Building Predictive Models on Tanzania Water Project using Machine Learning Techniques

Project Overview

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The Government of Tanzania through the Ministry of Water and Sanitation is running water projects in the country. Lack of water is a persistent problem in urban and rural areas. The Minisrty has secured financing to construct water pumps in various constiuencies across the country. In this project ,we are going to examine,analyze data,create predictive models,present findings and propose recommendations on three aspects of water pumps:

1. **Functional Waterpoints-the water point is operational and there are no repairs needed**
2. **Water point is functional but needs repair**
3. **Non Functional waterpoint**

The Project Presentation will assist the Ministry and agencies responsible to make data driven decisions.

Business Understanding

We aim to Predict which water pumps are faulty to promote access to clean,potable water across Tanzania. We shall create models that:

1. **Predict Functional Water points**
2. **Predict Functional water points but need repair**
3. **Predict Non Functional Waterpoints**

Data Understanding

In this Project we going to use data from Taarifa,an open source plartform which agregates data from the Tanzania Ministry of Water. The dataset is in .csv format and has three attributes

1. **Test Set Values-Independent variables that need predictions**
2. **Training set labels- Dependent variable for each of the rows in Training set values**
3. **Training set values- Independent variables for the training set**

Data Preparation

In [2]:

```
%pip install imbalanced-learn

#import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, roc_auc_score, roc_curve
from imblearn.over_sampling import SMOTE
```

```
Requirement already satisfied: imbalanced-learn in c:\users\administrator\anaconda3\envs\learn-env\lib\site-packages (0.12.4)Note: you may need to restart the kernel to use updated packages.

Requirement already satisfied: numpy>=1.17.3 in c:\users\administrator\anaconda3\envs\learn-env\lib\site-packages (from imbalanced-learn) (1.24.4)
Requirement already satisfied: scipy>=1.5.0 in c:\users\administrator\anaconda3\envs\learn-env\lib\site-packages (from imbalanced-learn) (1.10.1)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\administrator\anaconda3\envs\learn-env\lib\site-packages (from imbalanced-learn) (1.3.2)
Requirement already satisfied: joblib>=1.1.1 in c:\users\administrator\anaconda3\envs\learn-env\lib\site-packages (from imbalanced-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\administrator\anaconda3\envs\learn-env\lib\site-packages (from imbalanced-learn) (3.5.0)
```

In [3]:

```
#load Test set values data set
Tst_set_vals= pd.read_csv('Test set values.csv')  # Update the path as needed

#load Training set labels data set
Train_set_label = pd. read_csv('Training set labels.csv')

#load Training set values data set
Train_set_vals= pd. read_csv('Training set values.csv')
```

Data cleaning

Data cleaning will involve dropping irrelevant columns, checking for duplicates and missing values and taking necessary action. We also convert datatypes where necessary.

In [4]:

```
#checking data frame
Tst_set_vals.head(10)
```

Out[4]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_private	...
0	50785	0.0	2013-02-04	Dmdd	1996	DMDD	35.290799	-4.059696	Dinamu Secondary School	0	...
1	51630	0.0	2013-02-04	Government Of Tanzania	1569	DWE	36.656709	-3.309214	Kimnyak	0	...
2	17168	0.0	2013-02-01	NaN	1567	NaN	34.767863	-5.004344	Puma Secondary	0	...
3	45559	0.0	2013-01-22	Finn Water	267	FINN WATER	38.058046	-9.418672	Kwa Mzee Pange	0	...
4	49871	500.0	2013-03-27	Bruder	1260	BRUDER	35.006123	-10.950412	Kwa Mzee Turuka	0	...
5	52449	0.0	2013-03-04	Government Of Tanzania	1685	DWE	36.685279	-3.302420	Masaga	0	...
6	24806	0.0	2011-03-02	Government Of Tanzania	550	Gover	36.398041	-7.541382	none	0	...
7	28965	0.0	2013-01-25	Finw	234	FinW	39.607420	-10.893786	Kwa Mkwaa	0	...

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_private	...
8	36301	30.0	2013-01-28	Unicef	384	LGA	39.262061	-10.823588	Kwa Mzee Mpini	0	...
9	54122	0.0	2013-03-18	Lawatefuka Water Supply	1083	Lawatefuka water sup	37.096108	-3.251754	Kwa Flora Daud	0	...

10 rows × 40 columns

In [5]:

```
Tst_set_vals.info() #detailed information of the data frame
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14850 entries, 0 to 14849
Data columns (total 40 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     14850 non-null  int64  
 1   amount_tsh             14850 non-null  float64
 2   date_recorded          14850 non-null  object 
 3   funder                 13980 non-null  object 
 4   gps_height             14850 non-null  int64  
 5   installer              13973 non-null  object 
 6   longitude              14850 non-null  float64
 7   latitude               14850 non-null  float64
 8   wpt_name               14850 non-null  object 
 9   num_private            14850 non-null  int64  
 10  basin                  14850 non-null  object 
 11  subvillage             14751 non-null  object 
 12  region                 14850 non-null  object 
 13  region_code            14850 non-null  int64  
 14  district_code          14850 non-null  int64  
 15  lga                    14850 non-null  object 
 16  ward                   14850 non-null  object 
 17  population             14850 non-null  int64  
 18  public_meeting         14029 non-null  object 
 19  recorded_by            14850 non-null  object 
 20  scheme_management      13881 non-null  object 
 21  scheme_name            7608 non-null   object 
 22  permit                 14113 non-null  object 
 23  construction_year      14850 non-null  int64  
 24  extraction_type        14850 non-null  object 
 25  extraction_type_group  14850 non-null  object 
 26  extraction_type_class  14850 non-null  object 
 27  management             14850 non-null  object 
 28  management_group       14850 non-null  object 
 29  payment                14850 non-null  object 
 30  payment_type           14850 non-null  object 
 31  water_quality          14850 non-null  object 
 32  quality_group          14850 non-null  object 
 33  quantity               14850 non-null  object 
 34  quantity_group         14850 non-null  object 
 35  source                 14850 non-null  object 
 36  source_type            14850 non-null  object 
 37  source_class           14850 non-null  object 
 38  waterpoint_type        14850 non-null  object 
 39  waterpoint_type_group  14850 non-null  object 
dtypes: float64(3), int64(7), object(30)
memory usage: 4.5+ MB
```

In [6]:

```
#chech for missing values
Tst_set_vals.isna().sum()
```

Out[6]:

```
id                           0
amount_tsh                   0
date_recorded                0
funder                     870
```

```
gps_height                  0
installer                 877
longitude                   0
latitude                    0
wpt_name                    0
num_private                 0
basin                       0
subvillage                 99
region                      0
region_code                 0
district_code               0
lga                         0
ward                        0
population                  0
public_meeting            821
recorded_by                 0
scheme_management         969
scheme_name              7242
permit                    737
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
```

In [7]:

```
#check for duplicates
Tst_set_vals.duplicated().sum()
```

Out[7]:

```
0
```

In [8]:

```
#drop irrelevant columns
Tst_set_vals.drop(columns= ['scheme_name','scheme_management','permit','public_meeting','
installer','funder'],axis=1, inplace= True)
```

In [9]:

```
Tst_set_vals.info() # columsn dropped
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14850 entries, 0 to 14849
Data columns (total 34 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     14850 non-null  int64
 1   amount_tsh             14850 non-null  float64
 2   date_recorded          14850 non-null  object
 3   gps_height             14850 non-null  int64
 4   longitude              14850 non-null  float64
 5   latitude               14850 non-null  float64
 6   wpt_name               14850 non-null  object
 7   num_private            14850 non-null  int64
 8   basin                  14850 non-null  object
 9   subvillage             14751 non-null  object
```

```
 10  region                 14850 non-null  object
 11  region_code            14850 non-null  int64
 12  district_code          14850 non-null  int64
 13  lga                    14850 non-null  object
 14  ward                   14850 non-null  object
 15  population             14850 non-null  int64
 16  recorded_by            14850 non-null  object
 17  construction_year      14850 non-null  int64
 18  extraction_type        14850 non-null  object
 19  extraction_type_group  14850 non-null  object
 20  extraction_type_class  14850 non-null  object
 21  management             14850 non-null  object
 22  management_group       14850 non-null  object
 23  payment                14850 non-null  object
 24  payment_type           14850 non-null  object
 25  water_quality          14850 non-null  object
 26  quality_group          14850 non-null  object
 27  quantity               14850 non-null  object
 28  quantity_group         14850 non-null  object
 29  source                 14850 non-null  object
 30  source_type            14850 non-null  object
 31  source_class           14850 non-null  object
 32  waterpoint_type        14850 non-null  object
 33  waterpoint_type_group  14850 non-null  object
dtypes: float64(3), int64(7), object(24)
memory usage: 3.9+ MB
```

In [10]:

```
#check data frame
Train_set_label.head(10)
```

Out[10]:

	id	status_group
0	69572	functional
1	8776	functional
2	34310	functional
3	67743	non functional
4	19728	functional
5	9944	functional
6	19816	non functional
7	54551	non functional
8	53934	non functional
9	46144	functional

In [11]:

```
#check for duplicates
Train_set_label.duplicated() .sum()
```

Out[11]:

```
0
```

In [12]:

```
#check missing values
Train_set_label.isna().sum()
```

Out[12]:

```
id              0
status_group    0
dtype: int64
```

In [13]:

```
#check data frame
Train_set_vals.head()
```

Out[13]:

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

5 rows × 40 columns

In [14]:

```
#check for duplicates
Train_set_vals.duplicated().sum()
```

Out[14]:

```
0
```

In [15]:

```
#check for missing values
Train_set_vals.isna().sum()
```

Out[15]:

```
id                           0
amount_tsh                   0
date_recorded                0
funder                    3637
gps_height                   0
installer                 3655
longitude                    0
latitude                     0
wpt_name                     2
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         3878
scheme_name              28810
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
dtype: int64
```

In [16]:

```
#drop irrelevant columns
Train_set_vals.drop(columns=['funder','installer','subvillage', 'public_meeting','scheme_
management','scheme_name','permit'],axis=1,inplace=True)
```

In [17]:

```
Train_set_vals.info() #7 columns dropped from Data frame
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 33 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   gps_height             59400 non-null  int64
 4   longitude              59400 non-null  float64
 5   latitude               59400 non-null  float64
 6   wpt_name               59398 non-null  object
 7   num_private            59400 non-null  int64
 8   basin                  59400 non-null  object
 9   region                 59400 non-null  object
 10  region_code            59400 non-null  int64
 11  district_code          59400 non-null  int64
 12  lga                    59400 non-null  object
 13  ward                   59400 non-null  object
 14  population             59400 non-null  int64
 15  recorded_by            59400 non-null  object
 16  construction_year      59400 non-null  int64
 17  extraction_type        59400 non-null  object
 18  extraction_type_group  59400 non-null  object
 19  extraction_type_class  59400 non-null  object
 20  management             59400 non-null  object
 21  management_group       59400 non-null  object
 22  payment                59400 non-null  object
 23  payment_type           59400 non-null  object
 24  water_quality          59400 non-null  object
 25  quality_group          59400 non-null  object
 26  quantity               59400 non-null  object
 27  quantity_group         59400 non-null  object
 28  source                 59400 non-null  object
 29  source_type            59400 non-null  object
 30  source_class           59400 non-null  object
 31  waterpoint_type        59400 non-null  object
 32  waterpoint_type_group  59400 non-null  object
dtypes: float64(3), int64(7), object(23)
memory usage: 15.0+ MB
```

Explatory Data Analysis

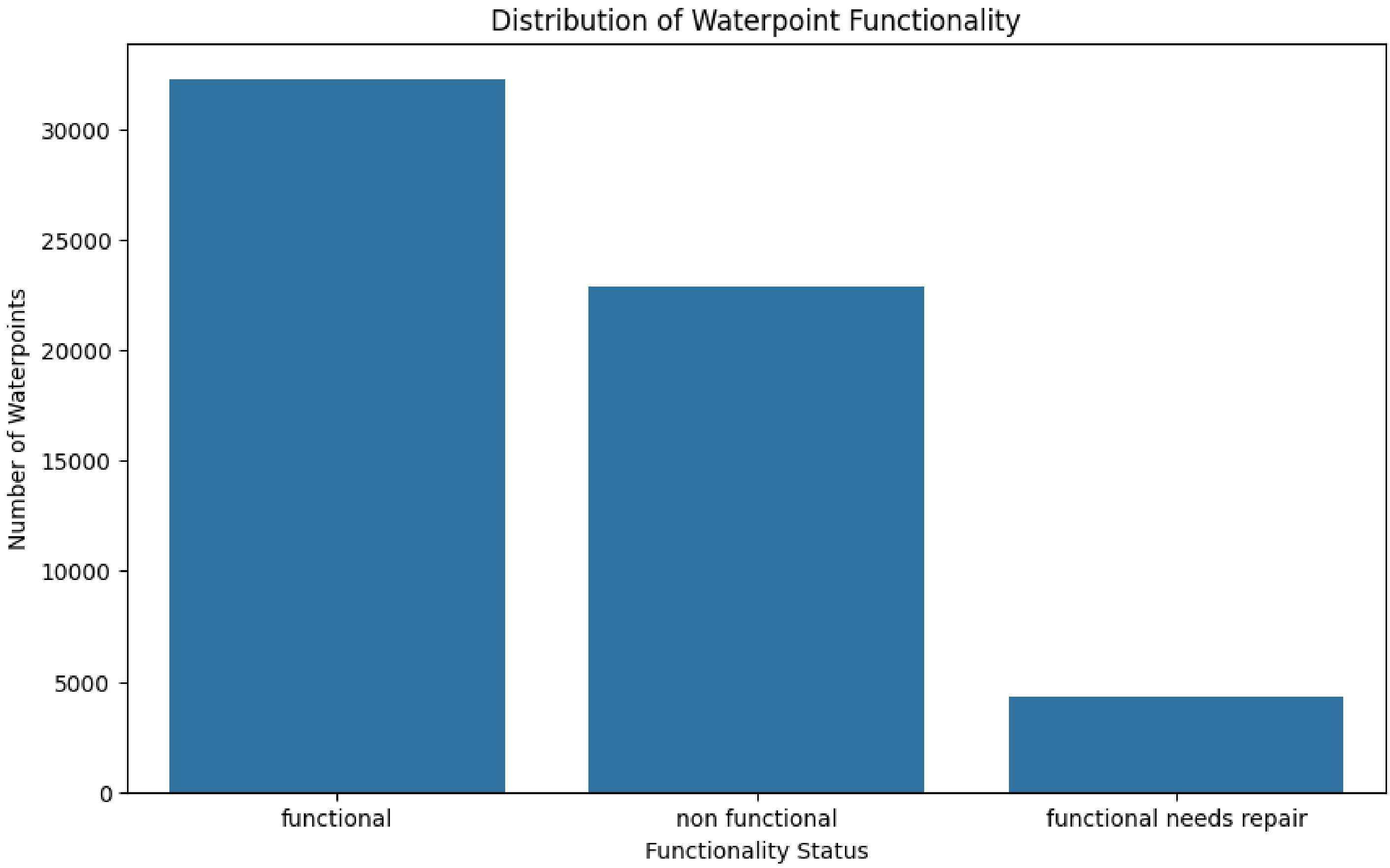
In [18]:

```
# Check the Waterpump vs its Functionality
```

```
# Plot the relationship between waterpump and functionality

# Merge Train_set_vals and Train_set_label on 'id' to get status_group for each waterpoin
t
merged_df = Train_set_vals.merge(Train_set_label, on='id')

# Plot the count of waterpoints by functionality
plt.figure(figsize=(10,6))
sns.countplot(data=merged_df, x='status_group')
plt.title('Distribution of Waterpoint Functionality')
plt.xlabel('Functionality Status')
plt.ylabel('Number of Waterpoints')
plt.show()
```



The Number of fuctional water pumps are in the range of 40,000 , Non functional water pumps around 22,000 and functional water pumps that need repair are less that 5,000

Modelling

Creating a Model that predicts Functional waterpumps from Training set values

In [20]:

```
#create a predictive model that predicts functional water pumps

# Use already loaded dataframes
X = Train_set_vals
y = Train_set_label

# Merge on 'id'
df = X.merge(y, on='id')
```

In [21]:

```
# Encode categorical variables
categorical_cols = df.select_dtypes(include='object').columns
```

```
le = LabelEncoder()
for col in categorical_cols:
    df[col] = le.fit_transform(df[col])

# Define features and target
X = df.drop(['status_group', 'id'], axis=1)
y = df['status_group']
```

In [22]:

```
#train/test split

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

In [23]:

```
# You can use RandomForest, XGBoost, etc.
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

Out[23]:

```
▾         RandomForestClassifier
RandomForestClassifier(random_state=42)
```

Evaluation

In [24]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score


y_pred = model.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.8098484848484848
[[5760  172  520]
 [ 437  282  144]
 [ 919   67 3579]]
              precision    recall  f1-score   support

           0       0.81      0.89      0.85      6452
           1       0.54      0.33      0.41       863
           2       0.84      0.78      0.81      4565

    accuracy                           0.81     11880
   macro avg       0.73      0.67      0.69     11880
weighted avg       0.80      0.81      0.80     11880
```

Our model using Random Forest classifier has achieved 81% accuracy

Label	Meaning	F1-Score	Comments
0	Functional	0.85	High precision & recall
1	Functional needs repair	0.41	Low recall (33%) → often misclassified
2	Non-functional	0.81	Balanced, good performance

There is class imbalance on Functional water pumps that needs repair category

In [25]:

```
#Handling class imbalance

from imblearn.over_sampling import SMOTE

sm = SMOTE(random_state=42)
X_res, y_res = sm.fit_resample(X_train, y_train)
model.fit(X_res, y_res)

#print
```

Out[25]:

```
▾         RandomForestClassifier
RandomForestClassifier(random_state=42)
```

Conclusion

Business Conclusions from the Model

1. Overall Performance

- The model can predict **functional status** of water pumps with ~81% accuracy.
- It performs **very well for predicting functional and non-functional pumps** .
- It struggles with identifying pumps that are **“functional but need repair”** , which are often hard to distinguish even for humans.

2. Current Water System Health

- From the test predictions or dataset distribution, you likely observed that a **significant portion of pumps are either non-functional or require maintenance.**
- The model reveals patterns in pump failure based on metadata like age, location, water quality, pump type, etc.

3. Key Risk Indicators

- Certain features (e.g., **construction year**, **pump installer**, **region**, **management type**) are strong predictors of failure.
- Older pumps, poorly managed pumps, or those with unknown installers are more likely to fail.

Business Recommendations

1. Proactive Maintenance Program

- Use the model predictions to **prioritize maintenance teams** to visit pumps that are likely to fail or are in "needs repair" condition.
- This can **prevent breakdowns before they occur**, saving cost and reducing downtime.

2. Targeted Investment

- Allocate **repair budgets more efficiently** to regions or pump types where the model shows higher failure probabilities.
- For example, if hand pumps installed before 2000 in Region X have a high failure rate, prioritize upgrades there.

3. Standardize and Monitor Installation

- Enforce **minimum standards for installation** (e.g., only certified installers) since installation method significantly affects pump longevity.
- Create **digital records** of new pump installations to track performance over time.

4. Improve Data Collection

- The model's weakness in predicting the "needs repair" class suggests a **data quality gap**.
- Train field teams to better categorize pump status during inspections.
- Consider using **sensors or mobile reporting tools** to collect real-time functionality data.

5. Community Engagement

- Engage local communities in pump monitoring.
- If the model identifies certain management schemes (e.g., community-managed pumps) as more effective, promote and fund those.

6. Performance Dashboard

- Build a **GIS-based dashboard** that visualizes model predictions by location.
- Stakeholders (government, NGOs, donors) can use this to make **data-driven decisions** on water access improvement.

Metrics for Ongoing Monitoring

- % of predicted "needs repair" pumps that actually fail within 3 months (model validation in the field).
- Reduction in pump downtime across districts using predictive maintenance vs. reactive repairs.
- Change in operational cost per functioning pump after model integration.
