettyTable()
table.title = " Summary "
table.field_names = ['Scaler','Encoder', 'Model','BalAcc_train', 'BalAcc_test','F1_train','F1_test','roc_train','roc_test']

table.add_row(["Robust","TE","LR", '0.6051', '0.6032', '0.6565', '0.6556', '0.7912', '0.7910' ])
table.add_row(["Robust","TE","KNN", '0.6941', '0.6108', '0.8233', '0.7490', '0.9467', '0.8311' ])
table.add_row(["Robust","TE","DT", '0.5519', '0.5529', '0.6757', '0.6768', '0.7304', '0.7299' ])
table.add_row(["Robust","TE","RF", '0.9738', '0.7031', '0.9667', '0.8034', '0.9967', '0.9032' ])
table.add_row(["Robust","TE+SMOTE","RF", '0.9787', '0.8071', '0.9787', '0.8074', '0.9988', '0.9352'])
table.add_row(["Robust","TE+SMOTE","Xgb", '0.8624', '0.8114', '0.8621', '0.8107', '0.9661', '0.9390'])
table.add_row(["Robust","LOO+SMOTE","Xgb", '0.8592', '0.8106', '0.8589', '0.8099', '0.9655', '0.9398'])
print(table)
```

```
+--------------------------------------------------------------------------------------------------+
|                                              Summary                                             |
+--------+-----------+-------+--------------+-------------+----------+---------+-----------+----------+
| Scaler |  Encoder  | Model | BalAcc_train | BalAcc_test | F1_train | F1_test | roc_train | roc_test |
+--------+-----------+-------+--------------+-------------+----------+---------+-----------+----------+
| Robust |     TE    |   LR  |    0.6051    |    0.6032   |  0.6565  |  0.6556 |   0.7912  |  0.7910  |
| Robust |     TE    |  KNN  |    0.6941    |    0.6108   |  0.8233  |  0.7490 |   0.9467  |  0.8311  |
| Robust |     TE    |   DT  |    0.5519    |    0.5529   |  0.6757  |  0.6768 |   0.7304  |  0.7299  |
| Robust |     TE    |   RF  |    0.9738    |    0.7031   |  0.9667  |  0.8034 |   0.9967  |  0.9032  |
| Robust |  TE+SMOTE |   RF  |    0.9787    |    0.8071   |  0.9787  |  0.8074 |   0.9988  |  0.9352  |
| Robust |  TE+SMOTE |  Xgb  |    0.8624    |    0.8114   |  0.8621  |  0.8107 |   0.9661  |  0.9390  |
| Robust | LOO+SMOTE |  Xgb  |    0.8592    |    0.8106   |  0.8589  |  0.8099 |   0.9655  |  0.9398  |
+--------+-----------+-------+--------------+-------------+----------+---------+-----------+----------+
```

Form the above summary, it is understood that the model 'XGBClassifier' with robust_scaler, Target_Encoder & SMOTE technique has been the best performer so far with the highest F1_score & Balanced_Accuracy as 0.81 with minimum overfitting.

In [ ]:

```

```