Tanzanian Water Wells Prediction

Authors: JOSPHAT KIMANI,

1. Business Understanding

Problem Statement

The purpose of this project is to address the challenge faced by Wells of Life, an NGO operating in Tanzania, in effectively identifying water wells in need of repair. With over 57 million people struggling to access clean water, many existing water points require maintenance or have failed entirely. The problem statement revolves around the inefficiency in prioritizing maintenance efforts due to limited resources and the lack of a systematic approach to assess the condition of water wells. To tackle this issue, the project aims to develop a classifier that utilizes various data points such as pump type, installation date, and other relevant variables to predict the condition of water wells accurately. By doing so, Wells of Life can optimize their resource allocation, prioritize critical repairs, and intervene proactively to prevent disruptions in water supply, ultimately improving access to clean water for communities in Tanzania.

Specific Objectives

- Develop insights into trends and patterns distinguishing between non-functional and functional wells.
- Utilize straightforward analysis to pinpoint non-functioning wells and forecast well functionality based on available variables.

Research Questions

- How can historical data accurately predict water well conditions?
- What challenges exist in predicting well conditions, and how can they be addressed?
- How does the classifier's performance compare to existing methods?
- hat insights can the classifier provide for decision-making and resource allocation?

Success Metrics

- To ensure that newly constructed wells are of good quality water for the communities.
- To correctly identify functionality of a well and determine its viability.
- Generating a model that will be able to correctly predict the quality status of the wells in Tanzania with an accuracy of 80%.

2. Data Understanding

- Data Source

The provided dataset from Taarifa and the Tanzanian Ministry of Water is instrumental in predicting the functionality of water pumps in Tanzania.

- Describe Data

By analyzing various factors such as pump type, installation date, and management practices, the dataset allows for the classification of pumps into three categories: functional, in need of repair, or non-functional. This intermediate-level practice competition aims to leverage the dataset to enhance maintenance operations and ensure access to clean water for Tanzanian communities. A thorough understanding of the dataset's source, properties, and suitability for addressing the real-world problem is essential for developing accurate predictive models. Overall, the dataset presents an opportunity to apply machine learning techniques to improve water infrastructure management and enhance water accessibility in Tanzania.

Load Libraries

```
# Loading all the neccessary modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn import datasets
from sklearn.model_selection import train_test_split, cross_validate,
GridSearchCV
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
from xgboost import XGBClassifier
from category_encoders import TargetEncoder
import pickle
import joblib
import warnings
plt.style.use('fivethirtyeight')
sns.set_style('whitegrid')
pd.set_option('display.max_columns', 40)
warnings.filterwarnings('ignore')
```

Load Data

```
# Loading well values as a pandas DataFrame
df_values = pd.read_csv("./Data/well_data_values.csv", index_col=0)

# Loading well labels as a pandas DataFrame
df_labels = pd.read_csv("./Data/well_data_labels.csv", index_col=0)

# Print shape of the two DataFrames
df_values.shape
```

```
df_labels.shape

# Create a combined DataFrame with both the value and label data
joined on the 'id' column
data = df_values.join(df_labels, on='id')

data.shape

# Preview DataFrame
data.head(5)
```

```
       amount_tsh date_recorded        funder  gps_height
installer  \
id

69572      6000.0    2011-03-14         Roman        1390
Roman
8776          0.0    2013-03-06       Grumeti        1399
GRUMETI
34310        25.0    2013-02-25  Lottery Club         686  World
vision
67743         0.0    2013-01-28        Unicef         263
UNICEF
19728         0.0    2011-07-13   Action In A           0
Artisan

       longitude   latitude              wpt_name  num_private  \
id
69572  34.938093  -9.856322                  none            0
8776   34.698766  -2.147466              Zahanati            0
34310  37.460664  -3.821329           Kwa Mahundi            0
67743  38.486161 -11.155298  Zahanati Ya Nanyumbu            0
19728  31.130847  -1.825359               Shuleni            0

                         basin  subvillage   region  region_code  \
id
69572               Lake Nyasa    Mnyusi B   Iringa           11
8776             Lake Victoria     Nyamara     Mara           20
34310                  Pangani     Majengo  Manyara           21
67743  Ruvuma / Southern Coast  Mahakamani   Mtwara           90
19728            Lake Victoria  Kyanyamisa   Kagera           18

       district_code        lga        ward  population public_meeting
\
id

69572              5     Ludewa    Mundindi         109           True

8776               2  Serengeti       Natta         280            NaN
```

```
34310                4  Simanjiro     Ngorika         250           True

67743               63   Nanyumbu    Nanyumbu          58           True

19728                1    Karagwe  Nyakasimbi           0           True


                   recorded_by scheme_management
scheme_name  \
id

69572  GeoData Consultants Ltd               VWC
Roman
8776   GeoData Consultants Ltd             Other
NaN
34310  GeoData Consultants Ltd               VWC  Nyumba ya mungu pipe
scheme
67743  GeoData Consultants Ltd               VWC
NaN
19728  GeoData Consultants Ltd               NaN
NaN

      permit  construction_year extraction_type extraction_type_group
\
id

69572  False               1999         gravity               gravity

8776    True               2010         gravity               gravity

34310   True               2009         gravity               gravity

67743   True               1986     submersible           submersible

19728   True                  0         gravity               gravity


      extraction_type_class management management_group
payment  \
id

69572               gravity        vwc       user-group    pay
annually
8776                gravity        wug       user-group       never
pay
34310               gravity        vwc       user-group  pay per
bucket
67743           submersible        vwc       user-group       never
pay
19728               gravity      other            other       never
pay
```

```
      payment_type water_quality quality_group      quantity
quantity_group  \
id

69572     annually          soft          good        enough
enough
8776     never pay          soft          good  insufficient
insufficient
34310   per bucket          soft          good        enough
enough
67743    never pay          soft          good           dry
dry
19728    never pay          soft          good      seasonal
seasonal

                     source           source_type source_class  \
id
69572                spring                spring  groundwater
8776   rainwater harvesting  rainwater harvesting      surface
34310                   dam                   dam      surface
67743           machine dbh              borehole  groundwater
19728  rainwater harvesting  rainwater harvesting      surface

                   waterpoint_type waterpoint_type_group
status_group
id

69572           communal standpipe    communal standpipe
functional
8776            communal standpipe    communal standpipe
functional
34310  communal standpipe multiple    communal standpipe
functional
67743  communal standpipe multiple    communal standpipe  non
functional
19728           communal standpipe    communal standpipe
functional

# View info of the dataFrame
data.info()

<class 'pandas.core.frame.DataFrame'>
Index: 59400 entries, 69572 to 26348
Data columns (total 40 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   amount_tsh             59400 non-null  float64
 1   date_recorded          59400 non-null  object
 2   funder                 55763 non-null  object
```

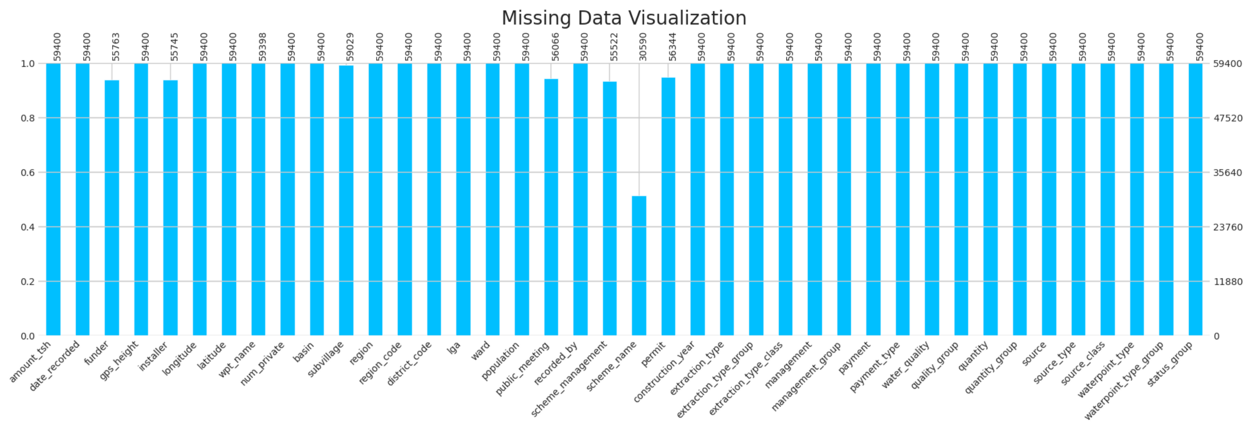
```
 3   gps_height             59400 non-null  int64
 4   installer              55745 non-null  object
 5   longitude              59400 non-null  float64
 6   latitude               59400 non-null  float64
 7   wpt_name               59398 non-null  object
 8   num_private            59400 non-null  int64
 9   basin                  59400 non-null  object
 10  subvillage             59029 non-null  object
 11  region                 59400 non-null  object
 12  region_code            59400 non-null  int64
 13  district_code          59400 non-null  int64
 14  lga                    59400 non-null  object
 15  ward                   59400 non-null  object
 16  population             59400 non-null  int64
 17  public_meeting         56066 non-null  object
 18  recorded_by            59400 non-null  object
 19  scheme_management      55522 non-null  object
 20  scheme_name            30590 non-null  object
 21  permit                 56344 non-null  object
 22  construction_year      59400 non-null  int64
 23  extraction_type        59400 non-null  object
 24  extraction_type_group  59400 non-null  object
 25  extraction_type_class  59400 non-null  object
 26  management             59400 non-null  object
 27  management_group       59400 non-null  object
 28  payment                59400 non-null  object
 29  payment_type           59400 non-null  object
 30  water_quality          59400 non-null  object
 31  quality_group          59400 non-null  object
 32  quantity               59400 non-null  object
 33  quantity_group         59400 non-null  object
 34  source                 59400 non-null  object
 35  source_type            59400 non-null  object
 36  source_class           59400 non-null  object
 37  waterpoint_type        59400 non-null  object
 38  waterpoint_type_group  59400 non-null  object
 39  status_group           59400 non-null  object
dtypes: float64(3), int64(6), object(31)
memory usage: 18.6+ MB

# View Numerical Columns
numerical_columns = data.select_dtypes(include='number').columns

# View Categorical Columns
categorical_columns = data.select_dtypes(include='object').columns
```

The dataset contains 40 columns and 59,400 records. Here's a breakdown of the columns:

- **Numerical Columns (9)**
  - `amount_tsh`: Total static head (amount of water available)

  - `gps_height`: Altitude of the well
  - `longitude`: GPS coordinate (longitude)
  - `latitude`: GPS coordinate (latitude)
  - `num_private`: Unspecified numerical attribute
  - `region_code`: Geographic location code (region)
  - `district_code`: Geographic location code (district)
  - `population`: Population around the well
  - `construction_year`: Year the waterpoint was built
- **Categorical Columns (31)**
  - `date_recorded`: Date the data was recorded
  - `installer`: Organization that installed the well
  - `funder`: Organization that funded the well
  - `wpt_name`: Name of the waterpoint
  - `basin`: Geographic water basin
  - `subvillage`: Specific location within a village
  - `region`: Geographic region
  - `lga`: Local government area
  - `ward`: Administrative ward
  - `public_meeting`: Whether there was a public meeting about the well (True/False)
  - `recorded_by`: Group entering the data
  - `scheme_management`: Entity managing the waterpoint
  - `scheme_name`: Name of the waterpoint scheme
  - `permit`: Whether the waterpoint is permitted (True/False)
  - `extraction_type`: Method of water extraction
  - `extraction_type_group`: Group of water extraction methods
  - `extraction_type_class`: Class of water extraction methods
  - `management`: How the waterpoint is managed
  - `management_group`: Group of management methods
  - `payment`: Payment type for water
  - `payment_type`: Type of payment for water
  - `water_quality`: Quality of the water
  - `quality_group`: Grouped quality of the water
  - `quantity`: Quantity of water available
  - `quantity_group`: Grouped quantity of water available
  - `source`: Water source
  - `source_type`: Type of water source
  - `source_class`: Class of water source
  - `waterpoint_type`: Type of waterpoint
  - `waterpoint_type_group`: Grouped type of waterpoint
  - `status_group`: Condition of the wells (target variable)

```python
# Visualize missing data in the DataFrame

msno.bar(data, figsize=(20, 5), fontsize=10, color='deepskyblue')  #
Changing color to ocean blue
plt.title("Missing Data Visualization")
plt.xticks(rotation=90, fontsize=10)
plt.show()
```



While the dataset as a whole has relatively few missing values, the `scheme_name` column stands out with nearly half of its data missing.

```python
# viewing numerical data
data.describe()
```

```
          amount_tsh     gps_height      longitude      latitude  
num_private  \
count   59400.000000  59400.000000  59400.000000  5.940000e+04  
59400.000000
mean      317.650385    668.297239     34.077427 -5.706033e+00  
0.474141
std      2997.574558    693.116350      6.567432  2.946019e+00  
12.236230
min         0.000000    -90.000000      0.000000 -1.164944e+01  
0.000000
25%         0.000000      0.000000     33.090347 -8.540621e+00  
0.000000
50%         0.000000    369.000000     34.908743 -5.021597e+00  
0.000000
75%        20.000000   1319.250000     37.178387 -3.326156e+00  
0.000000
max    350000.000000   2770.000000     40.345193 -2.000000e-08  
1776.000000

        region_code  district_code     population  construction_year
```

```
count  59400.000000   59400.000000  59400.000000        59400.000000
mean      15.297003       5.629747    179.909983        1300.652475
std       17.587406       9.633649    471.482176         951.620547
min        1.000000       0.000000      0.000000           0.000000
25%        5.000000       2.000000      0.000000           0.000000
50%       12.000000       3.000000     25.000000        1986.000000
75%       17.000000       5.000000    215.000000        2004.000000
max       99.000000      80.000000  30500.000000        2013.000000
```

The descriptive statistics table provides insights into the numerical attributes of the dataset, including measures of central tendency, variability, and distribution, offering a comprehensive overview of the data's characteristics.

3. Data Preparation

> This phase, commonly known as "data wrangling", involves preparing the dataset(s) for modeling by performing tasks such as:

- Data selection
- Data cleaning
- Exploratory Data Analysis (EDA)

3.1 Data Selection

> In this section, the aim is to determine the columns from the dataset that will be utilized.

The evaluation will begin by assessing the similarity among the columns, as many of the 40 columns in the dataset appear to be related, before proceeding to evaluate the remaining columns.

3.1.1 `scheme_management` | `management` | `management_group`

Within the context of the project, the columns `scheme_management`, `management`, and `management_group` all relate to the management of the well. An examination of their value counts will be conducted to ascertain the similarity of the data.

```
def display_value_counts(data, columns):
    """
    Display value counts of specified columns in a DataFrame.

    Parameters:
    - data: DataFrame
        The DataFrame containing the data.
    - columns: list
        A list of column names for which value counts are to be
displayed.
    """
    for column in columns:
        print(f"Value counts for {column}:")
```

```
        print(data[column].value_counts())
        print("\n")

# Define columns to analyze
columns_to_analyze = ['scheme_management', 'management',
'management_group']

# Call display_value_counts function
display_value_counts(data, columns_to_analyze)
```

```
Value counts for scheme_management:
scheme_management
VWC                    36793
WUG                     5206
Water authority         3153
WUA                     2883
Water Board             2748
Parastatal              1680
Private operator        1063
Company                 1061
Other                    766
SWC                       97
Trust                     72
Name: count, dtype: int64


Value counts for management:
management
vwc                    40507
wug                     6515
water board             2933
wua                     2535
private operator        1971
parastatal              1768
water authority          904
other                    844
company                  685
unknown                  561
other - school            99
trust                     78
Name: count, dtype: int64


Value counts for management_group:
management_group
user-group    52490
commercial     3638
parastatal     1768
other           943
unknown         561
```

```
Name: count, dtype: int64
```

Considering the project's context, it's evident that `scheme_management` and `management` are closely associated, both concerning the management of wells. However, `management_group` seems unrelated to the other two columns and has fewer unique values.

Given the prevalence of missing values in `scheme_management` compared to `management`, it's more practical to utilize `management` for further analysis.

To explore the relationship between `management_group` and `management`, a groupby operation will be conducted on the pandas dataframe. This will help ascertain how different management groups correspond to various management types, providing valuable insights for the project.

```
# Create a duplicate DataFrame and drop scheme_management column
new_data = data.copy().drop(['scheme_management'], axis=1)

# Group by management_group column and management column
pd.DataFrame(new_data.groupby(['management_group',
'management']).size())
```

management_group	management	0
commercial	company	685
	private operator	1971
	trust	78
	water authority	904
other	other	844
	other - school	99
parastatal	parastatal	1768
unknown	unknown	561
user-group	vwc	40507
	water board	2933
	wua	2535
	wug	6515

Since the "management_group" column has fewer different types compared to the "management" column, we're dropping the "management" column to keep things simpler. This helps avoid making our analysis and predictions too complicated, making it easier to understand and work with the data. By doing this, we still keep the important information about how wells are managed, but without unnecessary details that could confuse things.

```
# Drop management column
new_data = new_data.drop(['management'], axis=1)
```

3.1.2 `extraction_type` | `extraction_type_group` | `extraction_type_class`

The columns `extraction_type`, `extraction_type_group`, and `extraction_type_class` all pertain to the type of extraction used. An assessment of their value counts will be conducted to determine the similarity of the data.

```python
# Define columns to analyze
columns_to_analyze = ['extraction_type', 'extraction_type_group',
'extraction_type_class']

# Call display_value_counts function
display_value_counts(data, columns_to_analyze)
```

```
Value counts for extraction_type:
extraction_type
gravity                      26780
nira/tanira                   8154
other                         6430
submersible                   4764
swn 80                        3670
mono                          2865
india mark ii                 2400
afridev                       1770
ksb                           1415
other - rope pump              451
other - swn 81                 229
windmill                       117
india mark iii                  98
cemo                            90
other - play pump               85
walimi                          48
climax                          32
other - mkulima/shinyanga        2
Name: count, dtype: int64


Value counts for extraction_type_group:
extraction_type_group
gravity            26780
nira/tanira         8154
other               6430
submersible         6179
swn 80              3670
mono                2865
india mark ii       2400
afridev             1770
rope pump            451
other handpump       364
other motorpump      122
wind-powered         117
```

```
india mark iii        98
Name: count, dtype: int64


Value counts for extraction_type_class:
extraction_type_class
gravity          26780
handpump         16456
other             6430
submersible       6179
motorpump         2987
rope pump          451
wind-powered       117
Name: count, dtype: int64
```

it's noticeable that the "extraction_type" and "extraction_type_group" columns share similarities, representing various extraction methods. However, the "extraction_type_class" column appears unrelated to the other two, containing fewer unique values. Within the project context, it's apparent that these three columns redundantly convey information about extraction methods. Hence, we'll conduct a groupby operation on all three columns to assess their relationships and decide on the most suitable approach for analysis

```
# Group by extraction_type, extraction_type_group, and
extraction_type_class
pd.DataFrame(new_data.groupby(['extraction_type_class',
'extraction_type_group', 'extraction_type']).size())
```

```
0
extraction_type_class extraction_type_group extraction_type

gravity               gravity               gravity
26780
handpump              afridev               afridev
1770
                      india mark ii         india mark ii
2400
                      india mark iii        india mark iii
98
                      nira/tanira           nira/tanira
8154
                      other handpump        other - mkulima/shinyanga
2
                                            other - play pump
85
                                            other - swn 81
229
                                            walimi
```

```
48
                      swn 80                 swn 80
3670
motorpump             mono                   mono
2865
                      other motorpump        cemo
90
                                             climax
32
other                 other                  other
6430
rope pump             rope pump              other - rope pump
451
submersible           submersible            ksb
1415
                                             submersible
4764
wind-powered          wind-powered           windmill
117
```

Given the analysis conducted, it's evident that the "extraction_type_group" column provides a more detailed classification of extraction methods compared to the "extraction_type_class" column. Additionally, "extraction_type_group" contains fewer unique values than the "extraction_type" column. Therefore, within the project's context, opting to utilize the "extraction_type_group" column allows for a balance between addressing the curse of dimensionality and retaining relevant information. This decision is informed by the need to streamline the dataset while preserving essential details about extraction methods.

```python
# Drop extraction_type_class and extraction_type columns
new_data = new_data.drop(['extraction_type_class', 'extraction_type'],
axis=1)
```

3.1.3 `payment` | `payment_type`

The columns `payment` and `payment_type` both relate to monetary transactions. An examination of their value counts will be conducted to assess the similarity of data.

```python
# define columns to analyze
columns_to_analyze = ['payment', 'payment_type']

# Call display_value_counts function
display_value_counts(data,columns_to_analyze )
```

```
Value counts for payment:
payment
never pay                25348
pay per bucket            8985
pay monthly               8300
unknown                   8157
```

```
pay when scheme fails      3914
pay annually               3642
other                      1054
Name: count, dtype: int64


Value counts for payment_type:
payment_type
never pay     25348
per bucket     8985
monthly        8300
unknown        8157
on failure     3914
annually       3642
other          1054
Name: count, dtype: int64
```

Since the `payment` and `payment_type` columns exhibit a perfect relationship, we'll remove the `payment` column as it contains more verbose information compared to the `payment_type` column.

```
# Drop payment column
new_data = new_data.drop(['payment'], axis=1)
```

3.1.4 `water_quality` | `quality_group`

The `water_quality` and `quality_group` columns both pertain to the quality of water from the well. We will assess their value counts to determine the similarity of data.

```
# Define columns to analyze
columns_to_analyze = ['water_quality', 'quality_group']

# Call display_value_counts function
display_value_counts(data, columns_to_analyze)
```

```
Value counts for water_quality:
water_quality
soft                  50818
salty                  4856
unknown                1876
milky                   804
coloured                490
salty abandoned         339
fluoride                200
fluoride abandoned       17
Name: count, dtype: int64
```

```
Value counts for quality_group:
quality_group
good        50818
salty        5195
unknown      1876
milky         804
colored       490
fluoride      217
Name: count, dtype: int64
```

Given that the `water_quality` column has slightly more unique values compared to the `quality_group` column, though the disparity is not significant, we will drop the `quality_group` column due to its lower informational content.

```
# Drop the quantity_group column
new_data = new_data.drop(['quantity_group'], axis=1)
```

3.1.6 `source` | `source_type` | `source_class`

The columns `source`, `source_type`, and `source_class` all pertain to the source of water from the well. We will assess their value counts to determine the similarity of data.

```
# Define columns to analyze
columns_to_analyze = ['source', 'source_type', 'source_class']

# Call display_value_counts function
display_value_counts(data, columns_to_analyze)
```

```
Value counts for source:
source
spring                  17021
shallow well            16824
machine dbh             11075
river                    9612
rainwater harvesting     2295
hand dtw                  874
lake                      765
dam                       656
other                     212
unknown                    66
Name: count, dtype: int64


Value counts for source_type:
source_type
spring                  17021
```

```
shallow well            16824
borehole                11949
river/lake              10377
rainwater harvesting     2295
dam                       656
other                     278
Name: count, dtype: int64


Value counts for source_class:
source_class
groundwater    45794
surface        13328
unknown          278
Name: count, dtype: int64
```

Upon reviewing the value counts, we observe that the `source` column exhibits a greater diversity of unique values compared to the `source_type` column, and likewise, the `source_type` column contains more unique values than the `source_class` column. In the context of the project, we opt for the `source_type` column as it strikes a balance between reducing dimensionality and retaining relevant information. This choice is driven by the fact that the `source_type` column offers more detailed information than the `source_class` column while also presenting fewer unique values than the `source` column, thus aiding in simplifying the dataset without significant loss of information.

```
# Drop'source' and 'source_class' columns
new_data = new_data.drop(['source', 'source_class'], axis=1)
```

3.1.7 `waterpoint_type` | `waterpoint_type_group`

The `waterpoint_type` and `waterpoint_type_group` are both related columns that talk about the type of the waterpoint. We shall begin by evaluating their value counts in order to check the similarity of data.

```
# Define the columns to analyze
columns_to_analyze = ['waterpoint_type', 'waterpoint_type_group']

# Call the display_value_counts function
display_value_counts(data, columns_to_analyze)
```

```
Value counts for waterpoint_type:
waterpoint_type
communal standpipe             28522
hand pump                      17488
other                           6380
communal standpipe multiple     6103
improved spring                  784
```

```
cattle trough                         116
dam                                     7
Name: count, dtype: int64


Value counts for waterpoint_type_group:
waterpoint_type_group
communal standpipe    34625
hand pump             17488
other                  6380
improved spring         784
cattle trough           116
dam                       7
Name: count, dtype: int64
```

Upon examining the value counts, it's evident that the `waterpoint_type` column encompasses a greater variety of unique values compared to the `waterpoint_type_group` column. In the context of the project, we opt to retain the `waterpoint_type` column due to its richer granularity of information compared to the `waterpoint_type_group` column. This decision is guided by the need to preserve detailed insights about waterpoint types while maintaining a manageable dataset.

```
# Drop waterpoint_type_group column
new_data = new_data.drop(['waterpoint_type_group'], axis=1)
```

3.1.8 Dropping Unnecessary Columns |

```
def drop_columns_and_print_reason(data, columns):
    """
    Drop specified columns from a DataFrame and print a message
indicating the reason for dropping.

    Parameters:
    - data: DataFrame
        The DataFrame containing the data.
    - columns: list
        A list of column names to be dropped.
    """
    data.drop(columns=columns, axis=1, inplace=True)
    for column in columns:
        print(f"Dropped column '{column}' because it did not add any
value to our analysis.")

columns_to_drop = ['longitude', 'latitude', 'wpt_name', 'num_private',

                   'region_code', 'district_code', 'public_meeting',
                   'recorded_by', 'scheme_name']
```

```
drop_columns_and_print_reason(new_data, columns_to_drop)
```

```
Dropped column 'longitude' because it did not add any value to our analysis.
Dropped column 'latitude' because it did not add any value to our analysis.
Dropped column 'wpt_name' because it did not add any value to our analysis.
Dropped column 'num_private' because it did not add any value to our analysis.
Dropped column 'region_code' because it did not add any value to our analysis.
Dropped column 'district_code' because it did not add any value to our analysis.
Dropped column 'public_meeting' because it did not add any value to our analysis.
Dropped column 'recorded_by' because it did not add any value to our analysis.
Dropped column 'scheme_name' because it did not add any value to our analysis.
```

We have now finalized the selection of columns for our analysis. We will proceed to clean the data using the following columns:

Numerical Columns:

- `gps_height`
- `population`
- `amount_tsh`
- `date_recorded`
- `construction_year`

Categorical Columns:

- `funder`
- `installer`
- `basin`
- `subvillage`
- `region`
- `lga`
- `ward`
- `scheme_management`
- `permit`
- `extraction_type_group`
- `payment_type`
- `management_group`
- `water_quality`

- `quantity`
- `source_type`
- `waterpoint_type`
- `status_group`

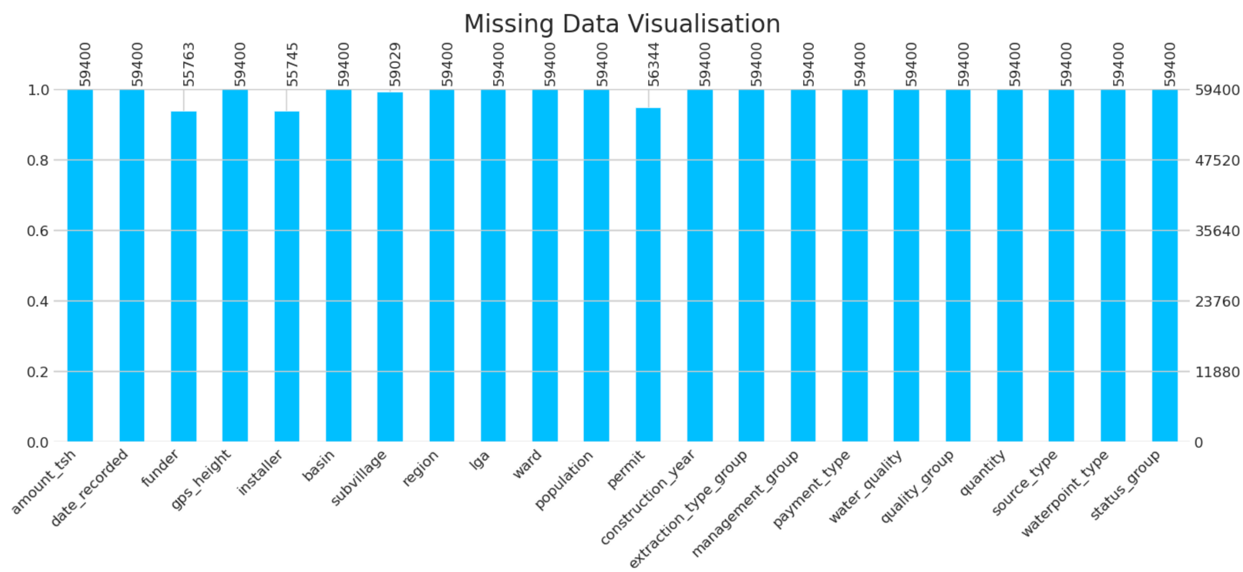
3.2 Data Cleaning

In this phase, we will address missing values and identify duplicate records within the dataset.

3.2.1 visualizing the new Data set

In this section, we will be looking at the missing values in the dataset.

```
msno.bar(new_data, figsize=(15, 5), color='deepskyblue', fontsize=12)
# Changing color to ocean blue
plt.title("Missing Data Visualisation")
plt.xticks(rotation=90)
plt.show()
```



Based on the visualization above, the following columns contain missing data:

- `funder`
- `installer`
- `subvillage`
- `permit`

```
print(new_data.columns)

Index(['amount_tsh', 'date_recorded', 'funder', 'gps_height',
'installer',
       'basin', 'subvillage', 'region', 'lga', 'ward', 'population',
'permit',
       'construction_year', 'extraction_type_group',
```

```
'management_group',
       'payment_type', 'water_quality', 'quality_group', 'quantity',
       'source_type', 'waterpoint_type', 'status_group'],
      dtype='object')
```

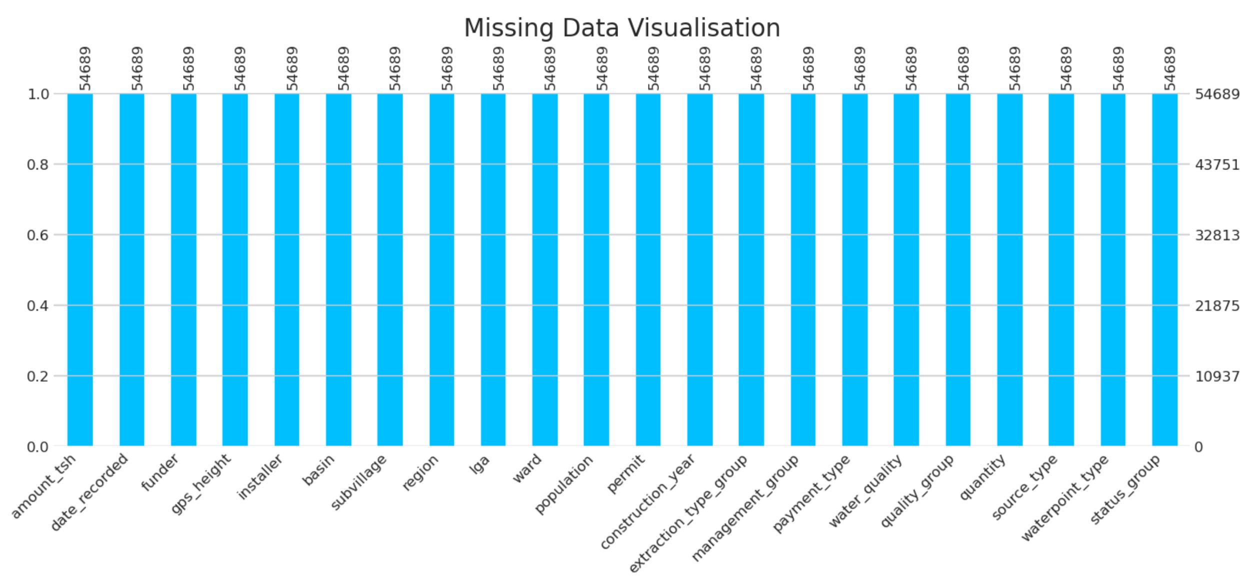
```
def missing_values_summary(data, columns=None):
    """
    Calculate the total missing values and their percentages for
specified columns in the DataFrame.

    Parameters:
    - data: DataFrame
        The DataFrame containing the data.
    - columns: list or None, optional (default=None)
        A list of columns to include in the summary. If None, all
columns will be included.

    Returns:
    - summary: DataFrame
        A DataFrame summarizing the total missing values and their
percentages for specified columns.
    """
    if columns is None:
        columns = data.columns
    total_missing = data[columns].isnull().sum()
    percent_missing = (total_missing / len(data)) * 100
    summary = pd.DataFrame({
        'Total Missing': total_missing,
        'Percentage Missing': percent_missing
    })
    summary = summary[summary['Total Missing'] > 0]  # Exclude columns
with no missing values
    return summary

missing_values_summary(new_data, columns=['funder', 'installer',
'subvillage', 'permit'])
```

```
            Total Missing  Percentage Missing
funder               3637            6.122896
installer            3655            6.153199
subvillage            371            0.624579
permit               3056            5.144781
```

3.2.1.1 Dropping Missing Values

```
def drop_columns_below_threshold(data, columns, threshold=7):
    """
    Drop rows from DataFrame if their missing percentage is below the
specified threshold.

    Parameters:
```

```
    - data: DataFrame
        DataFrame containing the data.
    - columns: list
        A list of column names to be evaluated for dropping.
    - threshold: float, optional (default=7)
        threshold below which rows will be dropped.

    Returns:
    - data: DataFrame
        DataFrame with rows dropped if their missing percentage is
below the threshold.
    """
    for column in columns:
        missing_percentage = (data[column].isnull().sum() / len(data))
* 100
        if missing_percentage < threshold:
            data = data[data[column].notna()]
    return data

# List of columns to evaluate
columns_to_evaluate = ['funder', 'installer', 'subvillage', 'permit']

# Drop columns if their missing percentage is below the threshold
new_data = drop_columns_below_threshold(new_data, columns_to_evaluate)



# Visualize the missing values in the new dataset
msno.bar(new_data, figsize=(15, 5), color='deepskyblue', fontsize=12)
# Changing color to ocean blue
plt.title("Missing Data Visualisation")
plt.xticks(rotation=90)
plt.show()
```



3.2.2 Check for Duplicates and Outliers

```
# Check for duplicated records
new_data[new_data.duplicated()]
```

```
       amount_tsh date_recorded                  funder  gps_height  \
id
59310         0.0    2011-07-18  Government Of Tanzania           0
2296          0.0    2011-07-31            Kkkt_makwale           0
53399         0.0    2011-07-23                  Danida           0
2859          0.0    2011-07-31            Kkkt_makwale           0
70330         0.0    2011-04-12               Rc Church           0
...           ...           ...                     ...         ...
16666         0.0    2011-07-26                      Md           0
5064          0.0    2011-07-12                  Hesawa           0
47527         0.0    2011-04-12               Rc Church           0
58255         0.0    2011-07-13                      Do           0
40607         0.0    2011-04-15  Government Of Tanzania           0

                 installer          basin subvillage  region
lga  \
id

59310           Government  Lake Victoria     Nyanza  Mwanza
Geita
2296   KKKT _ Konde and DWE     Lake Nyasa     Isimba   Mbeya
Kyela
53399    Central government     Lake Nyasa    Malungo   Mbeya
Kyela
2859   KKKT _ Konde and DWE     Lake Nyasa     Isimba   Mbeya
Kyela
70330            RC Church     Lake Nyasa  Matwalani   Mbeya   Mbeya
Rural
...                    ...            ...        ...     ...
...
16666                   DW  Lake Victoria  Kishoju 1  Kagera
Muleba
5064                HESAWA  Lake Victoria   Mishenye  Kagera  Bukoba
Rural
47527            RC Church     Lake Nyasa   Mjimwema   Mbeya   Mbeya
Rural
58255                   DO  Lake Victoria  Kaluyango  Kagera
Muleba
40607           Government     Lake Rukwa  Mbuyuni A   Mbeya
Chunya

              ward  population permit  construction_year  \
id
59310  Kalangalala           0   True                  0
2296       Makwale           0   True                  0
53399        Mwaya           0   True                  0
```

```
2859       Makwale          0   True                 0
70330       Ulenje          0  False                 0
...            ...        ...    ...               ...
16666      Nshamba          0   True                 0
5064   Buterankuzi          0   True                 0
47527       Ulenje          0  False                 0
58255       Ikondo          0   True                 0
40607      Mbuyuni          0   True                 0

      extraction_type_group management_group payment_type
water_quality  \
id

59310           submersible       user-group    never pay
soft
2296                gravity       user-group    never pay
soft
53399               gravity       user-group    never pay
soft
2859                gravity       user-group    never pay
soft
70330               gravity       user-group   on failure
soft
...                     ...              ...          ...            ..
.
16666           submersible       user-group    never pay
soft
5064                gravity       user-group      monthly
soft
47527               gravity       user-group   on failure
soft
58255               gravity       user-group    never pay
soft
40607               gravity       user-group    never pay
soft

      quality_group      quantity source_type     waterpoint_type  \
id
59310          good  insufficient    borehole  communal standpipe
2296           good        enough      spring  communal standpipe
53399          good           dry      spring  communal standpipe
2859           good        enough      spring  communal standpipe
70330          good        enough  river/lake  communal standpipe
...             ...           ...         ...                 ...
16666          good        enough      spring  communal standpipe
5064           good        enough  river/lake  communal standpipe
47527          good        enough  river/lake  communal standpipe
58255          good        enough      spring  communal standpipe
40607          good        enough      spring  communal standpipe
```

```
          status_group
id
59310       functional
2296        functional
53399   non functional
2859        functional
70330   non functional
...                ...
16666   non functional
5064        functional
47527       functional
58255       functional
40607   non functional

[2617 rows x 22 columns]
```

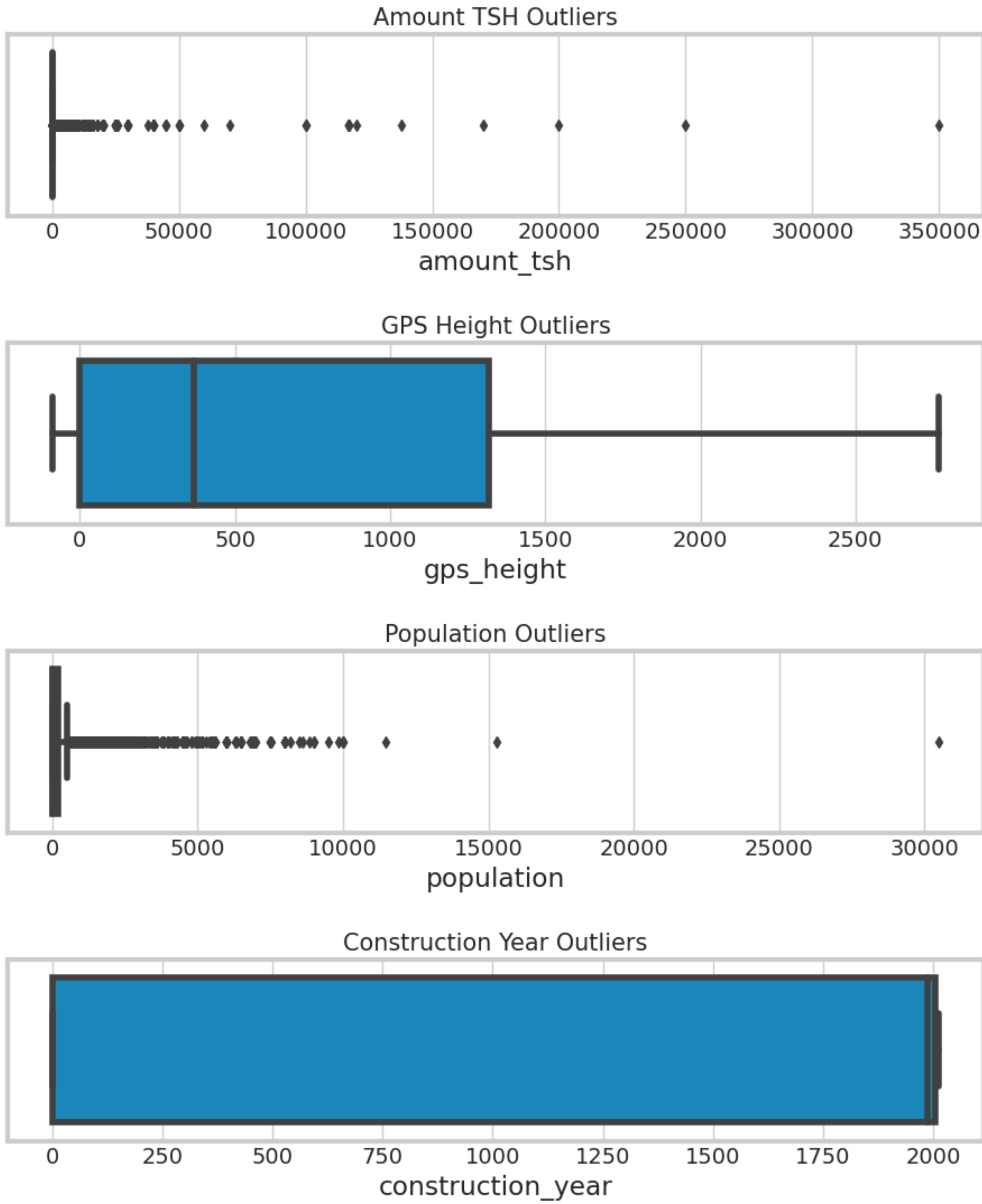
The presence of duplicated records in our dataset doesn't imply inaccuracies in the data. Rather, it suggests that multiple wells were constructed as part of the same project, resulting in identical features across these records.

3.2.2.1 Outliers

We'll address outliers in the numerical columns relevant to our project, including:

- `amount_tsh`
- `gps_height`
- `population`
- `construction_year`

```
# Function to visualize outliers as a box plot.
def visualize_outliers(df, col, title):
    """
    This function visualizes the outliers and outputs boxplots
    """
    plt.figure(figsize=(10, 2))
    sns.boxplot(x=col, data=df)
    plt.title(title, fontsize=15)
    plt.show()

visualize_outliers(data, 'amount_tsh', 'Amount TSH Outliers')
visualize_outliers(data, 'gps_height', 'GPS Height Outliers')
visualize_outliers(data, 'population', 'Population Outliers')
visualize_outliers(data, 'construction_year', 'Construction Year
Outliers')
```



In the boxplot of the total static head column, we observe outliers, but these values do not necessarily indicate erroneous data, as a total static head of even 250,000 is possible. Similarly, although the majority of data is clustered around 0, further investigation is needed to understand this distribution in univariate analysis.

Regarding the gps_height column, no outliers are present, indicating no need for outlier treatment.

In the population column, outliers exist, yet they do not signify erroneous data, as populations of up to 30,000 near a well are plausible. This variable's values are region-dependent.

Concerning the construction year column, no outliers are evident. However, some nonsensical years may indicate data errors, warranting further investigation in univariate analysis. Overall, no outlier treatment is necessary for the construction year column.

3.2.3 Uniformity

In this section, we will be looking at the uniformity of the data. Uniformity refers to the consistency of the data with respect to the formatting, labelling. We will be looking at the following:

- Labelling
- Formatting

```
# function to rename columns
def rename_columns(df, col):
    """
    This function re-formats the column names to ensure that they are
all in lower case and contain no spaces
    """
    new_col = col.strip().replace(' ', '_').lower()

    df.rename(columns = {col: new_col}, inplace = True)

    # Loop through all column names and reformat
for col in new_data.columns:
    rename_columns(new_data, col)

new_data.columns

Index(['amount_tsh', 'date_recorded', 'funder', 'gps_height',
'installer',
       'basin', 'subvillage', 'region', 'lga', 'ward', 'population',
'permit',
       'construction_year', 'extraction_type_group',
'management_group',
       'payment_type', 'water_quality', 'quality_group', 'quantity',
       'source_type', 'waterpoint_type', 'status_group'],
      dtype='object')

# Rename 'lga' column to 'local_government_area'
new_data.rename(columns = {'lga': 'local_government_area'}, inplace =
True)

new_data.columns

Index(['amount_tsh', 'date_recorded', 'funder', 'gps_height',
'installer',
```

```
       'basin', 'subvillage', 'region', 'local_government_area',
'ward',
       'population', 'permit', 'construction_year',
'extraction_type_group',
       'management_group', 'payment_type', 'water_quality',
'quality_group',
       'quantity', 'source_type', 'waterpoint_type', 'status_group'],
      dtype='object')
```

3.2.3.2 Formatting

```
# function to to convert the columns to the appropriate data types
def convert_to_category(df, col):
    """
    This function converts the object categories to category data type
    """
    df[col] = df[col].astype('category')

# for loop to convert the object categoris to a category datatype
for col in new_data.select_dtypes(include='object').columns:
    convert_to_category(new_data, col)


import numpy as np

# Replace "0" values in the 'construction_year' column with NaN
new_data['construction_year'] =
new_data['construction_year'].replace(0, np.nan)

# Convert the 'construction_year' column to datetime format
new_data['construction_year'] =
pd.to_datetime(new_data['construction_year'], format='%Y')
```

3.2.4 Data Consistency Check

This section focuses on assessing the consistency of the data.

We'll examine the consistency of the following columns:

- `installer`
- `subvillage`

```
def check_installer_consistency(data):
    """
    Check the consistency of the 'installer' column in the dataset.

    Parameters:
    data (DataFrame): The dataset containing the 'installer' column.

    Returns:
    list: A list of unique values in the 'installer' column.
```

```
    """
    unique_installers = data['installer'].unique()
    return unique_installers

print(new_data.columns)
```

```
Index(['amount_tsh', 'date_recorded', 'funder', 'gps_height',
'installer',
       'basin', 'subvillage', 'region', 'local_government_area',
'ward',
       'population', 'permit', 'construction_year',
'extraction_type_group',
       'management_group', 'payment_type', 'water_quality',
'quality_group',
       'quantity', 'source_type', 'waterpoint_type', 'status_group'],
      dtype='object')
```

```
# Call the function to check consistency in the 'installer' column
installer_consistency = check_installer_consistency(new_data)
print(installer_consistency)
```

```
['Roman', 'GRUMETI', 'World vision', 'UNICEF', 'Artisan', ...,
'DWE/Anglican church', 'VIFAI', 'Dina', 'brown', 'SELEPTA']
Length: 2040
Categories (2040, object): ['-', '0', 'A.D.B', 'AAR', ..., 'wizara ya
maji', 'world', 'world banks', 'world vision']
```

```
# From the most common 100 value counts we realized some spelling
mistakes or different syntax between same categories

# Replacing the spelling mistakes and collect same categories in same
name

new_data['installer'].replace(to_replace = ('District Water
Department', 'District water depar','Distric Water Department'),
                        value ='District water department' ,
inplace=True)

new_data['installer'].replace(to_replace = ('FinW','Fini water','FINI
WATER'), value ='Fini Water' , inplace=True)
new_data['installer'].replace(to_replace = 'JAICA', value ='Jaica' ,
inplace=True)

new_data['installer'].replace(to_replace = ('COUN', 'District
COUNCIL', 'DISTRICT COUNCIL','District Counci',
                                  'District
Council','Council','Counc','District  Council','Distri'),
                                 value ='District council' ,
inplace=True)
new_data
new_data['installer'].replace(to_replace = ('RC CHURCH', 'RC Churc',
```

```
'RC','RC Ch','RC C', 'RC CH','RC church',
                                   'RC CATHORIC',) , value ='RC
Church' , inplace=True)

new_data['installer'].replace(to_replace = ('Central
Government','Tanzania Government',
                                    'central government','Cental
Government', 'Cebtral Government',
                                  'Tanzanian Government','Tanzania
government', 'Centra Government' ,
                                    'CENTRAL GOVERNMENT', 'TANZANIAN
GOVERNMENT','Central govt', 'Centr',
                                    'Centra govt') , value ='Central
government' , inplace=True)

new_data['installer'].replace(to_replace = ('World vision', 'World
Division','World Vision'),
                                      value ='world vision' ,
inplace=True)

new_data['installer'].replace(to_replace = ('Unisef','UNICEF'),value
='Unicef' , inplace=True)
new_data['installer'].replace(to_replace = 'DANID', value ='DANIDA' ,
inplace=True)

new_data['installer'].replace(to_replace = ('villigers', 'villager',
'Villagers', 'Villa', 'Village', 'Villi',
                                    'Village Council','Village
Counil', 'Villages', 'Vill', 'Village community',
                                    'Villaers', 'Village Community',
'Villag','Villege Council', 'Village council',
                                    'Village  Council','Villagerd',
'Villager', 'Village Technician',
                                    'Village Office','Village
community members'),
                                     value ='villagers' ,
inplace=True)

new_data['installer'].replace(to_replace
=('Commu','Communit','commu','COMMU', 'COMMUNITY') ,
                                      value ='Community' ,
inplace=True)
new_data['installer'].replace(to_replace = ('GOVERNMENT', 'GOVER',
'GOVERNME', 'GOVERM','GOVERN','Gover','Gove',
                                      'Governme','Governmen' ) ,value
='Government' , inplace=True)

new_data['installer'].replace(to_replace = 'Hesawa' ,value ='HESAWA' ,
inplace=True)
```

```python
# continue to replacing spellin mistakes and getting together values
new_data['installer'].replace(to_replace = ('Colonial Government') , 
value ='Colonial government' , inplace=True)
new_data['installer'].replace(to_replace = ('Government of Misri') , 
value ='Misri Government' , inplace=True)
new_data['installer'].replace(to_replace = ('Italy government') , 
value ='Italian government' , inplace=True)
new_data['installer'].replace(to_replace = ('British colonial 
government') , value ='British government' , inplace=True)
new_data['installer'].replace(to_replace = ('Concern /government') , 
value ='Concern/Government' , inplace=True)
new_data['installer'].replace(to_replace = ('Village Government') , 
value ='Village government' , inplace=True)
new_data['installer'].replace(to_replace = ('Government and 
Community') , value ='Government /Community' , inplace=True)
new_data['installer'].replace(to_replace = ('Cetral government /RC') , 
value ='RC church/Central Gover' , inplace=True)
new_data['installer'].replace(to_replace = ('Government 
/TCRS','Government/TCRS') , value ='TCRS /Government' , inplace=True)
new_data['installer'].replace(to_replace = ('ADRA /Government') , 
value ='ADRA/Government' , inplace=True)

# Sub village

# Drop data that is less than 3 characters and more than 20 characters
new_data.drop(new_data[new_data['subvillage'].str.len() < 3].index, 
axis=0, inplace=True)

new_data[new_data['subvillage'].str.len() < 3]
```

```
Empty DataFrame
Columns: [amount_tsh, date_recorded, funder, gps_height, installer, 
basin, subvillage, region, local_government_area, ward, population, 
permit, construction_year, extraction_type_group, management_group, 
payment_type, water_quality, quality_group, quantity, source_type, 
waterpoint_type, status_group]
Index: []
```

```python
new_data.to_csv('wells_cleaned_data.csv', index=False)
```

3.3 Exploratory Data Analysis

This section involves exploring the columns in the dataset. We will conduct:

- Univariate Analysis
- Bivariate Analysis
- Multivariate Analysis

3.4.1 Univariate Analysis

This section focuses on exploring individual columns in the dataset to analyze their distributions and gather insights. We'll divide this analysis into two main parts:

- Categorical Columns Examination
- Numerical Columns Examination

```
categorical_columns = new_data.select_dtypes(include='object').columns
categorical_columns
```

```
Index([], dtype='object')
```

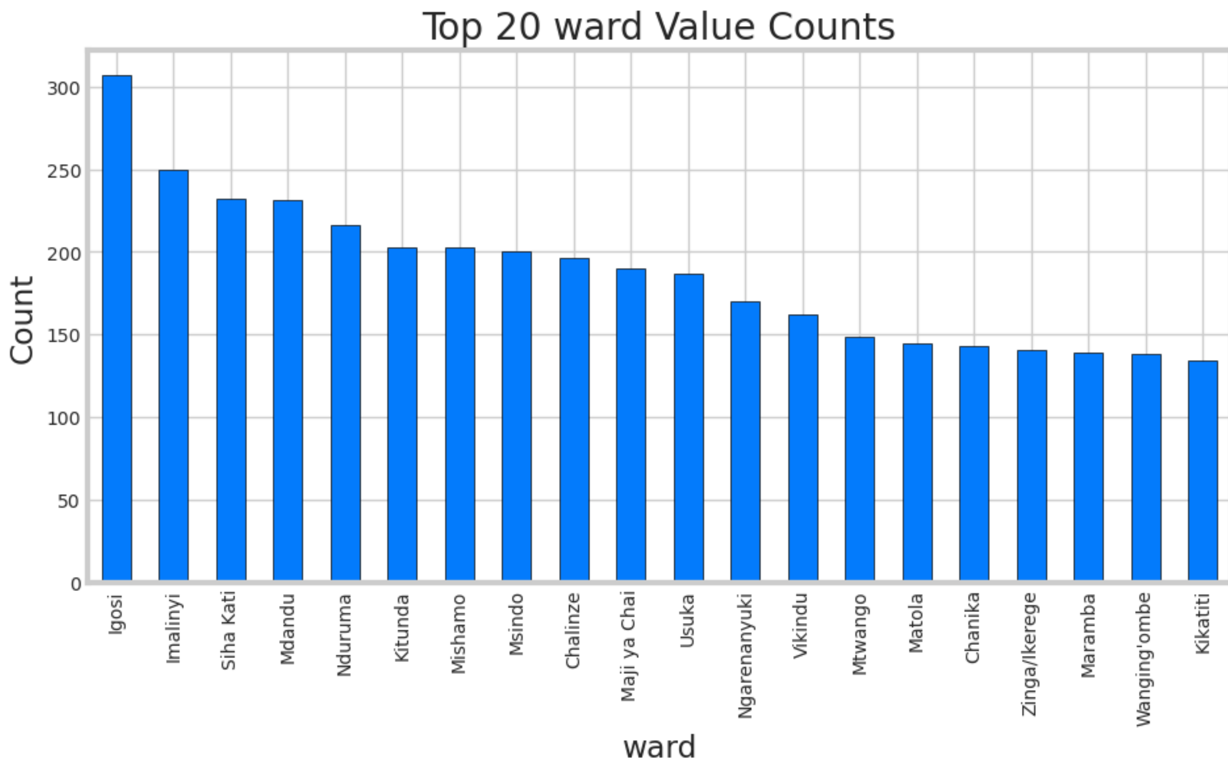
```
numerical_columns = new_data.select_dtypes(include='number').columns
numerical_columns
```

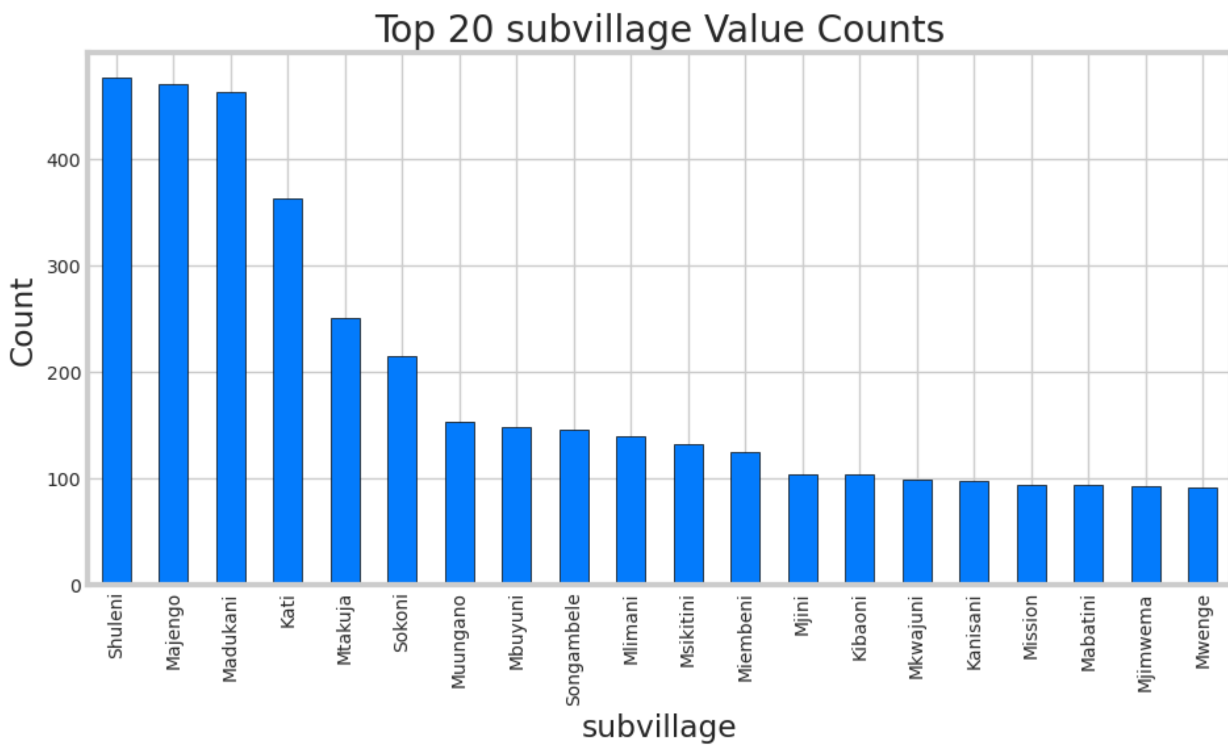
```
Index(['amount_tsh', 'gps_height', 'population'], dtype='object')
```

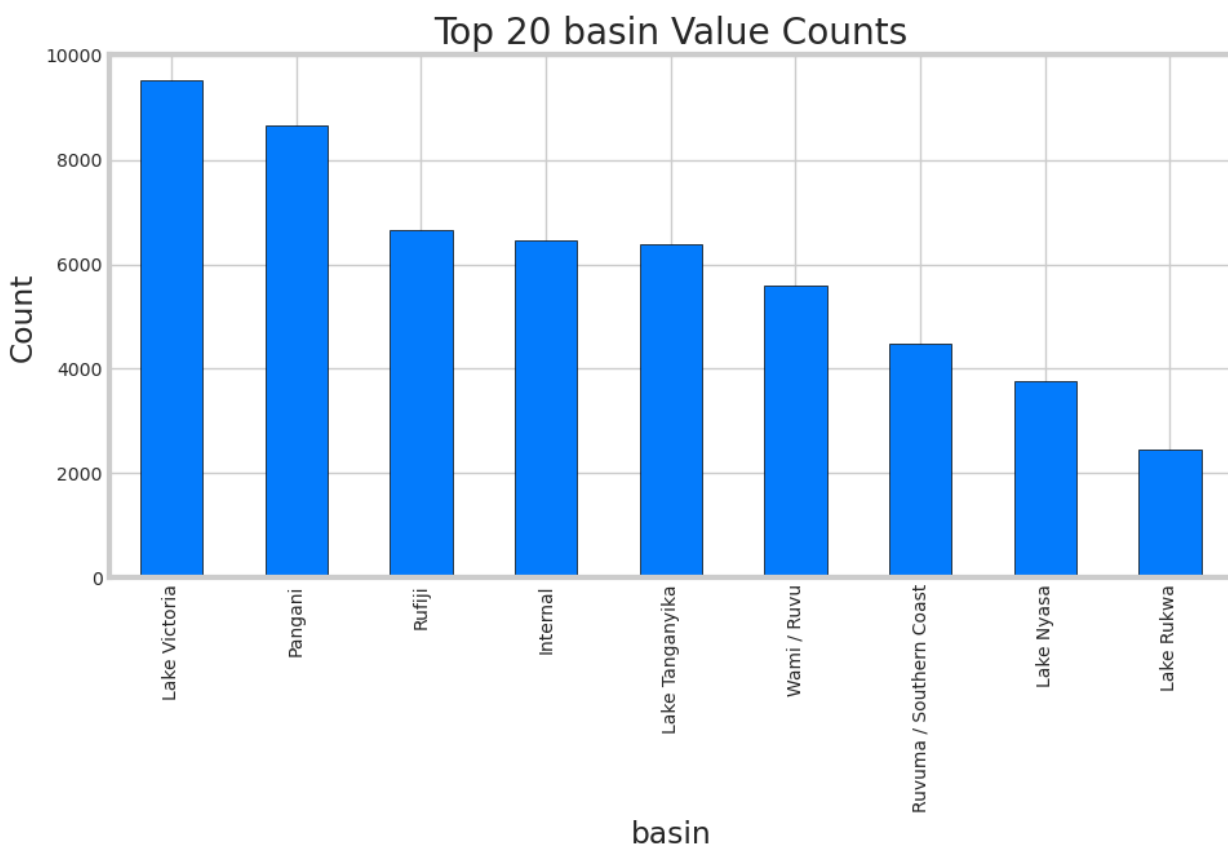
Function to Both plot and get value counts of a column

```
import matplotlib.pyplot as plt

def get_value_counts(df, col):
    '''
    Returns the value counts of a column in a dataframe including NaN
values, sorted in descending order.

    Parameters:
        df (DataFrame): The DataFrame containing the data.
        col (str): The name of the column for which value counts are
calculated.

    Returns:
        counts (Series): The value counts of the specified column.
    '''
    counts = df[col].value_counts(dropna=False)
    return counts

def plot_data(df, col, title):
    '''
    Plots the top 20 value counts of a column in a dataframe as a bar
chart and provides a description of the plot.

    Parameters:
        df (DataFrame): The DataFrame containing the data.
        col (str): The name of the column to be visualized.
        title (str): The title of the plot.
    '''
    top_20_counts = get_value_counts(df, col).head(20)
    plt.figure(figsize=(10, 5))
    top_20_counts.plot(kind='bar', color='#037bfc', edgecolor='black',
fontsize=10)
```

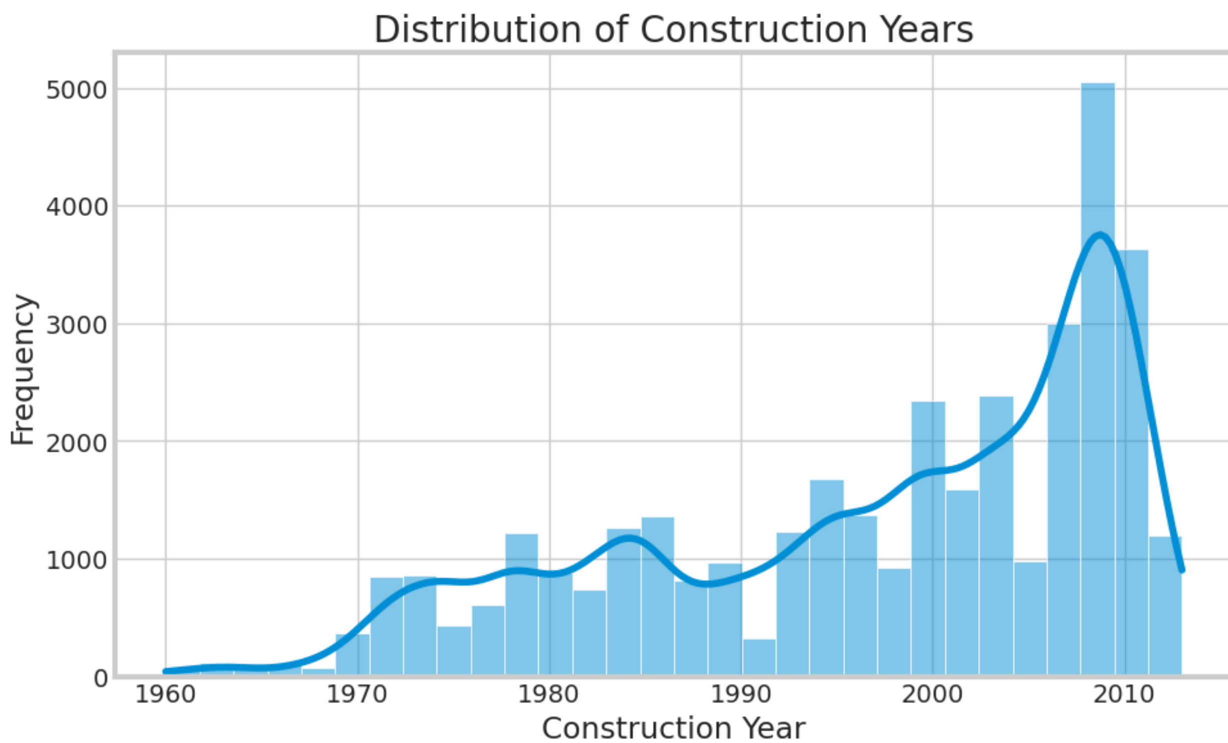
```
    plt.title(title)
    plt.xlabel(col)
    plt.ylabel('Count')
    plt.xticks(rotation=90)
    plt.show()

columns_to_plot = [ 'ward','subvillage',
                   'basin',]

for col in columns_to_plot:
    plot_data(new_data, col, f'Top 20 {col} Value Counts')
```




Top 20 subvillage Value Counts
Count
0
100
200
300
400
Shuleni
Majengo
Madukani
Kati
Mtakuja
Sokoni
Muungano
Mbuyuni
Songambele
Mlimani
Msikitini
Miembeni
Mjini
Kibaoni
Mkwajuni
Kanisani
Mission
Mabatini
Mjimwema
Mwenge
subvillage


Top 20 basin Value Counts
Count
0
2000
4000
6000
8000
10000
Lake Victoria
Pangani
Rufiji
Internal
Lake Tanganyika
Wami / Ruvu
Ruvuma / Southern Coast
Lake Nyasa
Lake Rukwa
basin

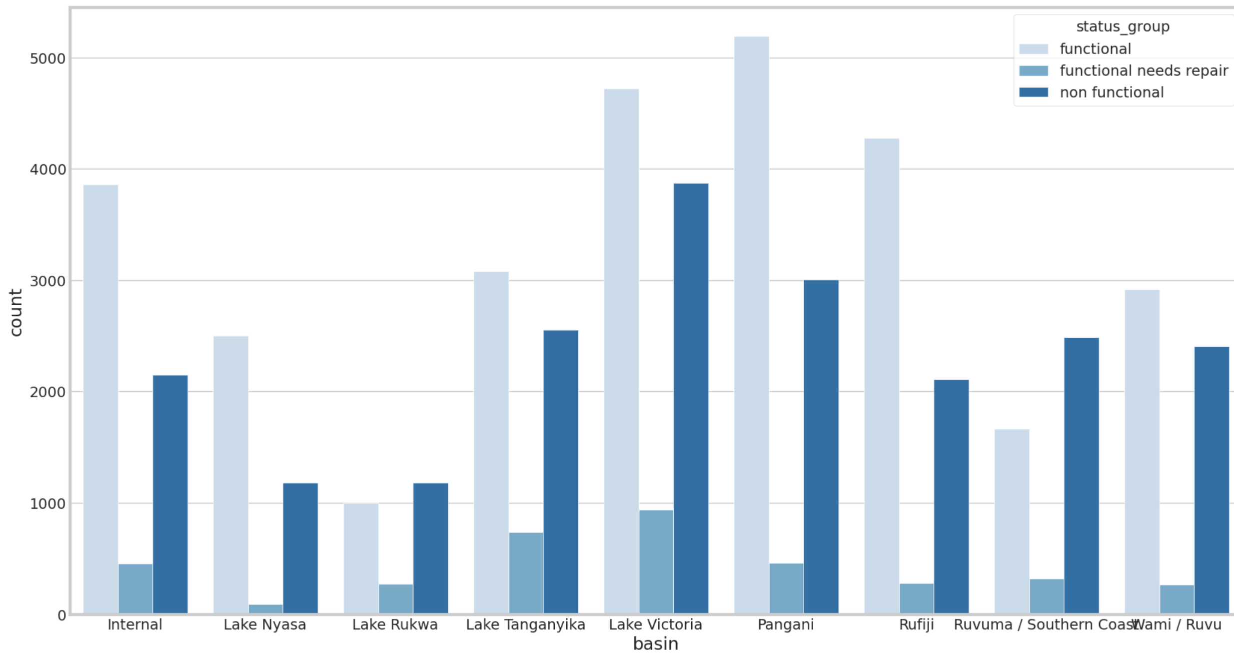
```
# Histogram for construction_year
plt.figure(figsize=(10, 6))
sns.histplot(data=new_data, x='construction_year', bins=30, kde=True)
plt.title('Distribution of Construction Years')
plt.xlabel('Construction Year')
plt.ylabel('Frequency')
plt.show()
```



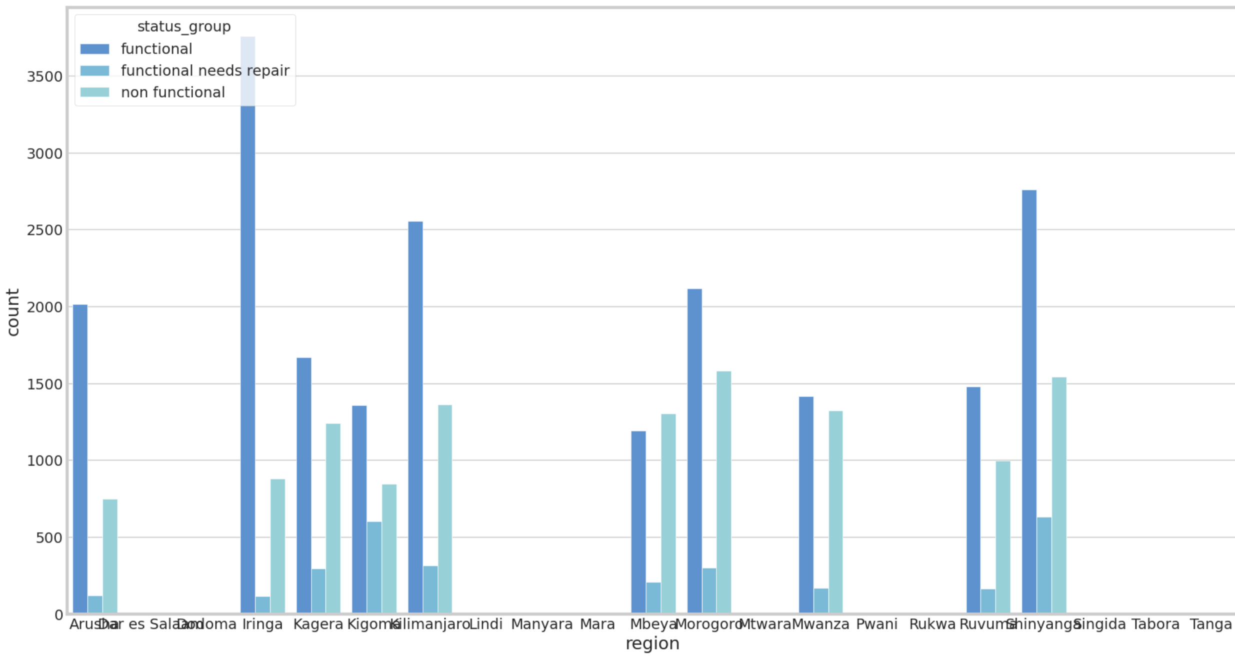
3.4.1.2 Analysis of Numerical Columns

In this subsection, we will focus on the analysis of the dataset's numerical columns. There are a total of four numerical columns, and we will conduct univariate analysis on each of them individually.

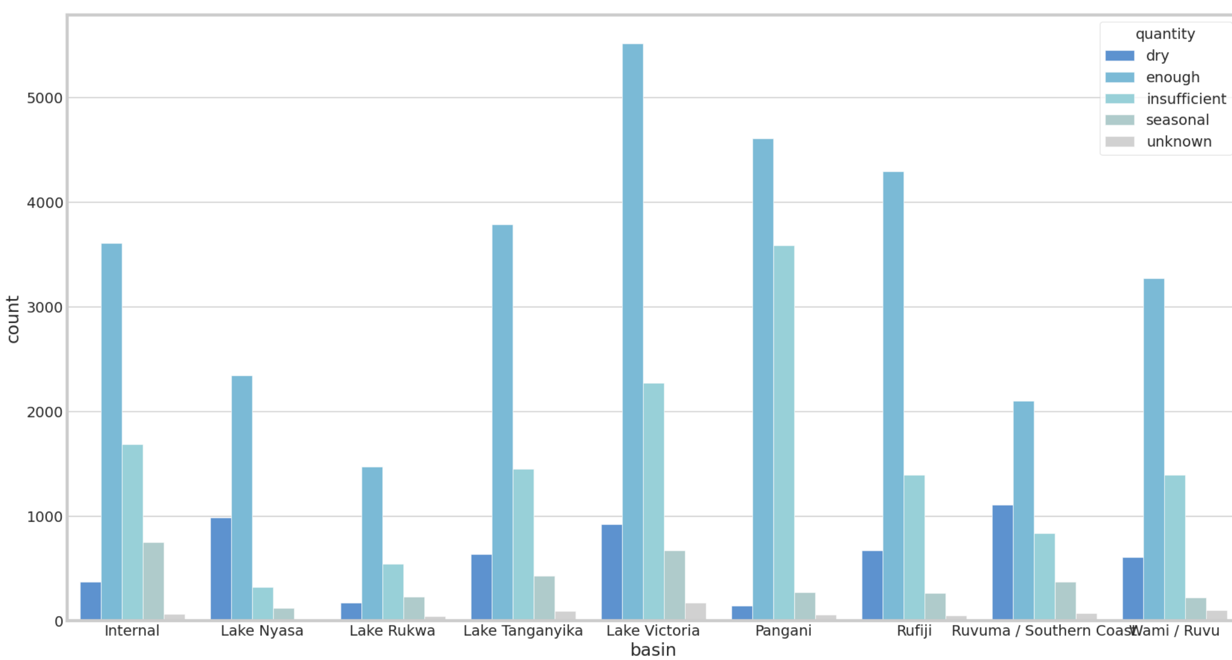
```
## Comparing basin and funcionality of wells columns
plt.figure(figsize=(18,10))
blue_palette = sns.color_palette("Blues", n_colors=3)  # Using 'Blues'
palette with 3 different shades of blue
ax = sns.countplot(x='basin', hue="status_group", data=new_data,
palette=blue_palette)
plt.show()
```



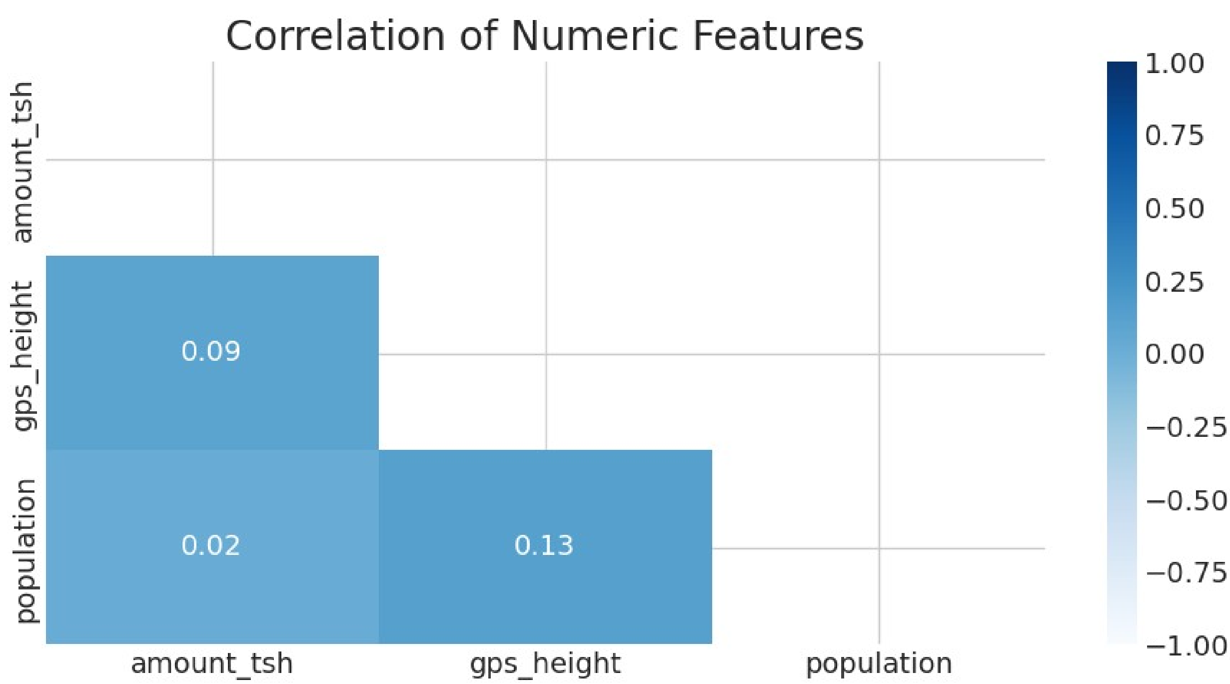

```
# Define a colorful blue palette
blue_palette = sns.color_palette(['#4A90E2', '#6CC0E5', '#8ED8E2',
'#AACFD0', '#D1D1D1'])

# Get the top 10 regions by count
top_regions = new_data['region'].value_counts().head(10).index

# Filter the data to include only the top 10 regions
filtered_data = new_data[new_data['region'].isin(top_regions)]

# Plot the countplot with the specified palette
plt.figure(figsize=(18, 10))
ax = sns.countplot(x='region', hue='status_group', data=filtered_data,
palette=blue_palette)
plt.show()
```




```
# Define a custom colorful blue palette
blue_palette = ['#4A90E2', '#6CC0E5', '#8ED8E2', '#AACFD0', '#D1D1D1',
'#FFC0CB', '#87CEEB', '#00BFFF', '#1E90FF', '#4682B4']

# Plot the countplot with the specified palette
plt.figure(figsize=(18, 10))
ax = sns.countplot(x='basin', hue='quantity', data=new_data,
palette=blue_palette)
plt.show()
```



```
def corrmatrix(df):
    ''' This function plots a correlation matrix for numeric features
in a given dataframe '''
    plt.figure(figsize=(10, 5))

    # Filter numeric columns
    numeric_cols = df.select_dtypes(include='number')

    # Calculate correlation matrix
    corr = numeric_cols.corr()

    # Generate a mask to only show the bottom triangle
    mask = np.triu(np.ones_like(corr, dtype=bool))

    # Generate heatmap
    sns.heatmap(round(corr, 2), annot=True, mask=mask, vmin=-1,
vmax=1, cmap='Blues')
    plt.title('Correlation of Numeric Features')
    plt.show()

# Call the function
corrmatrix(new_data)
```



4. Modeling

The objective of this notebook is to construct a predictive model that can classify the status of Tanzanian wells based on the available dataset. We will evaluate the model primarily based on its accuracy, aiming for a minimum threshold of 75% accuracy. To achieve this goal, we will employ several machine learning algorithms:

- Logistic Regression
- Decision Tree
- Random Forest
- XGBoost

Our evaluation will focus on accuracy as the primary metric. Additionally, to ensure the models generalize well and do not overfit, we will utilize cross-validation techniques during the evaluation process.

```
#view the new data
import pandas as pd
df = pd.read_csv('wells_cleaned_data.csv')
df.head()
```

```
   amount_tsh date_recorded        funder  gps_height     installer  \
0      6000.0    2011-03-14         Roman        1390         Roman
1         0.0    2013-03-06       Grumeti        1399       GRUMETI
2        25.0    2013-02-25  Lottery Club         686   world vision
3         0.0    2013-01-28        Unicef         263        Unicef
4         0.0    2011-07-13   Action In A           0       Artisan

                     basin  subvillage   region local_government_area
\
0               Lake Nyasa    Mnyusi B   Iringa                Ludewa

1            Lake Victoria     Nyamara     Mara             Serengeti

2                  Pangani     Majengo  Manyara             Simanjiro

3   Ruvuma / Southern Coast  Mahakamani   Mtwara              Nanyumbu

4            Lake Victoria  Kyanyamisa   Kagera               Karagwe


         ward  population  permit construction_year
extraction_type_group  \
0    Mundindi         109   False        1999-01-01
gravity
1       Natta         280    True        2010-01-01
gravity
2     Ngorika         250    True        2009-01-01
gravity
3    Nanyumbu          58    True        1986-01-01
submersible
4  Nyakasimbi           0    True               NaN
gravity

  management_group payment_type water_quality quality_group
```

```
quantity  \
0       user-group     annually          soft          good
enough
1       user-group    never pay          soft          good
insufficient
2       user-group   per bucket          soft          good
enough
3       user-group    never pay          soft          good
dry
4            other    never pay          soft          good
seasonal

            source_type              waterpoint_type    status_group
0                spring           communal standpipe      functional
1  rainwater harvesting           communal standpipe      functional
2                   dam  communal standpipe multiple      functional
3              borehole  communal standpipe multiple  non functional
4  rainwater harvesting           communal standpipe      functional

#get copy of our dataframe
dfcopy = df.copy()

#check value count of target group
dfcopy['status_group'].value_counts(normalize=True)

status_group
functional                 0.541287
non functional             0.387962
functional needs repair    0.070751
Name: proportion, dtype: float64
```

The "Functional" category constitutes the largest portion of the dataset, representing 54.1%. Meanwhile, the "Non-functional" category comprises 38.8% of the dataset, and the "Functional needs repair" category makes up 7% of the dataset.

```
new_status_group = {'non functional': 0, 'functional': 1, 'functional
needs repair' : 2}
dfcopy['status_group'] =
dfcopy['status_group'].replace(new_status_group)

dfcopy['status_group'].value_counts()

status_group
1    29210
0    20936
2     3818
Name: count, dtype: int64
```

The current data type is "object," necessitating conversion to an integer.

```
dfcopy['status_group'].dtypes
```

```
dtype('int64')
```

```
categorical = ['source_type', 'quantity', 'water_quality',
'payment_type', 'management_group', 'basin']

ohe = pd.get_dummies(df[categorical], prefix=categorical,
drop_first=True)
ohe
```

```
       source_type_dam  source_type_other  source_type_rainwater
harvesting  \
0                False              False
False
1                False              False
True
2                 True              False
False
3                False              False
False
4                False              False
True
...                ...                ...
...
53959            False              False
False
53960            False              False
False
53961            False              False
False
53962            False              False
False
53963            False              False
False

       source_type_river/lake  source_type_shallow well
source_type_spring  \
0                       False                     False
True
1                       False                     False
False
2                       False                     False
False
3                       False                     False
False
4                       False                     False
False
...                       ...                       ...
...
```

```
53959                    False                          False
False
53960                    False                          False
True
53961                     True                          False
False
53962                    False                           True
False
53963                    False                           True
False

       quantity_enough  quantity_insufficient  quantity_seasonal  \
0                 True                  False              False
1                False                   True              False
2                 True                  False              False
3                False                  False              False
4                False                  False               True
...                ...                    ...                ...
53959             True                  False              False
53960             True                  False              False
53961             True                  False              False
53962            False                   True              False
53963             True                  False              False

       quantity_unknown  water_quality_fluoride  \
0                 False                   False
1                 False                   False
2                 False                   False
3                 False                   False
4                 False                   False
...                 ...                     ...
53959             False                   False
53960             False                   False
53961             False                   False
53962             False                   False
53963             False                   False

       water_quality_fluoride abandoned  water_quality_milky  \
0                                 False                False
1                                 False                False
2                                 False                False
3                                 False                False
4                                 False                False
...                                 ...                  ...
53959                             False                False
53960                             False                False
53961                             False                False
53962                             False                False
53963                             False                False
```

```
       water_quality_salty  water_quality_salty abandoned
water_quality_soft  \
0                    False                          False
True
1                    False                          False
True
2                    False                          False
True
3                    False                          False
True
4                    False                          False
True
...                    ...                            ...
...
53959                False                          False
True
53960                False                          False
True
53961                False                          False
True
53962                False                          False
True
53963                 True                          False
False

       water_quality_unknown  payment_type_monthly  payment_type_never
pay  \
0                      False                 False
False
1                      False                 False
True
2                      False                 False
False
3                      False                 False
True
4                      False                 False
True
...                      ...                   ...
...
53959                  False                  True
False
53960                  False                 False
False
53961                  False                 False
False
53962                  False                 False
True
53963                  False                 False
False
```

```
       payment_type_on failure  payment_type_other  payment_type_per
bucket  \
0                        False               False
False
1                        False               False
False
2                        False               False
True
3                        False               False
False
4                        False               False
False
...                        ...                 ...
...
53959                    False               False
False
53960                    False               False
True
53961                    False               False
False
53962                    False               False
False
53963                     True               False
False

       payment_type_unknown  management_group_other  \
0                     False                   False
1                     False                   False
2                     False                   False
3                     False                   False
4                     False                    True
...                     ...                     ...
53959                 False                   False
53960                 False                   False
53961                 False                   False
53962                 False                   False
53963                 False                   False

       management_group_parastatal  management_group_unknown  \
0                            False                     False
1                            False                     False
2                            False                     False
3                            False                     False
4                            False                     False
...                            ...                       ...
53959                        False                     False
53960                        False                     False
53961                        False                     False
53962                        False                     False
```

```
53963                         False                      False

       management_group_user-group  basin_Lake Nyasa  basin_Lake Rukwa
\
0                             True              True             False

1                             True             False             False

2                             True             False             False

3                             True             False             False

4                            False             False             False

...                            ...               ...               ...

53959                         True             False             False

53960                         True             False             False

53961                         True             False             False

53962                         True             False             False

53963                         True             False             False


       basin_Lake Tanganyika  basin_Lake Victoria  basin_Pangani  \
0                      False                False          False
1                      False                 True          False
2                      False                False           True
3                      False                False          False
4                      False                 True          False
...                      ...                  ...            ...
53959                  False                False          False
53960                  False                False           True
53961                  False                False          False
53962                  False                False          False
53963                  False                False          False

       basin_Rufiji  basin_Ruvuma / Southern Coast  basin_Wami / Ruvu

0             False                          False              False

1             False                          False              False

2             False                          False              False

3             False                           True              False

4             False                          False              False
```

```
...            ...                              ...                 ...
53959        False                            False                True
53960        False                            False               False
53961         True                            False               False
53962         True                            False               False
53963        False                            False                True

[53964 rows x 35 columns]
```

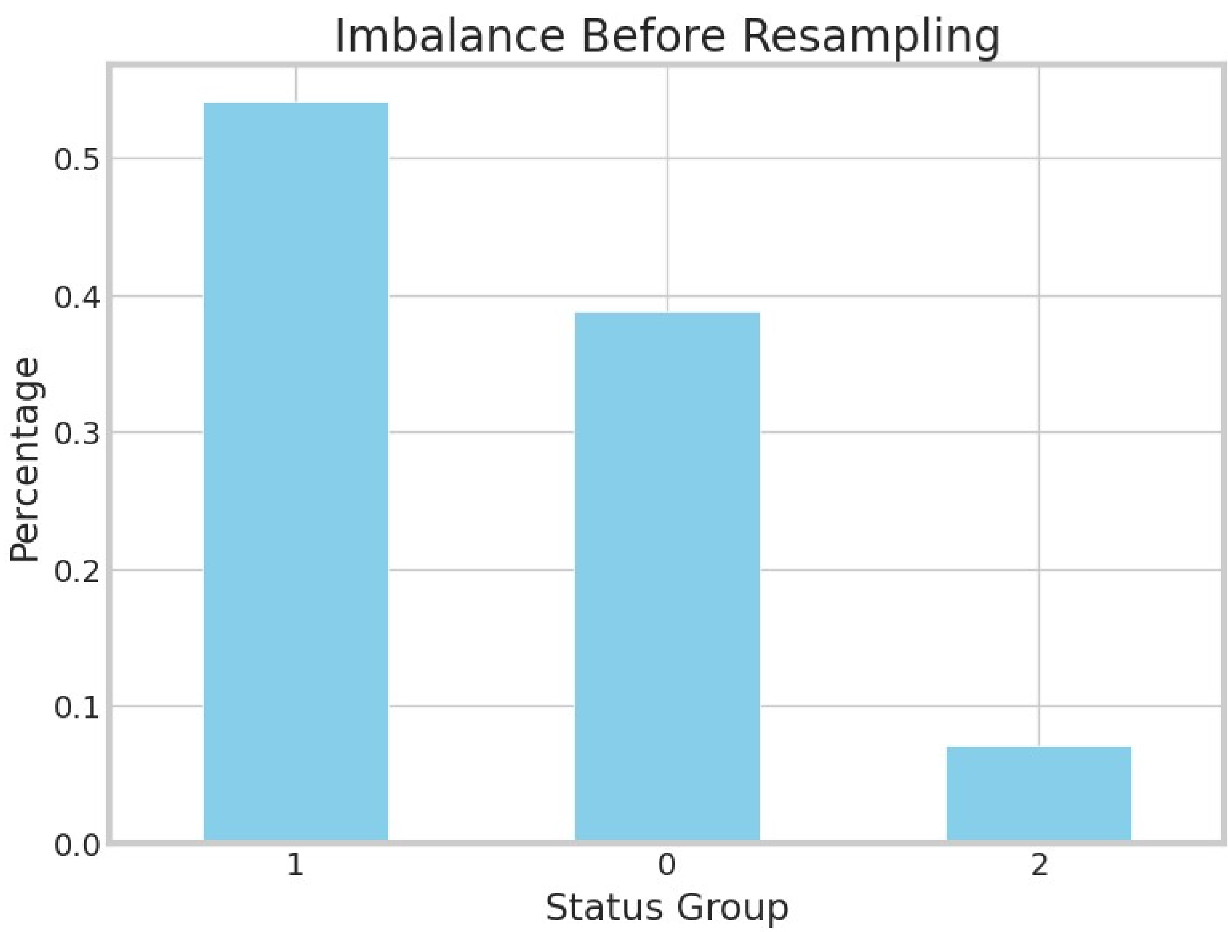
```
# Preview the one hot encoded datatypes
ohe.dtypes
```

```
source_type_dam                                bool
source_type_other                              bool
source_type_rainwater harvesting               bool
source_type_river/lake                         bool
source_type_shallow well                       bool
source_type_spring                             bool
quantity_enough                                bool
quantity_insufficient                          bool
quantity_seasonal                              bool
quantity_unknown                               bool
water_quality_fluoride                         bool
water_quality_fluoride abandoned               bool
water_quality_milky                            bool
water_quality_salty                            bool
water_quality_salty abandoned                  bool
water_quality_soft                             bool
water_quality_unknown                          bool
payment_type_monthly                           bool
payment_type_never pay                         bool
payment_type_on failure                        bool
payment_type_other                             bool
payment_type_per bucket                        bool
payment_type_unknown                           bool
management_group_other                         bool
management_group_parastatal                    bool
management_group_unknown                       bool
management_group_user-group                    bool
basin_Lake Nyasa                               bool
basin_Lake Rukwa                               bool
basin_Lake Tanganyika                          bool
basin_Lake Victoria                            bool
```

```
basin_Pangani                                   bool
basin_Rufiji                                    bool
basin_Ruvuma / Southern Coast                   bool
basin_Wami / Ruvu                               bool
dtype: object
```

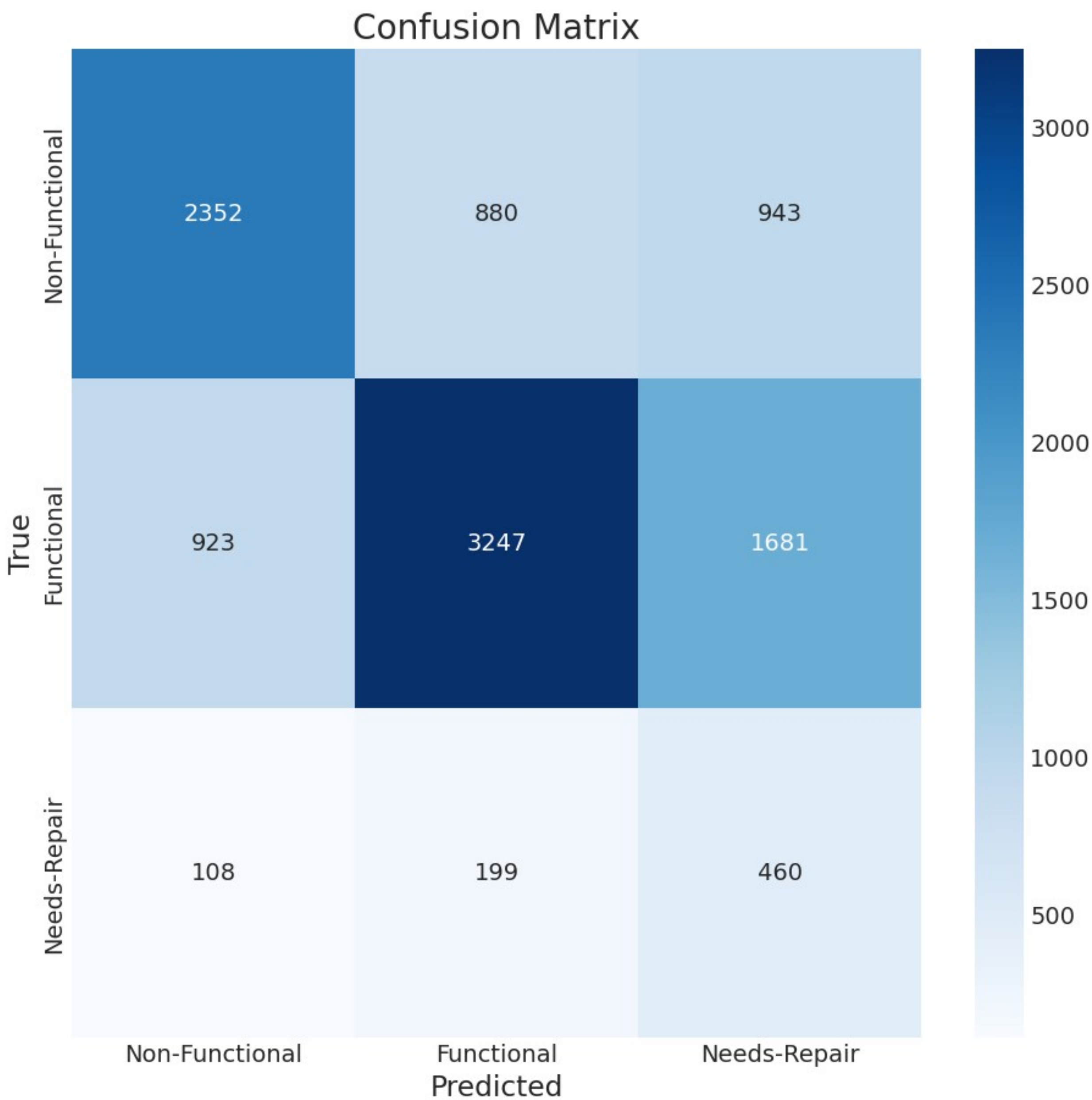
Check for Class Imbalance

```
import matplotlib.pyplot as plt

# Check imbalance before resampling
plt.figure(figsize=(8, 6))
dfcopy['status_group'].value_counts(normalize=True).plot(kind='bar',
color='skyblue')
plt.title('Imbalance Before Resampling')
plt.xlabel('Status Group')
plt.ylabel('Percentage')
plt.xticks(rotation=0)
plt.show()
```



```python
# Define X and y
X = ohe  # Assuming you have already performed one-hot encoding
y = dfcopy['status_group']

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=1)

# Instantiate logistic regression
logreg = LogisticRegression(class_weight='balanced', solver='lbfgs',
random_state=42)

# Build a pipeline with standard scaler and logistic regression
scaled_pipeline = Pipeline([('ss', StandardScaler()),
                            ('logreg', logreg)])

# Fit the training data to pipeline
scaled_pipeline.fit(X_train, y_train)

# Predict the labels of the test set: y_pred
y_pred_log = scaled_pipeline.predict(X_test)

# Perform cross-validation: cv_results
cv_results_log = cross_validate(scaled_pipeline, X_test, y_test, cv=3)

# Display cross-validation test scores
print("Cross Validation Test Scores:", cv_results_log['test_score'])

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred_log)

# Plot confusion matrix
plt.figure(figsize=(10, 10))
target_names = ['Non-Functional', 'Functional', 'Needs-Repair']
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=target_names, yticklabels=target_names)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

# Classification report
target_names = ['Non-Functional', 'Functional', 'Needs-Repair']
print(classification_report(y_test, y_pred_log,
target_names=target_names))
```

```
Cross Validation Test Scores: [0.56003335 0.55336298 0.54879066]
```



	precision	recall	f1-score	support
Non-Functional	0.70	0.56	0.62	4175
Functional	0.75	0.55	0.64	5851
Needs-Repair	0.15	0.60	0.24	767
accuracy			0.56	10793
macro avg	0.53	0.57	0.50	10793
weighted avg	0.69	0.56	0.60	10793

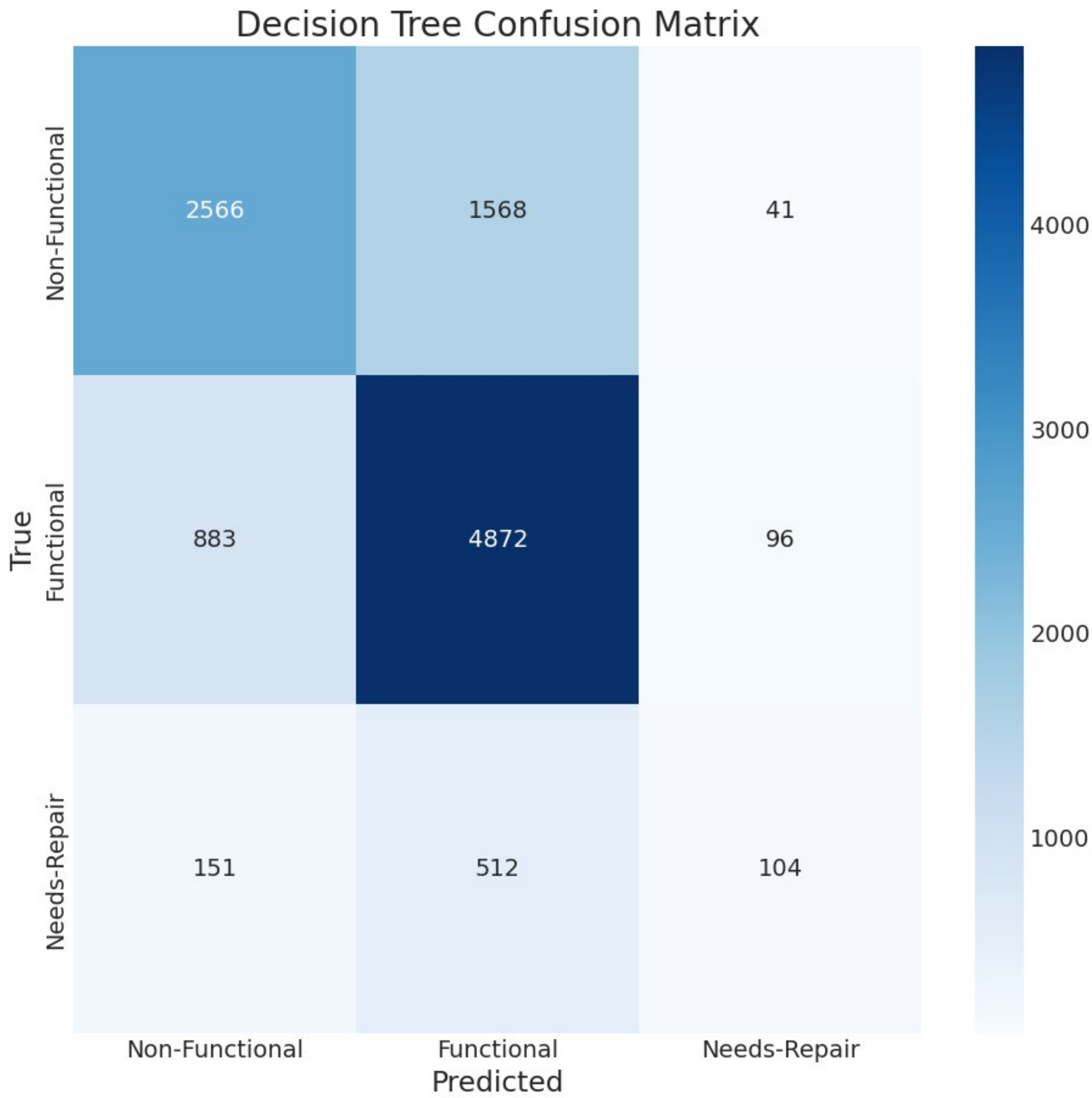
4.2 Decision Tree

Decision trees are a type of non-parametric supervised learning algorithm utilized for both classification and regression tasks. Their objective is to construct a model capable of predicting the target variable's value by discerning straightforward decision rules derived from the features within the data.

```
# Define X and y
X = ohe  # Assuming you have already performed one-hot encoding
y = dfcopy['status_group']

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=1)

# Instantiate the Decision Tree Classifier
clf = DecisionTreeClassifier(criterion='entropy', random_state=39)

# Build a pipeline with standard scaler and decision tree classifier
tree_pipeline = Pipeline([
    ('ss', StandardScaler()),  # Standard scaling (not really needed
for decision trees, but included for consistency)
    ('clf', clf)  # Decision Tree Classifier
])

# Fit train data to pipeline
tree_pipeline.fit(X_train, y_train)

# Predict the labels of the test set: y_pred
y_pred_dt = tree_pipeline.predict(X_test)

# Perform cross-validation: cv_results
cv_results_dt = cross_validate(tree_pipeline, X_test, y_test, cv=3)

# Display cross-validation test scores
print("Cross Validation Test Scores:", cv_results_dt['test_score'])

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred_dt)

# Plot confusion matrix
plt.figure(figsize=(10, 10))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=target_names, yticklabels=target_names)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Decision Tree Confusion Matrix')
plt.show()

# Classification report
target_names = ['Non-Functional', 'Functional', 'Needs-Repair']
```

```python
print(classification_report(y_test, y_pred_dt,
target_names=target_names))
```

```
Cross Validation Test Scores: [0.67898833 0.67954419 0.67528496]
```




```
                precision    recall  f1-score   support

Non-Functional       0.71      0.61      0.66      4175
    Functional       0.70      0.83      0.76      5851
  Needs-Repair       0.43      0.14      0.21       767

      accuracy                           0.70     10793
```

```
    macro avg       0.62      0.53      0.54     10793
 weighted avg       0.69      0.70      0.68     10793
```

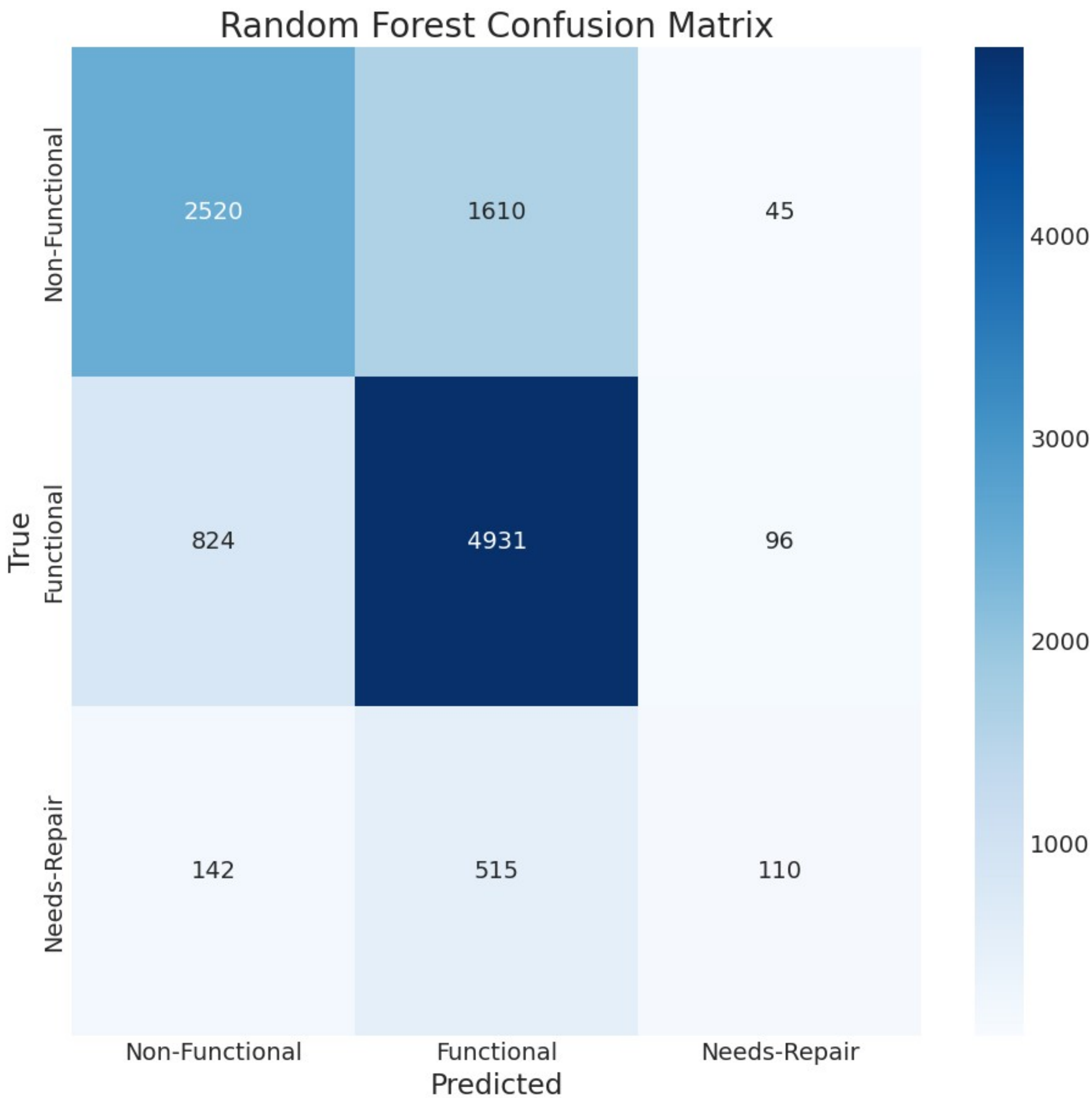
4.3 Random Forest

Random forests, also known as random decision forests, are a powerful ensemble learning technique used for classification, regression, and other tasks. They work by creating a large number of decision trees during training and then combining their predictions to determine the final outcome. For classification tasks, the mode of the classes predicted by individual trees is chosen, while for regression tasks, the mean prediction of the individual trees is taken.

```
# Define X and y
X = ohe  # Assuming you have already performed one-hot encoding
y = dfcopy['status_group']

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=1)

# Build a pipeline with StandardScaler and RandomForestClassifier
random_pipeline = Pipeline([('ss', StandardScaler()),
                            ('RF',
RandomForestClassifier(random_state=0))])

# Fit the training data to pipeline
random_pipeline.fit(X_train, y_train)

# Predict the labels of the test set: y_pred_rf
y_pred_rf = random_pipeline.predict(X_test)

# Perform cross-validation: cv_results_rf
cv_results_rf = cross_validate(random_pipeline, X_test, y_test, cv=3)

# Display cross-validation test scores
print("Cross Validation Test Scores:", cv_results_rf['test_score'])

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred_rf)

# Plot confusion matrix
plt.figure(figsize=(10, 10))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=target_names, yticklabels=target_names)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Random Forest Confusion Matrix')
plt.show()
```

```
# Classification report
target_names = ['Non-Functional', 'Functional', 'Needs-Repair']
print(classification_report(y_test, y_pred_rf,
target_names=target_names))
```

```
Cross Validation Test Scores: [0.68343524 0.68037799 0.67973311]
```




```
                precision    recall  f1-score   support

Non-Functional       0.72      0.60      0.66      4175
    Functional       0.70      0.84      0.76      5851
  Needs-Repair       0.44      0.14      0.22       767
```

```
    accuracy                           0.70     10793
   macro avg       0.62      0.53      0.55     10793
weighted avg       0.69      0.70      0.68     10793
```

4.5 XGBOOST

XGBoost is a highly efficient and flexible gradient boosting library that is optimized for distributed computing. It is designed to be portable and offers implementation of machine learning algorithms within the Gradient Boosting framework. XGBoost employs parallel tree boosting techniques, also referred to as GBDT or GBM, which enables solving various data science problems rapidly and accurately.

```
# Instantiate XGBClassifier
clf = XGBClassifier()

# Define X and y
X = ohe  # Assuming you have already performed one-hot encoding
y = dfcopy['status_group']

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=1)

# Build a pipeline with StandardScaler and XGBClassifier
xgb_pipeline = Pipeline([
    ('ss', StandardScaler()),
    ('xgb', clf)
])

# Fit XGBClassifier
xgb_pipeline.fit(X_train, y_train)

# Predict on training and test sets
training_preds = xgb_pipeline.predict(X_train)
test_preds = xgb_pipeline.predict(X_test)

# Accuracy of training and test sets
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))

# Define parameter grid for GridSearchCV
param_grid = {
    'xgb__learning_rate': [0.1, 0.2],
    'xgb__max_depth': [6],
    'xgb__min_child_weight': [1, 2],
```

```
    'xgb__subsample': [0.5, 0.7],
    'xgb__n_estimators': [100],
}

# Perform GridSearchCV
grid_clf = GridSearchCV(xgb_pipeline, param_grid, scoring='accuracy',
cv=None, n_jobs=1)
grid_clf.fit(X_train, y_train)

# Get best parameters
best_parameters = grid_clf.best_params_

print('Grid Search found the following optimal parameters: ')
for param_name in sorted(best_parameters.keys()):
    print('%s: %r' % (param_name, best_parameters[param_name]))

# Predict on training and test sets using best model
training_preds = grid_clf.predict(X_train)
test_preds = grid_clf.predict(X_test)

# Accuracy of training and test sets using best model
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('')
print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Training Accuracy: 71.78%
Validation accuracy: 70.17%
Grid Search found the following optimal parameters:
xgb__learning_rate: 0.2
xgb__max_depth: 6
xgb__min_child_weight: 1
xgb__n_estimators: 100
xgb__subsample: 0.7

Training Accuracy: 71.61%
Validation accuracy: 70.06%
```

Evaluation

In this project, we employed several machine learning algorithms to predict the status of Tanzanian wells. Here are the results:

Logistic Regression

- The logistic regression model achieved an accuracy of 56%. While this performance served as a baseline, it fell short of our desired accuracy of 75%.

- The confusion matrix revealed a bias towards predicting that a well is functional. However, the model demonstrated balanced performance with a higher number of true positives and true negatives than false positives and false negatives.
- Cross-validation consistently returned stable scores, indicating that the model wasn't overfitting the data.

Decision Tree

- The decision tree model improved upon the baseline, reaching an accuracy of 70%.
- Similar to logistic regression, the confusion matrix showed a bias towards predicting functional wells. The model displayed balanced performance, indicating no overfitting.
- Cross-validation results remained consistent across tests.

Random Forest

- The random forest model also achieved an accuracy of 70%, matching the performance of the decision tree model.
- Confusion matrix analysis and cross-validation yielded similar observations as with the decision tree model, indicating balanced performance.
- XGBoost
- After training the XGBoost model, we achieved a training accuracy of 71.78% and a validation accuracy of 70.17%.
- Grid search was employed to find the optimal hyperparameters, resulting in the following settings:
  - Learning Rate: 0.2
  - Maximum Depth: 6
  - Minimum Child Weight: 1
  - Number of Estimators: 100
  - Subsample: 0.7
- While the training and validation accuracies are slightly lower than those of other models, XGBoost still demonstrates robust performance and generalization capabilities.

How Models Were Evaluated

- Used a pipeline to scale the data and fit it to each model, followed by cross-validation to assess generalization performance.
- Confusion matrices provided insights into the models' prediction biases and overall performance.
- While models fell short of the desired 75% accuracy, achieving 70% accuracy indicates a promising start for the project.

Limitations

Despite our achievements, we encountered several limitations:

- Approximately 30% of the data remained unaccounted for by our models.

- Class imbalance across the output variables (functional, non-functional, needs-repair) may have affected model performance.

Conclusion

In this project, we applied several machine learning algorithms to predict the operational status of Tanzanian wells. Despite achieving an accuracy of around 70%, which is a decent baseline, there is room for improvement. Logistic regression, decision trees, and random forests were among the algorithms we explored, each offering unique insights into the data.

While our models performed reasonably well, there are several limitations and areas for improvement. The class imbalance across the three output variables (functional, non-functional, needs-repair) posed a challenge, potentially affecting the models' predictive accuracy.

Next Steps

Moving forward, there are several steps we can take to enhance the predictive capabilities of our models:

- **Investigate Additional Features:** Concentrating on geographical indicators like climate, population, and amount of water available in the area.
- **Time-Series Analysis:** Further consideration of the well ages should be analyzed to predict the average lifetime of more robust well structures.
- **Repairs:** Local governments should look at what type of water wells are needing repairs, and the severity of those repairs, to fine-tune non-functional indicators.