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Introduction

Tanzania, as a developing country, struggles with providing clean water to its population of over 57,000,000. There are many water points already established in the country, but some are in need of repair while others have failed altogether.

The purpose of this project is to build a classifier that can predict the condition of a water well, given information about the sort of pump, when it was installed, etc. Our audience is the Government of Tanzania which is looking to find patterns in non-functional wells in order to influence how new wells are built.

Note that this is a ternary classification problem by default, but can be engineered to be binary.

Lets get started

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OrdinalEncoder
```

Tuning Pandas

In [2]:
```
pd.options.mode.chained_assignment = None
pd.set_option('display.max_columns',None)
```

Data Undertsanding

The data for this project comes from the Taarifa waterpoints dashboard, which aggregates data from the Tanzanian Ministry of Water.

Learn More here [https://taarifa.org/ (https://taarifa.org/)](https://taarifa.org/)

In [3]:

```
#Reading files
X_train=pd.read_csv('data/trainingsetvalues.csv')
y_train=pd.read_csv('data/trainingsetlabels.csv')
#Merging files
df=pd.merge(X_train,y_train,on='id')
#Displaying first five rows
df.head()
```

Out[3]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_private	basin	
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	none	0	Lake Nyasa	
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	Zahanati	0	Lake Victoria	
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	Kwa Mahundi	0	Pangani	
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	Zahanati Ya Nanyumbu	0	Ruvuma / Southern Coast	M
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	Shuleni	0	Lake Victoria	K

We are provided the following set of information about the waterpoints:

`amount_tsh - Total static head (amount water available to waterpoint)`

`date_recorded - The date the row was entered`

`funder - Who funded the well`

`gps_height - Altitude of the well`

`installer - Organization that installed the well` longitude - GPS coordinate

latitude - GPS coordinate

wpt_name - Name of the waterpoint if there is one

num_private -

basin - Geographic water basin

subvillage - Geographic location

region - Geographic location

region_code - Geographic location (coded)

district_code - Geographic location (coded)

lga - Geographic location

ward - Geographic location

population - Population around the well

public_meeting - True/False

recorded_by - Group entering this row of data

scheme_management - Who operates the waterpoint

scheme_name - Who operates the waterpoint

permit - If the waterpoint is permitted

construction_year - Year the waterpoint was constructed

extraction_type - The kind of extraction the waterpoint uses

extraction_type_group - The kind of extraction the waterpoint uses

extraction_type_class - The kind of extraction the waterpoint uses

```
management - How the waterpoint is managed

management_group - How the waterpoint is managed

payment - What the water costs

payment_type - What the water costs

water_quality - The quality of the water

quality_group - The quality of the water

quantity - The quantity of water

quantity_group - The quantity of water

source - The source of the water

source_type - The source of the water

source_class - The source of the water

waterpoint_type - The kind of waterpoint

waterpoint_type_group - The kind of waterpoint
```

Exploratory Data Analysis

In [4]:

```
#(Number of rows,number of columns)
df.shape
```

Out[4]:

```
(59400, 41)
```

In [5]:

```
#Overall Data Information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 0 to 59399
Data columns (total 41 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     59400 non-null  int64  
 1   amount_tsh             59400 non-null  float64
 2   date_recorded          59400 non-null  object 
 3   funder                 55765 non-null  object 
 4   gps_height             59400 non-null  int64  
 5   installer              55745 non-null  object 
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   wpt_name               59400 non-null  object 
 9   num_private            59400 non-null  int64  
 10  basin                  59400 non-null  object 
 11  subvillage             59029 non-null  object 
 12  region                 59400 non-null  object 
 13  region_code            59400 non-null  int64  
 14  district_code          59400 non-null  int64  
 15  lga                    59400 non-null  object 
 16  ward                   59400 non-null  object 
 17  population             59400 non-null  int64  
 18  public_meeting         56066 non-null  object 
 19  recorded_by            59400 non-null  object 
 20  scheme_management      55523 non-null  object 
 21  scheme_name            31234 non-null  object 
 22  permit                 56344 non-null  object 
 23  construction_year      59400 non-null  int64  
 24  extraction_type        59400 non-null  object 
 25  extraction_type_group  59400 non-null  object 
 26  extraction_type_class  59400 non-null  object 
 27  management             59400 non-null  object 
 28  management_group       59400 non-null  object 
 29  payment                59400 non-null  object 
 30  payment_type           59400 non-null  object 
 31  water_quality          59400 non-null  object 
 32  quality_group          59400 non-null  object 
 33  quantity               59400 non-null  object 
 34  quantity_group         59400 non-null  object 
 35  source                 59400 non-null  object 
 36  source_type            59400 non-null  object 
 37  source_class           59400 non-null  object 
```

```
 38  waterpoint_type        59400 non-null  object
 39  waterpoint_type_group  59400 non-null  object
 40  status_group           59400 non-null  object
dtypes: float64(3), int64(7), object(31)
memory usage: 19.0+ MB
```

In [6]:
```
#Basic Data Statistics
df.describe()
```

Out[6]:

	id	amount_tsh	gps_height	longitude	latitude	num_private	region_code	district_code	pop
count	59400.000000	59400.000000	59400.000000	59400.000000	5.940000e+04	59400.000000	59400.000000	59400.000000	59400.
mean	37115.131768	317.650385	668.297239	34.077427	-5.706033e+00	0.474141	15.297003	5.629747	179.
std	21453.128371	2997.574558	693.116350	6.567432	2.946019e+00	12.236230	17.587406	9.633649	471.
min	0.000000	0.000000	-90.000000	0.000000	-1.164944e+01	0.000000	1.000000	0.000000	0.
25%	18519.750000	0.000000	0.000000	33.090347	-8.540621e+00	0.000000	5.000000	2.000000	0.
50%	37061.500000	0.000000	369.000000	34.908743	-5.021597e+00	0.000000	12.000000	3.000000	25.
75%	55656.500000	20.000000	1319.250000	37.178387	-3.326156e+00	0.000000	17.000000	5.000000	215.
max	74247.000000	350000.000000	2770.000000	40.345193	-2.000000e-08	1776.000000	99.000000	80.000000	30500.

In [7]:
```
#Unique Target Variables
df['status_group'].value_counts(normalize=True)
```

Out[7]:
```
functional                 0.543081
non functional             0.384242
functional needs repair    0.072677
Name: status_group, dtype: float64
```

In [8]:

```
#Null Values
df.isnull().sum()
```

```
Out[8]: id                           0
        amount_tsh                   0
        date_recorded                0
        funder                    3635
        gps_height                   0
        installer                 3655
        longitude                    0
        latitude                     0
        wpt_name                     0
        num_private                  0
        basin                        0
        subvillage                 371
        region                       0
        region_code                  0
        district_code                0
        lga                          0
        ward                         0
        population                   0
        public_meeting            3334
        recorded_by                  0
        scheme_management         3877
        scheme_name              28166
        permit                    3056
        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
        status_group                 0
        dtype: int64
```

Preprocessing

Encoding and Imputing All Categorical Features

In [9]:

```
#Initializing Encoder
encoder = OrdinalEncoder()

#Extracting Categorical Data
categorical_data=df.select_dtypes('object')
categorical_columns=categorical_data.columns

#Defining Encoder Function
def encode_data(col_data):
    #function to encode non-null data and replace it in the original data
    non_nulls=np.array(col_data.dropna())
    #reshaping the data for encoding
    reshaped_data=non_nulls.reshape(-1,1)
    #encoding
    encoded_data=encoder.fit_transform(reshaped_data)
    #replace data
    col_data.loc[col_data.notnull()]=np.squeeze(encoded_data)
    return col_data

#Defining Imputer Function
def impute_data(col_data):
    col_data.fillna(col_data.value_counts().index[0], inplace=True)
    return col_data

#Transforming Data
for column in categorical_columns:
    encode_data(categorical_data[column])
    impute_data(categorical_data[column])
categorical_data
```

Out[9]:

	date_recorded	funder	installer	wpt_name	basin	subvillage	region	lga	ward	public_meeting	recorded_by	scheme_
0	47.0	1369.0	1518.0	37399.0	1.0	11807.0	3.0	51.0	1426.0	1.0	0.0	
1	309.0	469.0	545.0	37195.0	4.0	15838.0	9.0	103.0	1576.0	1.0	0.0	
2	300.0	825.0	2048.0	14572.0	5.0	9074.0	8.0	108.0	1624.0	1.0	0.0	
3	272.0	1741.0	1852.0	37285.0	7.0	8982.0	12.0	87.0	1571.0	1.0	0.0	
4	104.0	20.0	119.0	35529.0	4.0	7698.0	4.0	26.0	1687.0	1.0	0.0	
...	...	...	...	...	...	...	...	...	...	...	...	
59395	338.0	436.0	201.0	513.0	5.0	5681.0	6.0	16.0	1090.0	1.0	0.0	
59396	90.0	177.0	265.0	24074.0	6.0	2980.0	3.0	91.0	353.0	1.0	0.0	
59397	75.0	456.0	390.0	27926.0	6.0	8784.0	10.0	59.0	177.0	1.0	0.0	
59398	41.0	884.0	1213.0	29693.0	6.0	14012.0	2.0	11.0	1449.0	1.0	0.0	
59399	56.0	1865.0	2040.0	18700.0	8.0	5892.0	11.0	71.0	1610.0	1.0	0.0	

59400 rows × 31 columns

In [10]:

```python
#Null values
categorical_data.isnull().sum()
```

Out[10]:

```
date_recorded            0
funder                   0
installer                0
wpt_name                 0
basin                    0
subvillage               0
region                   0
lga                      0
ward                     0
public_meeting           0
recorded_by              0
scheme_management        0
scheme_name              0
permit                   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
status_group             0
dtype: int64
```

Checking Numeric Features and Updating DataFrame

In [11]:

```
#Extracting numeric data
numeric_data=df.select_dtypes(['float64','int64'])
#Checking null values
numeric_data.isnull().sum()
```

Out[11]:

```
id                   0
amount_tsh           0
gps_height           0
longitude            0
latitude             0
num_private          0
region_code          0
district_code        0
population           0
construction_year    0
dtype: int64
```

In [12]:

```
#Updating DataFrame
df[categorical_columns]=categorical_data
df.head()
```

Out[12]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_private	basin	subvilla
0	69572	6000.0	47.0	1369.0	1390	1518.0	34.938093	-9.856322	37399.0	0	1.0	1180
1	8776	0.0	309.0	469.0	1399	545.0	34.698766	-2.147466	37195.0	0	4.0	1583
2	34310	25.0	300.0	825.0	686	2048.0	37.460664	-3.821329	14572.0	0	5.0	907
3	67743	0.0	272.0	1741.0	263	1852.0	38.486161	-11.155298	37285.0	0	7.0	898
4	19728	0.0	104.0	20.0	0	119.0	31.130847	-1.825359	35529.0	0	4.0	769

Standardizing Features

In [13]:

```
#Importing Function
from sklearn.preprocessing import StandardScaler
#Scaling data
scaler=StandardScaler()
df=pd.DataFrame(scaler.fit_transform(df),columns=df.columns)
df.head()
```

Out[13]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_private	basi
0	1.512933	1.895665	-1.218793	0.988022	1.041252	1.430269	0.131052	-1.408791	1.356556	-0.038749	-1.24427
1	-1.320990	-0.105970	1.188774	-0.607329	1.054237	-0.316377	0.094610	1.207934	1.339574	-0.038749	-0.03120
2	-0.130757	-0.097630	1.106072	0.023721	0.025541	2.381679	0.515158	0.639751	-0.543605	-0.038749	0.37315
3	1.427676	-0.105970	0.848774	1.647433	-0.584751	2.029837	0.671308	-1.849720	1.347066	-0.038749	1.18186
4	-0.810478	-0.105970	-0.695009	-1.403231	-0.964200	-1.081096	-0.448669	1.317271	1.200893	-0.038749	-0.03120

Dropping `id` Column in preparation for modeling

In [14]:

```
df.drop('id',axis=1,inplace=True)
df[:1]
```

Out[14]:

	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_private	basin	subvillage
0	1.895665	-1.218793	0.988022	1.041252	1.430269	0.131052	-1.408791	1.356556	-0.038749	-1.244276	0.39553

Building, Tuning and Evaluating Models

In [15]:

```
#Performing a train-test split
from sklearn.model_selection import train_test_split
X=df.drop('status_group',axis=1)
y=df['status_group'].astype(int)
X_train,X_test,y_train,y_test=train_test_split(X,y,random_state=42,test_size=0.4)
```

We will be using GridSearchCV as our hyperparameter tuning method and accuracy score as our evaluation metric

In [16]:

```
# Importing Tools
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
rs=11
```

In [17]:
```python
# Function for fitting and testing
def fit_and_test(model):
    model.fit(X_train,y_train)
    #Making Predictions
    train_predictions=model.predict(X_train)
    test_predictions=model.predict(X_test)
    #Computing Accuracy
    train_accuracy=accuracy_score(y_train,train_predictions)
    test_accuracy=accuracy_score(y_test,test_predictions)

    print(f'{str(model)} Results: \
    \n Train Accuracy: {train_accuracy}\
    \n Test Accuracy: {test_accuracy}')

# Function for hyperparameter tuning
def find_params(model,param_grid):
    model_cv=GridSearchCV(model,param_grid,cv=5)
    model_cv.fit(X_train,y_train)
    params=model_cv.best_params_
    values=list(params.values())
    return (values[i] for i in range(len(values)))
```

MultiClass Logistic Regressor

Vanilla

In [18]:
```python
#Importing modules
from sklearn.linear_model import LogisticRegression
#Initializing Model
logistic_model=LogisticRegression(multi_class='multinomial',solver='lbfgs',random_state=rs)
#Fitting and Testing Model
fit_and_test(logistic_model)
```

```
LogisticRegression(multi_class='multinomial', random_state=11) Results:
 Train Accuracy: 0.7056397306397306
 Test Accuracy: 0.7114057239057239
```

Tuned

In [19]:
```
# lg_param_grid = {'C': [1,5],
#                 'max_iter': [100, 500],
#                 'tol': [0.0001]}
# #Extracting Optimal Parameters
# c,m,t=find_params(logistic_model,lg_param_grid)
# #Building Tuned Model
# tuned_logistic_model=LogisticRegression(C=c,max_iter=m,tol=t)
# #Fitting and Testing Model
# fit_and_test(tuned_logistic_model)
```

Decision Tree Classifier

Vanilla

In [20]:
```
#Importing functions
from sklearn.tree import DecisionTreeClassifier
#Initializing Model
decision_tree_model=DecisionTreeClassifier(max_depth=14)
#Fitting and Testing Model
fit_and_test(decision_tree_model)
```

```
DecisionTreeClassifier(max_depth=14) Results:
 Train Accuracy: 0.8712682379349046
 Test Accuracy: 0.8183080808080808
```

Tuned

In [21]:
```
# dt_param_grid = {'criterion': ['entropy','gini'],
#                   'min_samples_split': [20,26]}
# c,ms=find_params(decision_tree_model,dt_param_grid)
# #Building Tuned Model
# tuned_decision_tree_model=DecisionTreeClassifier(criterion=c,min_samples_split=ms)
# #Fitting and Testing Model
# fit_and_test(tuned_decision_tree_model)
```

K-Nearest Neighbors

Vanilla

In [22]:
```
#Importing Functions
from sklearn.neighbors import KNeighborsClassifier
# import warnings filter
from warnings import simplefilter
# ignore all future warnings
simplefilter(action='ignore', category=FutureWarning)
#Initializing model
knn_model=KNeighborsClassifier(n_neighbors=5)
#Fitting and Testing Model
fit_and_test(knn_model)
```

```
KNeighborsClassifier() Results:
 Train Accuracy: 0.8656285072951739
 Test Accuracy: 0.8058080808080809
```

Tuned

In [23]:

```
# kn_param_grid = {'n_neighbors': [3, 5, 7],
#                   'weights': ['uniform', 'distance']}
# n,w=find_params(knn_model,kn_param_grid)
# #Building tuned model
# tuned_knn_model=KNeighborsClassifier(n_neighbors=n,weights=w)
# #Fitting and Testing Model
# fit_and_test(tuned_knn_model)
```

Random Forest

Vanilla

In [24]:

```
#Importing Function
from sklearn.ensemble import RandomForestClassifier
#Initializing Model
forest_model=RandomForestClassifier()
#Fitting and Testing Model
fit_and_test(forest_model)
```

```
RandomForestClassifier() Results:
 Train Accuracy: 1.0
 Test Accuracy: 0.8602693602693603
```

Tuned

In [25]:

```
# rf_param_grid = {
#     'n_estimators': [50, 100],
#     'max_depth' : [40,80]
# }
# n,mf,md,c=find_params(forest_model,rf_param_grid)
# #Building Tuned Model
# tuned_forest_model = RandomForestClassifier(n_estimators=n,max_features=mf,max_depth=md,criterion=c)
# #Fitting and Testing Model
# fit_and_test(tuned_forest_model)
```

Bayesian Classifier

Vanilla

In [26]:
```
#Importing module
from sklearn.naive_bayes import GaussianNB
#Initializing model
bayes_model=GaussianNB()
#Fitting and Testing Model
fit_and_test(bayes_model)
```

```
GaussianNB() Results:
 Train Accuracy: 0.6661335578002244
 Test Accuracy: 0.6731481481481482
```

Tuned

In [27]:
```
# bayes_param_grid = {
#     'var_smoothing': np.logspace(0,-9, num=100)
# }
# var=find_params(bayes_model,bayes_param_grid)
# #Building Tuned Model
# tuned_bayes_model=GaussianNB(var_smoothing=var)
# #Fitting and Testing Model
# fit_and_test(tuned_bayes_model)
```

Adaptive Boosting Classifier

Vanilla

In [28]:
```
#Importing module
from sklearn.ensemble import AdaBoostClassifier
#Initializing model
adaboost_model=AdaBoostClassifier()
#Fitting and Testing Model
fit_and_test(adaboost_model)
```

```
AdaBoostClassifier() Results:
 Train Accuracy: 0.7926206509539843
 Test Accuracy: 0.7922138047138048
```

Tuned

In [29]:
```
# ab_param_grid = {
#     'base_estimator': [DecisionTreeClassifier(max_depth=1), DecisionTreeClassifier(max_depth=2)],
#     'n_estimators': [50, 100, 200],
#     'learning_rate': [0.01, 0.1, 1],
# }
# b,n,l=find_params(adaboost_model,ab_param_grid)
# #Building tuned model
# tuned_adaboost_model=AdaBoostClassifier(base_estimator=b,n_estimators=n,learning_rate=l)
# #Fitting and testing Model
# fit_and_test(tuned_adaboost_model)
```

Extra Trees Classifier

Vanilla

In [30]:
```python
#Importing Module
from sklearn.ensemble import ExtraTreesClassifier
#Initializing model
extra_trees_model=ExtraTreesClassifier()
#Fitting and Testing Model
fit_and_test(extra_trees_model)
```

```
ExtraTreesClassifier() Results:
 Train Accuracy: 1.0
 Test Accuracy: 0.8518518518518519
```

Tuned

In [31]:
```python
# et_param_grid = {
#     'n_estimators': [50, 100, 200],
#     'max_depth': [1, 2, 3],
#     'min_samples_split': [2, 4],
#     'min_samples_leaf': [1, 2],
# }
# n,md,ms,ml=find_params(extra_trees_model,et_param_grid)
# #Building Tuned Model
# tuned_extra_trees_model=ExtraTreesClassifier(n_estimators=n,max_depth=md,min_samples_split=ms,min_sampl
# #Fitting and Testing Model
# fit_and_test(tuned_extra_trees_model)
```

Gradient Boosting Classifier

Vanilla

In [32]:
```python
#Importing module
from sklearn.ensemble import GradientBoostingClassifier
#Initializing model
gradient_boost_model=GradientBoostingClassifier()
#Fitting Model
fit_and_test(gradient_boost_model)
```

```
GradientBoostingClassifier() Results:
 Train Accuracy: 0.8087822671156004
 Test Accuracy: 0.8058922558922559
```

Tuned

In [33]:
```python
# gb_param_grid = {
#     'n_estimators': [50, 100, 200],
#     'max_depth': [1, 2, 3],
#     'min_samples_split': [2, 4],
#     'min_samples_leaf': [1, 2],
# }
# n,md,ms,ml=find_params(gradient_boost_model,gb_param_grid)
# #Building Tuned Model
# tuned_gradient_boost_model=GradientBoostClassifier(n_estimators=n,max_depth=md,min_samples_split=ms,min
# #Fitting and Testing model
# fit_and_test(tuned_gradient_boost_model)
```

XG Boost Classifier

Vanilla

```
In [34]:  #Importing Module
          from xgboost import XGBClassifier
          #Initializing model
          xg_boost_model=XGBClassifier(booster=RandomForestClassifier)
          #Fitting Modelb
          fit_and_test(xg_boost_model)
```

```
XGBClassifier(base_score=None,
              booster=<class 'sklearn.ensemble._forest.RandomForestClassifier'>,
              callbacks=None, colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...) Results:
 Train Accuracy: 0.9010381593714927
 Test Accuracy: 0.8472643097643098
```

Tuned

```
In [35]:  # xg_param_grid = {
          #     'max_depth': [3, 4, 5],
          #     'learning_rate': [0.1, 0.01, 0.001],
          #     'n_estimators': [100, 500, 1000],
          #     'gamma': [0.5, 1, 1.5]
          # }
          # #Extracting optimal parameters
          # md,lr,n,g=find_params(xg_boost_model,xg_param_grid)
          # #Building tuned model
          # tuned_xg_model=XGBoostClassifier(max_depth=md,learning_rate=lr,n_estimators=n,gamma=g)\
          # #Fitting and Testing model
          # fit_and_test(new_mg)
```

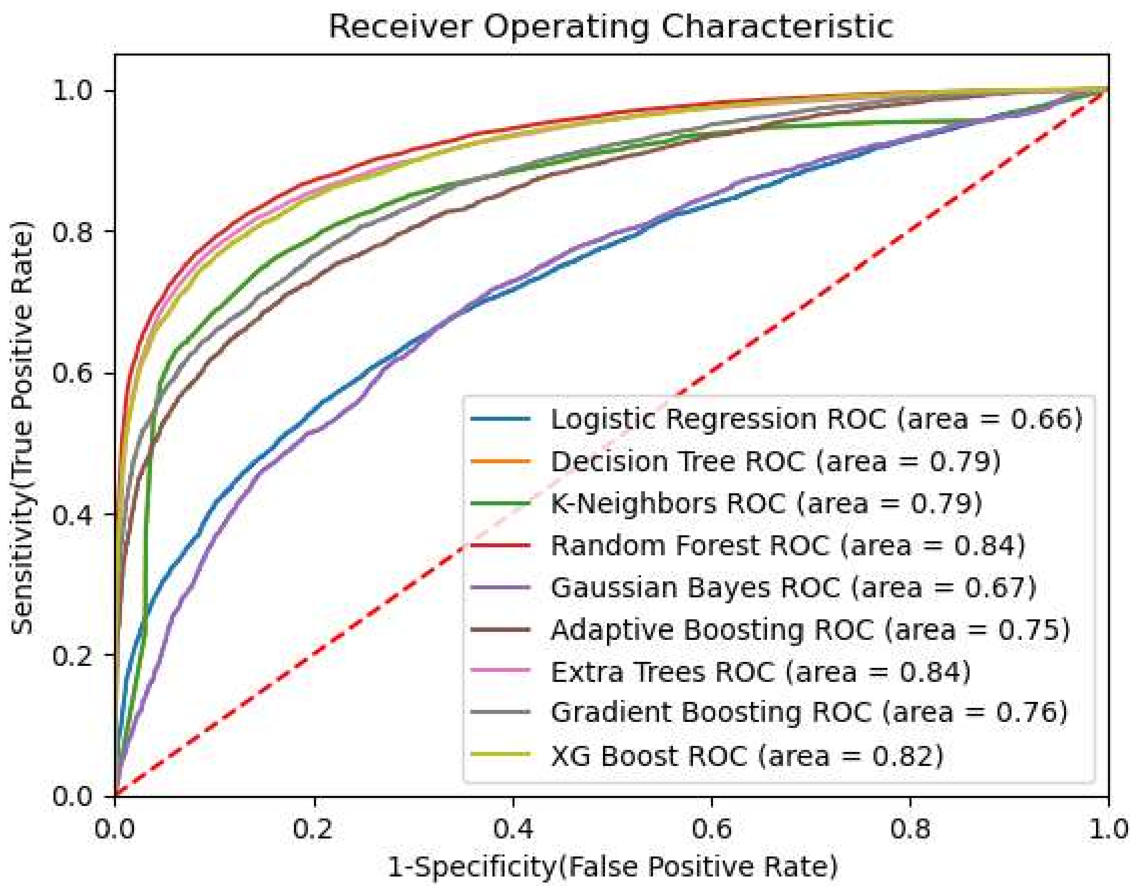
Model Selection

ROC and AUC

(Receiver Operating Characteristics)

In [36]:

```
#Importing Module
import sklearn.metrics as metrics
#Listing models
models = [
    { 'label': 'Logistic Regression', 'model': logistic_model},
    { 'label': 'Decision Tree', 'model': decision_tree_model},
    { 'label': 'K-Neighbors', 'model': decision_tree_model},
    { 'label': 'Random Forest', 'model': forest_model},
    { 'label': 'Gaussian Bayes', 'model': bayes_model},
    { 'label': 'Adaptive Boosting', 'model': adaboost_model},
    { 'label': 'Extra Trees', 'model': extra_trees_model},
    { 'label': 'Gradient Boosting', 'model': gradient_boost_model},
    { 'label': 'XG Boost', 'model': xg_boost_model}
]
#Plotting ROC
plt.figure()
for m in models:
    model = m['model'] # select the model
    y_pred=model.predict(X_test) # predict the test data
# Compute False postive rate, and True positive rate
    fpr, tpr, thresholds = metrics.roc_curve(y_test, model.predict_proba(X_test)[:,1])
# Calculate Area under the curve to display on the plot
    auc = metrics.roc_auc_score(y_test,y_pred)
# Now, plotting the computed values
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (m['label'], auc))
# Custom settings for the plot
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('1-Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()   # Display
```



> The **Random Forests** model has the highest `AUC` (0.84) as well as the highest `accuracy score` (86%). We shall therefore be selecting it as our final and best model. **Our model of choice**

Pickling the model

In [37]:
```
import pickle
import joblib

# Save the model as a pickle in a file
joblib.dump(forest_model, 'random_forest_model.pkl')
```

Out[37]:
```
['random_forest_model.pkl']
```

Testing Pickled Model

In [38]:
```
f = open('random_forest_model.pkl','rb')
loaded_model = joblib.load(f)
f.close()
load_prediction = loaded_model.predict(X_test)
load_prediction_accuracy = accuracy_score(y_test,load_prediction)
print(f'Loaded model accuracy: {np.round(load_prediction_accuracy*100,2)}%')
```

```
Loaded model accuracy: 86.03%
```

Recommendation

With such predictive power, the Government of Tanzania can now forecast and infer the condition of a water well. We therefore recommend the utilization of this algorithm to improve operational efficiency

Conclusion

More and more businesses are leveraging on the use of data and machine learning to drive decision making. It has been an honor working with the Tanzanian Government. When we work together we grow together

In [ ]:
```

```