```
#importing all the important libraries
import sklearn.preprocessing
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings

import sklearn as sk
from sklearn import metrics
from sklearn.model_selection import train_test_split, ShuffleSplit, learning_cu
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import SelectKBest
from sklearn.pipeline import Pipeline
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC

warnings.filterwarnings('ignore')
```

```
df_train=pd.read_csv('/content/drive/MyDrive/ML/ML A2/Train - Train.csv')
df_test=pd.read_csv('/content/drive/MyDrive/ML/ML A2/test - test.csv')
display(df_train.shape)
display(df_test.shape)
```

```
(44550, 41)
(14850, 41)
```

```
#checking the sample of train data

df_train.head()
```

```
        id  amount_tsh  date_recorded     funder  gps_height  installer  longituc
```

```
#unique and null values
for col in df_train.columns.values:
  list_vals = pd.unique(df_train[col]) #list of unique values
  print('\033[1m' + col + '\033[0m' + ' has ' + str(len(list_vals))  +' unique v
  if len(list_vals) < 10:
    list_str = ''
    for n in range(0, len(list_vals)):
      list_str = list_str + str(list_vals[n]) + ', '
    print('\033[1m' + '    ##### These are: '+ '\033[0m' +list_str[0:len(list_s
```

```
id has 44550 unique values, 0 null entries and datatype int64
amount_tsh has 85 unique values, 0 null entries and datatype float64
date_recorded has 346 unique values, 0 null entries and datatype object
funder has 1652 unique values, 2793 null entries and datatype object
gps_height has 2396 unique values, 0 null entries and datatype int64
installer has 1855 unique values, 2807 null entries and datatype object
longitude has 43155 unique values, 0 null entries and datatype float64
latitude has 43155 unique values, 0 null entries and datatype float64
wpt_name has 28991 unique values, 0 null entries and datatype object
num_private has 59 unique values, 0 null entries and datatype int64
basin has 9 unique values, 0 null entries and datatype object
    ##### These are: Pangani, Lake Nyasa, Rufiji, Lake Tanganyika, Lake Vic
subvillage has 16618 unique values, 287 null entries and datatype object
region has 21 unique values, 0 null entries and datatype object
region_code has 27 unique values, 0 null entries and datatype int64
district_code has 20 unique values, 0 null entries and datatype int64
lga has 125 unique values, 0 null entries and datatype object
ward has 2080 unique values, 0 null entries and datatype object
population has 956 unique values, 0 null entries and datatype int64
public_meeting has 3 unique values, 2491 null entries and datatype object
    ##### These are: True, False, nan
recorded_by has 1 unique values, 0 null entries and datatype object
    ##### These are: GeoData Consultants Ltd
scheme_management has 13 unique values, 2832 null entries and datatype obje
scheme_name has 2507 unique values, 21110 null entries and datatype object
permit has 3 unique values, 2336 null entries and datatype object
    ##### These are: True, False, nan
construction_year has 55 unique values, 0 null entries and datatype int64
extraction_type has 18 unique values, 0 null entries and datatype object
extraction_type_group has 13 unique values, 0 null entries and datatype obj
extraction_type_class has 7 unique values, 0 null entries and datatype obje
    ##### These are: gravity, handpump, motorpump, submersible, other, rope
management has 12 unique values, 0 null entries and datatype object
management_group has 5 unique values, 0 null entries and datatype object
    ##### These are: user-group, commercial, parastatal, unknown, other
payment has 7 unique values, 0 null entries and datatype object
    ##### These are: pay per bucket, never pay, pay annually, pay monthly, u
payment_type has 7 unique values, 0 null entries and datatype object
    ##### These are: per bucket, never pay, annually, monthly, unknown, on
water_quality has 8 unique values, 0 null entries and datatype object
    ##### These are: soft, salty abandoned, unknown, salty, fluoride, milky
quality_group has 6 unique values, 0 null entries and datatype object
    ##### These are: good, salty, unknown, fluoride, milky, colored
quantity has 5 unique values, 0 null entries and datatype object
    ##### These are: enough, insufficient, dry, unknown, seasonal
quantity_group has 5 unique values, 0 null entries and datatype object

    ##### These are: enough, insufficient, dry, unknown, seasonal
```

```
    ##### These are: enough, insufficient, dry, unknown, seasonal
source has 10 unique values, 0 null entries and datatype object
source_type has 7 unique values, 0 null entries and datatype object
    ##### These are: spring, river/lake, shallow well, borehole, rainwater |
source_class has 3 unique values, 0 null entries and datatype object
    ##### These are: groundwater, surface, unknown
waterpoint_type has 7 unique values, 0 null entries and datatype object
    ##### These are: communal standpipe, hand pump, other, communal standpi
waterpoint_type_group has 6 unique values, 0 null entries and datatype obje
    ##### These are: communal standpipe, hand pump, other, cattle trough, i
status group has 3 unique values, 0 null entries and datatype object
```

DATA PREPROCESSING

```
#Dropping of the varible which has too many numerical value
#since it will not play significant role in the output


#dropping the variable wpt_name since it has too many distinct  numerical value
#Dropping the wpt_name variable more than 50% different values
df_train.drop(['wpt_name'], axis=1, inplace=True)
df_test.drop(['wpt_name'], axis=1, inplace=True)
```

```
#Dropping the id variable since it does not have any significance in the water
df_train.drop(['id'], axis=1, inplace=True)
df_test.drop(['id'], axis=1, inplace=True)
```

```
#DATA PREPROCESSING
#we have date recorded as datatype object converting it to integer
#converting the date format dd-mm-yyyy to yyyymmdd and converting it to the int
#for training
df_train['date_recorded'] = pd.to_datetime(df_train['date_recorded']).dt.strfti
df_train['date_recorded'] = df_train['date_recorded'].astype(int)
print( 'datatype od df_test changed to ', df_train['date_recorded'].dtype )

#for testing
df_test['date_recorded'] = pd.to_datetime(df_test['date_recorded']).dt.strftime
df_test['date_recorded'] = df_test['date_recorded'].astype(int)
print( 'datatype od df_test changed to ',df_test['date_recorded'].dtype )
```

```
datatype od df_test changed to  int64
datatype od df_test changed to  int64
```

```
df_train['date_recorded'].nunique() #no. of unique values in date recorded
```

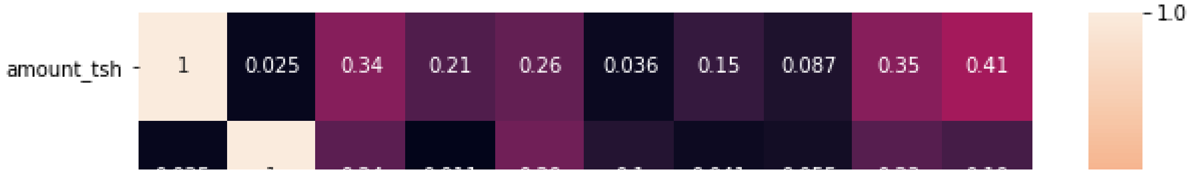
```
346
```

```
# Find columns with 'object' dtypes.
list(df_train.select_dtypes(np.number))
```

```
['amount_tsh',
 'date_recorded',
 'gps_height',
 'longitude',
 'latitude',
 'num_private',
 'region_code',
 'district_code',
 'population',
 'construction_year']
```

initially checking the correlation between variables to amongst the numerical values

```
# visualization of correlation by heatmap for red wine

corr = df_train.corr(method = 'spearman')
fig, ax = plt.subplots(figsize = (10,10))
sns.heatmap(abs(corr), annot = True)
plt.show()
```



From above its comes to notice that Most of the numerical varible columns are not correlated with each other.

```
# Find columns with 'object' dtypes.
list(df_train.select_dtypes(exclude=[np.number]))
```

```
['funder',
 'installer',
 'basin',
 'subvillage',
 'region',
 'lga',
 'ward',
 'public_meeting',
 'recorded_by',
 'scheme_management',
 'scheme_name',
 'permit',
 'extraction_type',
 'extraction_type_group',
 'extraction_type_class',
 'management',
 'management_group',
 'payment',
 'payment_type',
 'water_quality',
 'quality_group',
 'quantity',
 'quantity_group',
 'source',
 'source_type',
 'source_class',
 'waterpoint_type',
 'waterpoint_type_group',
 'status_group']
```

features having **Non-Numeric Value** as content are:

['funder','installer','basin','subvillage','region','lga', 'ward','public_meeting','recorded_by','scheme_management','scheme_name','permit','extraction_type', 'extraction_type_group','extraction_type_class','management', 'management_group', 'payment','payment_type','water_quality','quality_group', 'quantity','quantity_group', 'source', 'source_type', 'source_class','waterpoint_type','waterpoint_type_group', 'status_group']

Missing value

funder has , 2793 null entries and datatype object

installer , 2807 null entries and datatype object

subvillage, 287 null entries and datatype object

public_meeting , 2491 null entries and datatype object

scheme_management , 2832 null entries and datatype object

scheme_name , 21110 null entries and datatype object

permit has , 2336 null entries and datatype object

Imputation of the missing values with most frequent values using **mode** value of the column.

And cross checking after the imputation

```
#Imputation of the missing values with most frequent values using mode.
#Imputing the missing values
df_train['permit'].fillna(df_train['permit'].mode()[0], inplace=True)
df_train['funder'].fillna(df_train['funder'].mode()[0], inplace=True)
df_train['scheme_management'].fillna(df_train['scheme_management'].mode()[0], i
df_train['public_meeting'].fillna(df_train['public_meeting'].mode()[0], inplace
df_train['subvillage'].fillna(df_train['subvillage'].mode()[0], inplace=True)
df_train['installer'].fillna(df_train['installer'].mode()[0], inplace=True)
df_train['scheme_name'].fillna(df_train['scheme_name'].mode()[0], inplace=True)
```

```
#Imputation of the missing values with most frequent values using mode.
#Imputing the missing values
df_test['permit'].fillna(df_test['permit'].mode()[0], inplace=True)
df_test['funder'].fillna(df_test['funder'].mode()[0], inplace=True)
df_test['scheme_management'].fillna(df_test['scheme_management'].mode()[0], inp
df_test['public_meeting'].fillna(df_test['public_meeting'].mode()[0], inplace=T
df_test['subvillage'].fillna(df_test['subvillage'].mode()[0], inplace=True)
df_test['installer'].fillna(df_test['installer'].mode()[0], inplace=True)
df_test['scheme_name'].fillna(df_test['scheme_name'].mode()[0], inplace=True)
```

```
#Dropping of the unnecessary column from the test data
df_test.drop(['Unnamed: 0'], axis=1, inplace=True)
```

```
#After the imputation of the vlues in the columns of the dataframe checking if
df_test.isnull().sum()
```

```
amount_tsh            0
date_recorded         0
funder                0
gps_height            0
installer             0
longitude             0
latitude              0
num_private           0
```

```
basin                    0
subvillage               0
region                   0
region_code              0
district_code            0
lga                      0
ward                     0
population               0
public_meeting           0
recorded_by              0
scheme_management        0
scheme_name              0
permit                   0
construction_year        0
extraction_type          0
extraction_type_group    0
extraction_type_class    0
management               0
management_group         0
payment                  0
payment_type             0
water_quality            0
quality_group            0
quantity                 0
quantity_group           0
source                   0
source_type              0
source_class             0
waterpoint_type          0
waterpoint_type_group    0
dtype: int64
```

```
df_train.shape
```

```
(44550, 39)
```

```
#encoding with ordinal encoder to train data
from sklearn.preprocessing import OrdinalEncoder
enc = OrdinalEncoder()
for col in df_train.columns:
  df_train[col] = enc.fit_transform(df_train[[col]])
```

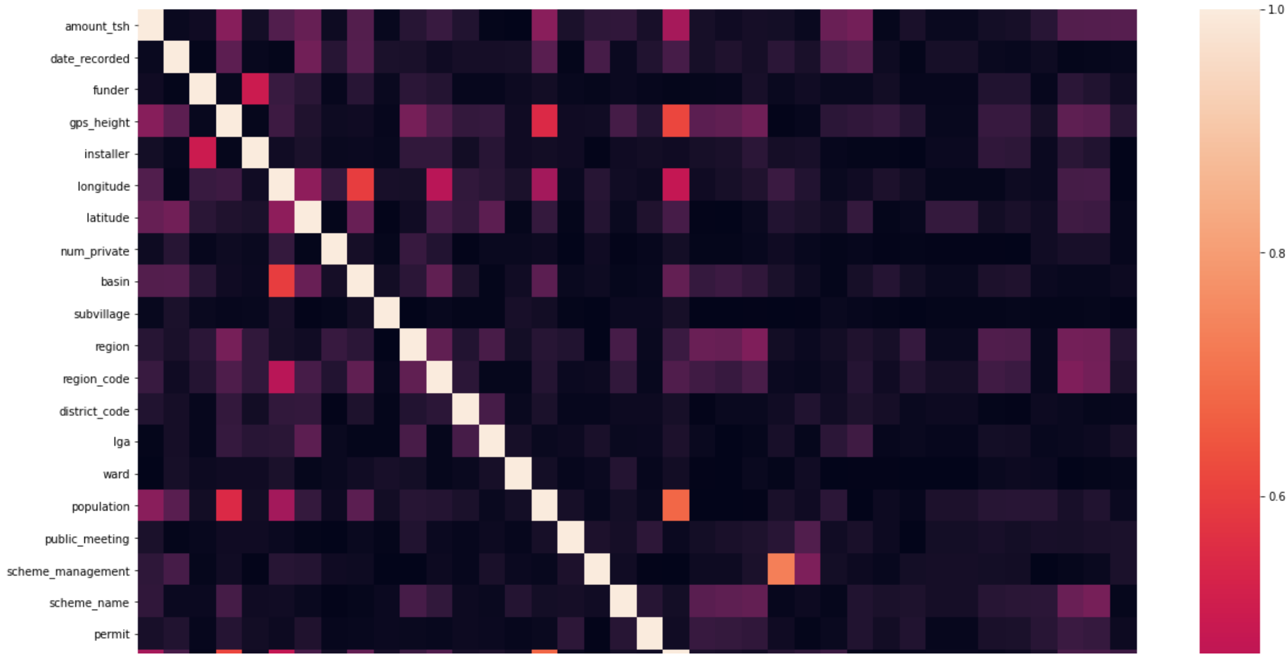
```
#for test data
for col in df_test.columns:
  df_test[col] = enc.fit_transform(df_test[[col]])
```

```
#Dropping the variables
df_test.drop(['recorded_by'], axis=1, inplace=True)

```

```
df_train.drop(['recorded_by'], axis=1, inplace=True)
```

```
#Correlation of the newly encoded variables
```

```
# visualization of correlation by heatmap

corr = df_train.corr(method = 'spearman')
fig, ax = plt.subplots(figsize = (20,20))
sns.heatmap(abs(corr), annot = False)
plt.show()
```




```
#extraction type
df_train.columns.values
```

```
array(['amount_tsh', 'date_recorded', 'funder', 'gps_height', 'installer',
       'longitude', 'latitude', 'num_private', 'basin', 'subvillage',
       'region', 'region_code', 'district_code', 'lga', 'ward',
       'population', 'public_meeting', 'scheme_management', 'scheme_name',
       'permit', 'construction_year', 'extraction_type',
       'extraction_type_group', 'extraction_type_class', 'management',
       'management_group', 'payment', 'payment_type', 'water_quality',
       'quality_group', 'quantity', 'quantity_group', 'source',
       'source_type', 'source_class', 'waterpoint_type',
       'waterpoint_type_group', 'status_group'], dtype=object)
```

```
df_test.columns.values
```

```
array(['amount_tsh', 'date_recorded', 'funder', 'gps_height', 'installer',
       'longitude', 'latitude', 'num_private', 'basin', 'subvillage',
       'region', 'region_code', 'district_code', 'lga', 'ward',
       'population', 'public_meeting', 'scheme_management', 'scheme_name',
       'permit', 'construction_year', 'extraction_type',
       'extraction_type_group', 'extraction_type_class', 'management',
       'management_group', 'payment', 'payment_type', 'water_quality',
       'quality_group', 'quantity', 'quantity_group', 'source',
       'source_type', 'source_class', 'waterpoint_type',
       'waterpoint_type_group'], dtype=object)
```

```
#Dropping the variables extraction_type_class , and group has near to unity cor
df_train.drop(['extraction_type_group'], axis=1, inplace=True)
df_train.drop(['extraction_type_class'], axis=1, inplace=True)
```

```
#test Dropping the variables extraction_type_class , and group has near to unity
df_test.drop(['extraction_type_group'], axis=1, inplace=True)
df_test.drop(['extraction_type_class'], axis=1, inplace=True)
```

```
#train test Dropping the variables quantity_group has near to unity correlation
df_train.drop(['quantity_group'], axis=1, inplace=True)
df_test.drop(['quantity_group'], axis=1, inplace=True)
```

```
#train test Dropping the variables source_type and source has near to unity cor
df_train.drop(['source_type'], axis=1, inplace=True)
df_test.drop(['source_type'], axis=1, inplace=True)
```

```
#train test Dropping the variables waterpoint_type_group and waterpoint_type ha
df_train.drop(['waterpoint_type_group'], axis=1, inplace=True)
df_test.drop(['waterpoint_type_group'], axis=1, inplace=True)
```

```
display(df_train.shape)
display(df_test.shape)
```

```
(44550, 33)
(14850, 32)
```

```
#train data
X = pd.DataFrame(df_train.iloc[:,0:-1])
Y = pd.DataFrame(df_train['status_group'])
```

```
#test data processed
Xt = pd.DataFrame(df_test)
```

```
from sklearn.feature_selection import RFECV
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33, rando

```

1.0 RFClassification

```
#RFC
#Hyperparameter tunung
rf = RandomForestClassifier(criterion='gini',n_estimators=500,max_features='aut
param_grid = {"min_samples_split" : [4, 6, 8],"n_estimators" : [500, 700, 1000]

gs = GridSearchCV(estimator=rf,param_grid=param_grid,scoring='accuracy',cv=2,n_

gs = gs.fit(X_train, y_train.values.ravel())

print(gs.best_score_)
print(gs.best_params_)
```

```
0.7888970785312248
```

```
{'min_samples_split': 6, 'n_estimators': 700}
```

```
gs.best_estimator_.feature_importances_
```

```
array([0.02624758, 0.0505222 , 0.0342603 , 0.04281361, 0.02975738,
       0.07936963, 0.07577333, 0.00122261, 0.01328392, 0.05208837,
       0.01676589, 0.0150217 , 0.01824166, 0.02666965, 0.03985745,
       0.03146935, 0.00521997, 0.01155649, 0.02730021, 0.00587742,
       0.04370495, 0.04067509, 0.01491027, 0.0058288 , 0.01897732,
       0.01638281, 0.01035214, 0.01162825, 0.1380757 , 0.02323805,
       0.00654654, 0.06636136])
```

```
rf32 = RandomForestClassifier(criterion='gini',min_samples_split=6,n_estimators=

rf32.fit(X_train, y_train.values.ravel())
print('RFC has oob score after 1st elimination is :',rf32.oob_score_)

```

```
RFC has oob score after 1st elimination is : 0.8056486196730099
```

```
prediction = rf32.predict(X_test)
print('Accuracy for RFC is', metrics.accuracy_score(y_test, prediction))
```

```
Accuracy for RFC is 0.8000952251394368
```

```
rf32.feature_importances_
```

```
array([0.02624758, 0.0505222 , 0.0342603 , 0.04281361, 0.02975738,
       0.07936963, 0.07577333, 0.00122261, 0.01328392, 0.05208837,
       0.01676589, 0.0150217 , 0.01824166, 0.02666965, 0.03985745,
       0.03146935, 0.00521997, 0.01155649, 0.02730021, 0.00587742,
       0.04370495, 0.04067509, 0.01491027, 0.0058288 , 0.01897732,
       0.01638281, 0.01035214, 0.01162825, 0.1380757 , 0.02323805,
       0.00654654, 0.06636136])
```

2.0 XGBoost Classification

```
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.model_selection import StratifiedKFold
xgb = XGBClassifier(learning_rate=0.02, n_estimators=600, objective='binary:log
folds = 3
param_comb = 5
skf = StratifiedKFold(n_splits=folds, shuffle = True, random_state = 1001)
scorer = sklearn.metrics.make_scorer(sklearn.metrics.f1_score, average = 'weigh
params = {'min_child_weight': [1, 5, 10],'gamma': [0.5, 1, 1.5, 2, 5],'subsampl
random_search = RandomizedSearchCV(xgb, param_distributions=params, n_iter=para
random_search.fit(X_train, y_train )
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits
```

```
[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  15 out of  15 | elapsed: 10.5min finished
RandomizedSearchCV(cv=<generator object _BaseKFold.split at 0x7fe66e890c50>,
                   error_score=nan,
                   estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                           colsample_bylevel=1,
                                           colsample_bynode=1,
                                           colsample_bytree=1, gamma=0,
                                           learning_rate=0.02,
max_delta_step=0,
                                           max_depth=3, min_child_weight=1,
                                           missing=None, n_estimators=600,
                                           n_jobs=1, nthread=1,
                                           objective='binary:logist...
                                           seed=None, silent=True,
subsample=1,
                                           verbosity=1),
                   iid='deprecated', n_iter=5, n_jobs=4,
                   param_distributions={'colsample_bytree': [0.6, 0.8, 1.0],
                                        'gamma': [0.5, 1, 1.5, 2, 5],
                                        'max_depth': [3, 4, 5],
                                        'min_child_weight': [1, 5, 10],
                                        'subsample': [0.6, 0.8, 1.0]},
                   pre_dispatch='2*n_jobs', random_state=1001, refit=True,
                   return_train_score=False,
                   scoring=make_scorer(f1_score, average=weighted),
verbose=3)
```

```
print('best score xgb ' ,random_search.best_score_ )
print('xgb best parameters ' ,random_search.best_params_ )
print('best indexx xgb ' ,random_search.best_index_ )
print('best estimator xgb ' ,random_search.best_estimator_ )
```

```
best score xgb  0.75399236221129
xgb best parameters  {'subsample': 0.6, 'min_child_weight': 1, 'max_depth': 5
best indexx xgb  1
best estimator xgb  XGBClassifier(base_score=0.5, booster='gbtree', colsample
              colsample_bynode=1, colsample_bytree=0.8, gamma=1.5,
              learning_rate=0.02, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=None, n_estimators=600, n_jobs=1,
              nthread=1, objective='multi:softprob', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=True, subsample=0.6, verbosity=1)
```

```
#Applying the best parameters of the xgboost to model and testing the model on
xgb32=random_search.best_estimator_

xgb32.fit(X_train, y_train.values.ravel())
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.8, gamma=1.5,
              learning_rate=0.02, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=None, n_estimators=600, n_jobs=1,
              nthread=1, objective='multi:softprob', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=True, subsample=0.6, verbosity=1)
```

```
xgb32.feature_importances_
```

```
array([0.0462949 , 0.01619986, 0.01752931, 0.01707107, 0.01616328,
       0.02376452, 0.01640674, 0.01277481, 0.02424673, 0.01005085,
       0.02871218, 0.02235642, 0.01806406, 0.02134535, 0.01183366,
       0.0141106 , 0.02705525, 0.01536601, 0.01416728, 0.0191035 ,
       0.02868589, 0.03501341, 0.03257824, 0.02063816, 0.03585385,
       0.02510552, 0.01965024, 0.02040447, 0.20942442, 0.03958386,
       0.02705507, 0.11339048], dtype=float32)
```

```
prediction = xgb32.predict(X_test)
print('Accuracy xgb is', metrics.accuracy_score(y_test, prediction))
```

```
Accuracy xgb is 0.7749285811454224
```

3.0 KNN

```

from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import Pipeline
k_range = list(range(5,10))

param_grid = dict(n_neighbors=k_range)

pipe = Pipeline([('sc', StandardScaler()),('knn', KNeighborsClassifier(algorithm
params = {'knn__n_neighbors': k_range }
clf = GridSearchCV(estimator=pipe,param_grid=params, cv=5,return_train_score=Tr
clf.fit(X_train, y_train)
```

```
GridSearchCV(cv=5, error_score=nan,
             estimator=Pipeline(memory=None,
                                steps=[('sc',
                                        StandardScaler(copy=True,
                                                       with_mean=True,
                                                       with_std=True)),
                                       ('knn',

KNeighborsClassifier(algorithm='brute',
                                                             leaf_size=30,

metric='minkowski',

metric_params=None,
                                                             n_jobs=None,
                                                             n_neighbors=5,
p=2,

weights='uniform'))],
                                verbose=False),
             iid='deprecated', n_jobs=None,
             param_grid={'knn__n_neighbors': [5, 6, 7, 8, 9]},
```

```
             pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
             scoring=None, verbose=0)
```

```
print('best score knn ' ,clf.best_score_ )
print('knn best parameters ' ,clf.best_params_ )
print('best indexx knn ' , clf.best_index_ )
print('best estimator knn ' ,clf.best_estimator_ )
```

```
best score knn  0.7319751603272407
knn best parameters  {'knn__n_neighbors': 5}
best indexx knn  0
best estimator knn  Pipeline(memory=None,
         steps=[('sc',
                 StandardScaler(copy=True, with_mean=True, with_std=True)),
                ('knn',
                 KNeighborsClassifier(algorithm='brute', leaf_size=30,
                                      metric='minkowski', metric_params=None,
                                      n_jobs=None, n_neighbors=5, p=2,
                                      weights='uniform'))],
         verbose=False)
```

Observations We are having 3 frameworks for prediction of the

1. RandomForestClassifer having accuracy of **80** percent approx
2. XGBoost Classifier having the accuracy of the **78** percent approx
3. KNN Classifier having Accuracy of **77** percent

So we will select the RFClassification for the further round of the best feature extraction

1.1 RFC Round 2 of feature elimination.

2. Checking the importance of a particular feature with respect to the feature importance score

```
#Round 2 of feature elimination
#Checking the importance of the features with respect to the feature importance
RFC_feature=rf32.feature_importances_
column_name=X.columns
dff=pd.DataFrame(X.columns,rf32.feature_importances_)
val=pd.DataFrame(RFC_feature)
nam=pd.DataFrame(column_name)
nam.rename( columns={0 :'Feaures'}, inplace=True )
```

```
val.rename( columns={0 :'Importance'}, inplace=True )
df1 = pd.concat([val,nam], axis=1)
df1.sort_values(by=['Importance'])
```

	Importance	Feaures
7	0.001223	num_private
16	0.005220	public_meeting

1.1.1 Round 2Feature elimination

As from above it is clear that the minimum importance is of the variable

1. 0.001223 num_private
2. 0.005220 public_meeting
3. 0.005829 management_group
4. 0.005877 permit
5. 0.006547 source_class

```
#storing the original dataset to new variable for feature elimination
X2=X
Y2=Y
Xt2=Xt
```

```
#31
X2.drop(['num_private'], axis=1, inplace=True)
Xt2.drop(['num_private'], axis=1, inplace=True)
```

```
#30
X2.drop(['public_meeting'], axis=1, inplace=True)
Xt2.drop(['public_meeting'], axis=1, inplace=True)
```

```
#29
X2.drop(['management_group'], axis=1, inplace=True)
Xt2.drop(['management_group'], axis=1, inplace=True)
```

```
#28
X2.drop(['permit'], axis=1, inplace=True)
Xt2.drop(['permit'], axis=1, inplace=True)
```

```
#27
X2.drop(['source_class'], axis=1, inplace=True)
Xt2.drop(['source_class'], axis=1, inplace=True)
```

```
X2.shape
```

```
(44550, 27)
```

```
Xt2.shape
```

```
(14850, 27)
```

```
X1_train, X1_test, y1_train, y1_test = train_test_split(X2, Y2, test_size=0.33,
```

```
#RFC
#Hyperparameter tunung
rf = RandomForestClassifier(criterion='gini',n_estimators=500,max_features='aut
param_grid = {"min_samples_split" : [4, 6, 8],"n_estimators" : [500, 700, 1000]

gs1 = GridSearchCV(estimator=rf,param_grid=param_grid,scoring='accuracy',cv=2,n

gs1 = gs1.fit(X1_train, y1_train.values.ravel())

print(gs1.best_score_)
print(gs1.best_params_)
```

```
0.7888300723666577
{'min_samples_split': 8, 'n_estimators': 500}
```

```
rf321 = RandomForestClassifier(criterion='gini',min_samples_split=8,n_estimator

rf321.fit(X1_train, y1_train.values.ravel())
print('oob score RFC after r2 elimination is',rf321.oob_score_)
```

```
oob score RFC after r2 elimination is 0.8059836504958456
```

```
prediction = rf321.predict(X1_test)
print('Accuracy is', metrics.accuracy_score(y1_test, prediction))
```

```
Accuracy is 0.7996190994422527
```

```
p=rf321.feature_importances_
```

```
#Currently after round 2 of feature elimination we have pretty much the
```

Checking the importance of a particular feature with respect to the feature importance score

```
#Round 3 checking of feature elimination
#Checking the importance of the features with respect to the feature importance
RFC_feature=rf321.feature_importances_
column_name=X2.columns
dff=pd.DataFrame(X.columns,rf321.feature_importances_)
val=pd.DataFrame(RFC_feature)
nam=pd.DataFrame(column_name)
nam.rename( columns={0 :'Feaures'}, inplace=True )
val.rename( columns={0 :'Importance'}, inplace=True )
```

```
10 df1 = pd.concat([val,nam], axis=1)
11 df1.sort_values(by=['Importance'])
```

	Importance	Feaures
23	0.010668	quality_group
22	0.010682	water_quality
15	0.012704	scheme_management
7	0.013083	basin
10	0.015136	region_code
21	0.016205	payment_type
19	0.016685	management
9	0.017143	region
11	0.017885	district_code
20	0.018762	payment
25	0.026157	source
0	0.027088	amount_tsh
16	0.027700	scheme_name
12	0.028662	lga
4	0.029721	installer
14	0.030869	population
2	0.034615	funder
13	0.039538	ward
3	0.041569	gps_height
18	0.043368	extraction_type
17	0.044465	construction_year
8	0.049241	subvillage
1	0.050352	date_recorded
26	0.073274	waterpoint_type
6	0.074597	latitude
5	0.078750	longitude
24	0.151078	quantity

After feature reduction 2 accuracy is pretty much same

Accuracy is 0.7996190994422527 ,slightly deceased \ oob score is 0.8059836504958456

Trying to reduce further more features.

1.1.2 Features to eliminate for round 3

0.010350 quality_group

22 0.010504 water_quality

15 0.012171 scheme_management

7 0.012798 basin

10 0.014712 region_code

```
X3=X2
Y3=Y2
Xt3=Xt2
```

```
#26
X3.drop(['quality_group'], axis=1, inplace=True)
Xt3.drop(['quality_group'], axis=1, inplace=True)

#25
X3.drop(['water_quality'], axis=1, inplace=True)
Xt3.drop(['water_quality'], axis=1, inplace=True)

#24
X3.drop(['scheme_management'], axis=1, inplace=True)
Xt3.drop(['scheme_management'], axis=1, inplace=True)

#23
X3.drop(['basin'], axis=1, inplace=True)
Xt3.drop(['basin'], axis=1, inplace=True)

#22
X3.drop(['region_code'], axis=1, inplace=True)
Xt3.drop(['region_code'], axis=1, inplace=True)

#X3.shape is (44550, 22)
#Xt3.shape is (14850, 22)
```

Applying the RFC Framework again by tuning the model and cross checking with the data

```
#Round 3 of tuning of parameters
X2_train, X2_test, y2_train, y2_test = train_test_split(X3, Y3, test_size=0.33,

#RFC
#Hyperparameter tuning
```

```
rf = RandomForestClassifier(criterion='gini',n_estimators=500,max_features='aut
param_grid = {"min_samples_split" : [4, 6, 8],"n_estimators" : [500, 700, 1000]

gs2 = GridSearchCV(estimator=rf,param_grid=param_grid,scoring='accuracy',cv=2,n_

gs2= gs2.fit(X2_train, y2_train.values.ravel())

print(gs2.best_score_)
print(gs2.best_params_)
```

```
0.7896341463414633
{'min_samples_split': 6, 'n_estimators': 1000}
```

```
rf3 = RandomForestClassifier(criterion='gini',min_samples_split=6,n_estimators=

rf3.fit(X2_train, y2_train.values.ravel())
print('after 3 round of elimination oob score is : ', rf3.oob_score_)
```

```
after 3 round of elimination oob score is :  0.8053135888501742
```

```
prediction = rf3.predict(X2_test)
print('Accuracy after 3rd round of elimination is', metrics.accuracy_score(y_te
```

```
Accuracy after 3rd round of elimination is 0.798938919874847
```

Observation After reducing the 5 more features out of 27 remaining feature we are getting pretty much same oob score and the accuracy of the model is increased very slightly

As we got the accuracy highest for the RFC

Accuracy of RFC initially(32 features): 0.8000952251394368 ,oob score is :0.8056486196730099
After 2nd round of elimination(27 features): 0.7996190994422527 ,oob score is :0.8059836504958456
After 3rd round of elimination(22 features) : 0.798938919874847 , oob score is :0.8053135888501742

This shows we should consider 1st model only.

Prediction of the output after round 3 of elimination

We are left with total 22 features almost the accuracy of all the models is same so considering the one

```
final_prediction=rf3.predict(Xt3)
final_prediction=pd.DataFrame(final_prediction)
final_prediction
```

	0
0	2.0
1	2.0
2	0.0
3	2.0
4	0.0
...	...
14845	0.0
14846	0.0
14847	2.0
14848	0.0
14849	0.0

14850 rows × 1 columns

```
final_prediction.columns[0]
```

```
di = {0: "functional", 1: "functional needs repair", 2: "non functional"}
final=final_prediction.replace({final_prediction.columns[0] : di })
final.to_csv('final_203079016.csv', header=False)
```

```
Y=Y.replace({Y.columns[0] : di })
df2 = pd.concat([X,Y], axis=1)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-1-cfb5bd20ea9c> in <module>()
----> 1 Y=Y.replace({Y.columns[0] : di })
      2 df2 = pd.concat([X,Y], axis=1)

NameError: name 'Y' is not defined
```

SEARCH STACK OVERFLOW

```
from sklearn.manifold import TSNE
import seaborn as sns
m= TSNE(learning_rate=50)
tsne_features=m.fit_transform(X)
tsne_features[1:4,:]
df['x']= tsne_features[:,0]
df['x']= tsne_features[:,1]

```