TANZANIA WATER PROJECT

Objective of the study

Overview

Tanzania, as a developing country, struggles with providing clean water to its population of over 57,000,000. There are many water points already established in the country, but some are in need of repair while others have failed altogether. Addressing the persistent water problem involves classifying wells as functional or non-functional to provide actionable insights for stakeholders, particularly the governments and NGO's.

This project aims to identify key factors that influence well functionality such as maybe the age of wells, payment methods for maintenance, and even the role of community involvement.

Preliminary findings suggest that newer wells may possibly exhibit fewer faults, indicating apotential need for investment in modern infrastructure. Additionally, efficient payment methods to enhance the well maintenance which are probably fascilitated by technology appear to enhance well upkeep. And lastly community involvement in maintenance practices could help boost sustainability and even operational efficiency of the wells. By focusing on areas like these, the government could develop targted interventions to ensure reliable water access across Tanzania.

Objectives

1. To identify which payment methods best contribute to maintenance of the wells.
2. To distinguish the different factors that contribute to functionality of the wells in Tanzania.
3. To find the best classification method for analysing the dataset.

Data description

The datasets obtained were from [https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/data/ (https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/data/)](https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/data/) of which provided four datasets whereby we had

- Submission format which was the format of submitting the predictions,
- Test set values which contained the independent variables that need prediction,
- Training set labels which contains the dependent variable (status_group) for each of the rows in Training set values and lastly the
- Training set values which contains the independent variables for the training set

Some of the features in this dataset are:

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

date_recorded - The date the row was entered funder - Who funded the well

gps_height - Altitude of the well

installer - Organization that installed the well

longitude - GPS coordinate

latitude - GPS coordinate

wpt_name - Name of the waterpoint if there is one

basin - Geographic water basin

subvillage - Geographic location

region - Geographic location

region_code - Geographic location (coded)

district_code - Geographic location (coded)

lga - Geographic location

ward - Geographic location

population - Population around the well

public_meeting - True/False

recorded_by - Group entering this row of data

scheme_management - Who operates the waterpoint

scheme_name - Who operates the waterpoint

permit - If the waterpoint is permitted

construction_year - Year the waterpoint was constructed

extraction_type - The kind of extraction the waterpoint uses

extraction_type_group - The kind of extraction the waterpoint uses

extraction_type_class - The kind of extraction the waterpoint uses

management - How the waterpoint is managed

management_group - How the waterpoint is managed

payment - What the water costs

payment_type - What the water costs

water_quality - The quality of the water

quality_group - The quality of the water

quantity - The quantity of water

quantity_group - The quantity of water

source - The source of the water

source_type - The source of the water

source_class - The source of the water

waterpoint_type - The kind of waterpoint

waterpoint_type_group - The kind of waterpoint

we also have the labels in the dataset whic are;

functional - the waterpoint is operational and there are no repairs needed

functional needs repair - the waterpoint is operational, but needs repairs

non functional - the waterpoint is not operational

Some of these features will be considered highly useful in trying to answer the ibjectives of the projcet while others may dropped to avoid using a heavy dataset.

Stakeholder

The stakeholders of this project are the Government Ministry of water & NGO's that will find this information useful in order to decide on which wells to repair and how much to allocate to each of them as well as help them identify which sources are best for the wells, what mode of payments to focus on for high efficiency and if they should involve the local communities.

Type *Markdown* and LaTeX: α^2

In [1]:
```
# we start by importing libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,
    precision_score, recall_score, accuracy_score, f1_score, log_loss,
    roc_curve, roc_auc_score, classification_report
from sklearn.tree import DecisionTreeClassifier, plot_tree, export_gra
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import SMOTE
from sklearn import tree
```

In [2]:
```
#lets first view all the datasets to confirm on what they entail
df1 = pd.read_csv("Training set labels.csv") #this is the target class
df2 = pd.read_csv("Test set values.csv") #most likely the dataset from
df3 = pd.read_csv("Training set values.csv")
```

In [3]:
```
df1.head()
#we cann see this is our target class or rather the dependent variable
```

Out[3]:

	id	status_group
0	69572	functional
1	8776	functional
2	34310	functional
3	67743	non functional
4	19728	functional

In [4]:
```
df2.head()
#We see that these are the independent variables that need predictions
```

Out[4]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude
0	50785	0.0	2013-02-04	Dmdd	1996	DMDD	35.290799	-4.059696
1	51630	0.0	2013-02-04	Government Of Tanzania	1569	DWE	36.656709	-3.309214
2	17168	0.0	2013-02-01	NaN	1567	NaN	34.767863	-5.004344
3	45559	0.0	2013-01-22	Finn Water	267	FINN WATER	38.058046	-9.418672
4	49871	500.0	2013-03-27	Bruder	1260	BRUDER	35.006123	-10.950412

5 rows × 40 columns

In [5]:
```
df3.head()
#these are the independent variables for the training set hence we wil
```

Out[5]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	v
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	N
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	

5 rows × 40 columns

In [6]:
```
df3.info() #we have 40 columns so we should have 41 columns when we me
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 40 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     59400 non-null  int64  
 1   amount_tsh             59400 non-null  float64
 2   date_recorded          59400 non-null  object 
 3   funder                 55765 non-null  object 
 4   gps_height             59400 non-null  int64  
 5   installer              55745 non-null  object 
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   wpt_name               59400 non-null  object 
 9   num_private            59400 non-null  int64  
 10  basin                  59400 non-null  object 
 11  subvillage             59029 non-null  object 
 12  region                 59400 non-null  object 
 13  region_code            59400 non-null  int64  
 14  district_code          59400 non-null  int64  
 15  lga                    59400 non-null  object 
 16  ward                   59400 non-null  object 
 17  population             59400 non-null  int64  
 18  public_meeting         56066 non-null  object 
 19  recorded_by            59400 non-null  object 
 20  scheme_management      55523 non-null  object 
 21  scheme_name            31234 non-null  object 
 22  permit                 56344 non-null  object 
 23  construction_year      59400 non-null  int64  
 24  extraction_type        59400 non-null  object 
 25  extraction_type_group  59400 non-null  object 
 26  extraction_type_class  59400 non-null  object 
 27  management             59400 non-null  object 
 28  management_group       59400 non-null  object 
 29  payment                59400 non-null  object 
 30  payment_type           59400 non-null  object 
 31  water_quality          59400 non-null  object 
 32  quality_group          59400 non-null  object 
 33  quantity               59400 non-null  object 
 34  quantity_group         59400 non-null  object 
 35  source                 59400 non-null  object 
 36  source_type            59400 non-null  object 
 37  source_class           59400 non-null  object 
 38  waterpoint_type        59400 non-null  object 
 39  waterpoint_type_group  59400 non-null  object 
dtypes: float64(3), int64(7), object(30)
memory usage: 18.1+ MB
```

In [7]:

```
data = pd.merge (df1, df3, on='id') #after combining we still have 594
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 0 to 59399
Data columns (total 41 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     59400 non-null  int64  
 1   status_group           59400 non-null  object 
 2   amount_tsh             59400 non-null  float64
 3   date_recorded          59400 non-null  object 
 4   funder                 55765 non-null  object 
 5   gps_height             59400 non-null  int64  
 6   installer              55745 non-null  object 
 7   longitude              59400 non-null  float64
 8   latitude               59400 non-null  float64
 9   wpt_name               59400 non-null  object 
 10  num_private            59400 non-null  int64  
 11  basin                  59400 non-null  object 
 12  subvillage             59029 non-null  object 
 13  region                 59400 non-null  object 
 14  region_code            59400 non-null  int64  
 15  district_code          59400 non-null  int64  
 16  lga                    59400 non-null  object 
 17  ward                   59400 non-null  object 
 18  population             59400 non-null  int64  
 19  public_meeting         56066 non-null  object 
 20  recorded_by            59400 non-null  object 
 21  scheme_management      55523 non-null  object 
 22  scheme_name            31234 non-null  object 
 23  permit                 56344 non-null  object 
 24  construction_year      59400 non-null  int64  
 25  extraction_type        59400 non-null  object 
 26  extraction_type_group  59400 non-null  object 
 27  extraction_type_class  59400 non-null  object 
 28  management             59400 non-null  object 
 29  management_group       59400 non-null  object 
 30  payment                59400 non-null  object 
 31  payment_type           59400 non-null  object 
 32  water_quality          59400 non-null  object 
 33  quality_group          59400 non-null  object 
 34  quantity               59400 non-null  object 
 35  quantity_group         59400 non-null  object 
 36  source                 59400 non-null  object 
 37  source_type            59400 non-null  object 
 38  source_class           59400 non-null  object 
 39  waterpoint_type        59400 non-null  object 
 40  waterpoint_type_group  59400 non-null  object 
dtypes: float64(3), int64(7), object(31)
memory usage: 19.0+ MB
```

The target feature in this dataset is the 'status_group' feature as it is an indicator of whether or not a well is functional non-functional or needs repair. Also this are some of the features we are going to use:

.amount_tsh: Amount water available to waterpoint

.population - Population around the well

.date_recorded: The date the row was entered

.funder: Who funded the well

.gps_height: Altitude of the well

.installer: Organization that installed the well

.longitude: GPS coordinate

.latitude: GPS coordinate

.wpt_name: Name of the waterpoint if there is

.payment_type - What the water costs

.management_group - How the waterpoint is managed

.public_meeting - True/False

And many others

Data cleaning

In [8]:
```
#we will use a function
def data_cleaning_result(df):
    """
    To try and generate a report of missing values and duplicate rows

    Parameters:
    df (pd.DataFrame): The DataFrame to be checked.

    Returns:
    None: Prints the report.
    """
    # here, I calculate the percentage of missing values for each colu
    missing_percentage = (df.isnull().sum() * 100 /len(df)).round(2)
    missing_percentage = missing_percentage[missing_percentage > 0]

    #display the missing percentage for each column
    if not missing_percentage.empty:
        print('Missing values percentage:')
        print(missing_percentage) #to print the missing percentage of
    else:
        print("No missing values have been found.")

    #checking for duplicates
    duplicates = df.duplicated()
    number_duplicates = duplicates.sum()

    #Display the number of dulicate rows
    print(f"\nNumber of duplicate rows: {number_duplicates}")

    # Optionally, display the duplicate rows if they exist
    if number_duplicates > 0:
        duplicate_rows = df[duplicates]
        print("\nDuplicate rows:")
        print(duplicate_rows)

# Assuming your merged dataset is called 'data'
# Generate the data cleaning report
data_cleaning_result(data)
```

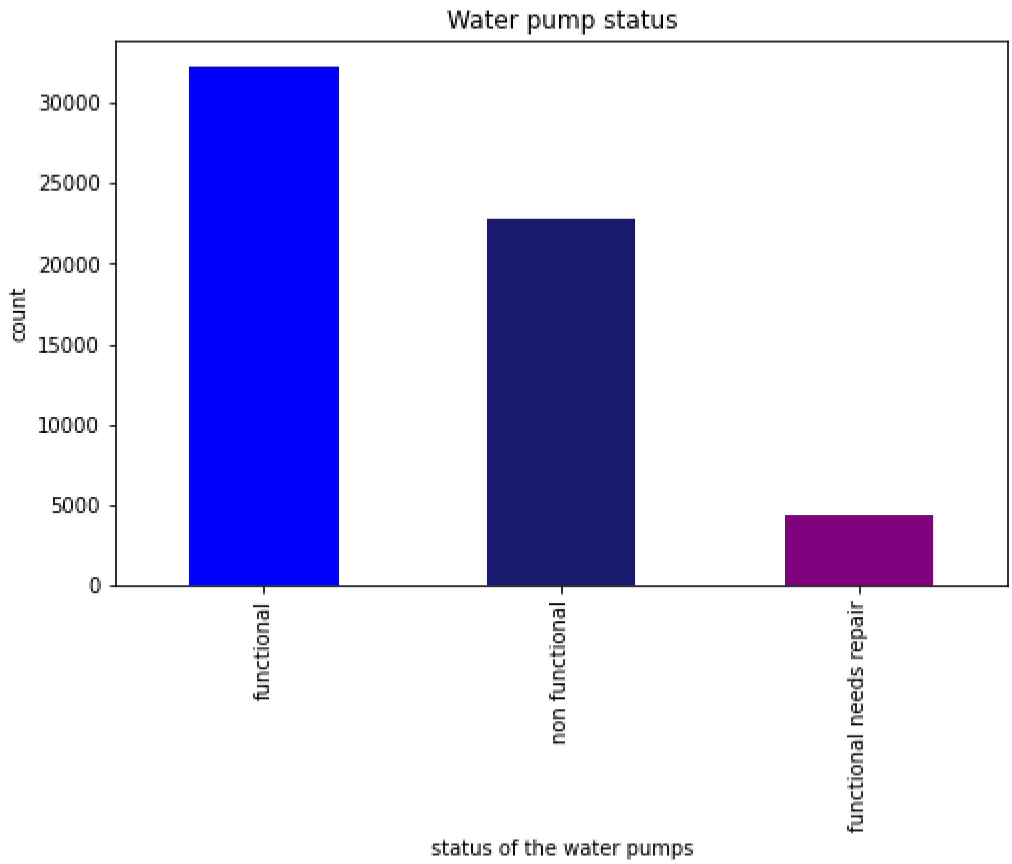
```
Missing values percentage:
funder                6.12
installer             6.15
subvillage            0.62
public_meeting        5.61
scheme_management     6.53
scheme_name          47.42
permit                5.14
dtype: float64

Number of duplicate rows: 0
```

The percentages don't seem to be that high while our highest percentage of missing values is scheme_name, we may not even need that column. We ca nthen move forward with our cleaning we will eventually deal with these columns later on.

In [9]:
```
onvert the 'status_group' column to a categorical data type so that it
a['status_group'] = data['status_group'].astype('category')

onvert the categorical values into numerical codes and creating  a new
a['target'] = data['status_group'].cat.codes

isplay the counts of each numerical code in the 'target' column
a['target'].value_counts()
```

Out[9]:
```
0    32259
2    22824
1     4317
Name: target, dtype: int64
```

In [10]:
```
#Now i want to plot them
data['status_group'].value_counts().plot(kind = 'bar',figsize= (8,5),
plt.title('Water pump status')
plt.xlabel('status of the water pumps')
plt.ylabel ('count')
plt.show()
```

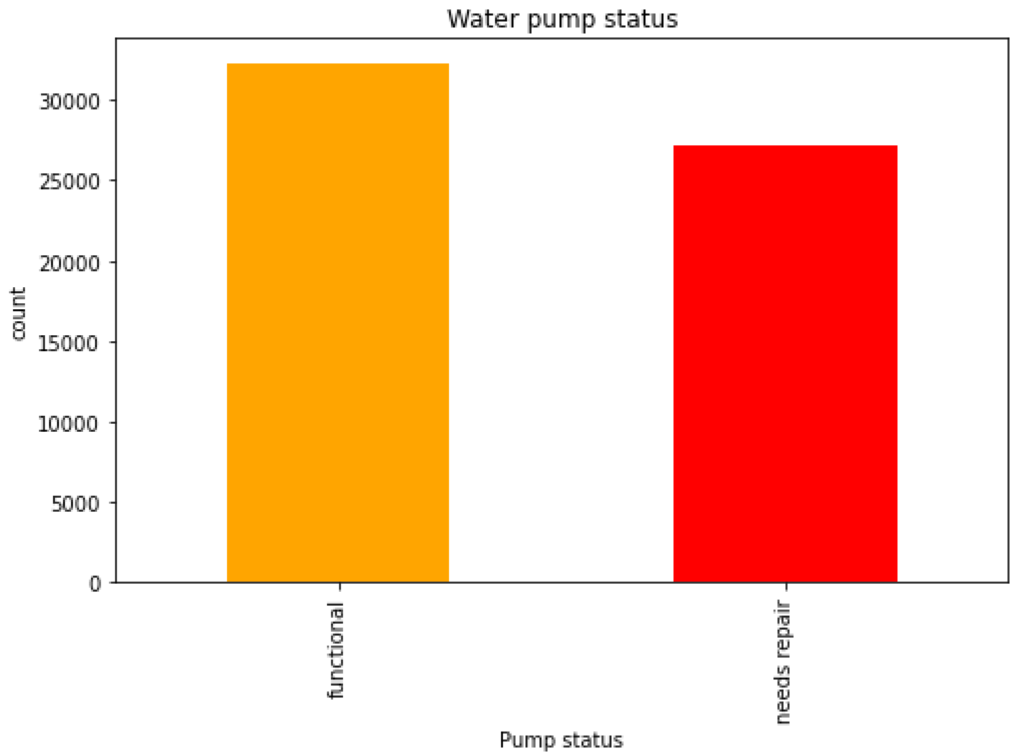


Clearly there is quite animbalance amongst the three classes hence I will therefore combine the non-functional and functional needs repair into one class so that eventually we can drop the status group and use the target column.

In [11]:
```
# Replace "functional needs repair" and "non functional" with "needs r
data['status_group'] = data['status_group'].replace(to_replace=["funct

# Display the value counts of each category in the 'status_group' colu
data['status_group'].value_counts()
```

Out[11]:
```
functional      32259
needs repair    27141
Name: status_group, dtype: int64
```

In [12]:
```
#Now let's plot the new features we have after combining the two grouḍ
data['status_group'].value_counts().plot(kind= 'bar', figsize= (8,5),
plt.title('Water pump status')
plt.xlabel('Pump status')
plt.ylabel('count')
plt.show()
```



In [13]:
```
# Convert the 'status_group' column to a categorical data type
data['status_group'] = data['status_group'].astype('category')

# Convert the categorical values into numerical codes
data['target'] = data['status_group'].cat.codes

# Display the counts of each numerical code in the 'target' column
data['target'].value_counts()
```

Out[13]:
```
0    32259
1    27141
Name: target, dtype: int64
```

In [14]:
```
data.head()
```

Out[14]:

	id	status_group	amount_tsh	date_recorded	funder	gps_height	installer	longitude
0	69572	functional	6000.0	2011-03-14	Roman	1390	Roman	34.938093
1	8776	functional	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766
2	34310	functional	25.0	2013-02-25	Lottery Club	686	World vision	37.460664
3	67743	needs repair	0.0	2013-01-28	Unicef	263	UNICEF	38.486161
4	19728	functional	0.0	2011-07-13	Action In A	0	Artisan	31.130847

5 rows × 42 columns

In [15]:
```
# Calculate the relative frequency of each unique value in the 'status
data['status_group'].value_counts(normalize=True)
```

Out[15]:
```
functional      0.543081
needs repair    0.456919
Name: status_group, dtype: float64
```

We are going to use these numbers as a baseline when comparing subgroups. For example,if a region has less than 54% functionality, we know they are below average and some features within that region are affecting the functionality of the wells.

This will help us identify important features more easily, and give us references for further data exploration.

In [16]:
```
# here there will be the creation of  dummies for status group to make
dummies_status = pd.get_dummies(data['status_group'])
data = data.join(dummies_status) #so that I can add the dummy variable

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 0 to 59399
Data columns (total 44 columns):
 #   Column                 Non-Null Count  Dtype   
---  ------                 --------------  -----   
 0   id                     59400 non-null  int64   
 1   status_group           59400 non-null  category
 2   amount_tsh             59400 non-null  float64 
 3   date_recorded          59400 non-null  object  
 4   funder                 55765 non-null  object  
 5   gps_height             59400 non-null  int64   
 6   installer              55745 non-null  object  
 7   longitude              59400 non-null  float64 
 8   latitude               59400 non-null  float64 
 9   wpt_name               59400 non-null  object  
 10  num_private            59400 non-null  int64   
 11  basin                  59400 non-null  object  
 12  subvillage             59029 non-null  object  
 13  region                 59400 non-null  object  
 14  region_code            59400 non-null  int64   
 15  district_code          59400 non-null  int64   
 16  lga                    59400 non-null  object  
 17  ward                   59400 non-null  object  
 18  population             59400 non-null  int64   
 19  public_meeting         56066 non-null  object  
 20  recorded_by            59400 non-null  object  
 21  scheme_management      55523 non-null  object  
 22  scheme_name            31234 non-null  object  
 23  permit                 56344 non-null  object  
 24  construction_year      59400 non-null  int64   
 25  extraction_type        59400 non-null  object  
 26  extraction_type_group  59400 non-null  object  
 27  extraction_type_class  59400 non-null  object  
 28  management             59400 non-null  object  
 29  management_group       59400 non-null  object  
 30  payment                59400 non-null  object  
 31  payment_type           59400 non-null  object  
 32  water_quality          59400 non-null  object  
 33  quality_group          59400 non-null  object  
 34  quantity               59400 non-null  object  
 35  quantity_group         59400 non-null  object  
 36  source                 59400 non-null  object  
 37  source_type            59400 non-null  object  
 38  source_class           59400 non-null  object  
 39  waterpoint_type        59400 non-null  object  
 40  waterpoint_type_group  59400 non-null  object  
 41  target                 59400 non-null  int8    
 42  functional             59400 non-null  uint8   
 43  needs repair           59400 non-null  uint8   
dtypes: category(1), float64(3), int64(7), int8(1), object(30), uint
8(2)
memory usage: 21.3+ MB
```

Data exploration

Plotting of functions for the categorical variables

In [17]:
```
# Define a function named plot_percent with one parameter: col (columr
#Basically trying to represent the column name I want to compare the n
def plot_percent(col):
    if data[col].nunique() > 4:
        rows, cols, width, height = 2, 1, 12 if data[col].nunique() >
    else:
        rows, cols, width, height = 1, 2, 12, 3
     # Create a new figure with subplots based on the determined layou
    fig, ax = plt.subplots(rows, cols, figsize=(width, height))

    for idx, status in enumerate(data['status_group'].unique().tolist(
        data.groupby(col).mean()[status].sort_values().plot.bar(ax=ax[
        ax[idx].axhline(y=data[status].mean(), color='r', linestyle='-
        ax[idx].set_title(f"{status.title()} pumps by {col.title()}",
        ax[idx].set_ylabel('Percent')
        ax[idx].set_xlabel('')
        ax[idx].set_ylim(0, data.groupby(col).mean()[status].max() * 1

    fig.tight_layout()
```

In [18]:
```
#Let's now analyze those misisng variables we found before
def analyze_column(data,column):
    """
    Analyze a specified column:
    - Get the missing values count
    - Get the unique values
    - Count occurrences of '0' as a possible placeholder for missing v
    - Display the top 20 most frequent values

    Args:
        data (pd.DataFrame): DataFrame containing the specified column
        column (str): Name of the column to analyze

    Returns:
        None: Prints the analysis results
    """
    #to get the missing values count
    missing_values_count = data[column].isnull().sum()
    print(f"Missing Values: {missing_values_count}/{len(data)}")


    #To get the unique values
    num_unique_values = data[column].nunique()
    print(f"\nNumber of Unique Values in '{column}': {num_unique_value

    # Count occurrences of '0' as a possible placeholder for missing v
    zero_count = (data[column] == '0').sum()
    print(f"\nCount of '0' as Placeholder for Missing Values in '{colu

    #To display the top 20 most frequent values
    print(f"\nTop 20 Most Frequent Values in '{column}':")
    print(data[column].value_counts().head(20))

# Example usage:
analyze_column(data, 'installer')
```

```
Missing Values: 3655/59400

Number of Unique Values in 'installer': 2145

Count of '0' as Placeholder for Missing Values in 'installer': 777

Top 20 Most Frequent Values in 'installer':
DWE                    17402
Government              1825
RWE                     1206
Commu                   1060
DANIDA                  1050
KKKT                     898
Hesawa                   840
0                        777
TCRS                     707
Central government       622
CES                      610
Community                553
DANID                    552
District Council         551
HESAWA                   539
World vision             408
LGA                      408
WEDECO                   397
TASAF                    396
District council         392
Name: installer, dtype: int64
```

In [19]:
```
analyze_column(data, 'funder')
```

```
Missing Values: 3635/59400

Number of Unique Values in 'funder': 1897

Count of '0' as Placeholder for Missing Values in 'funder': 777

Top 20 Most Frequent Values in 'funder':
Government Of Tanzania    9084
Danida                    3114
Hesawa                    2202
Rwssp                     1374
World Bank                1349
Kkkt                      1287
World Vision              1246
Unicef                    1057
Tasaf                      877
District Council           843
Dhv                        829
Private Individual         826
Dwsp                       811
0                          777
Norad                      765
Germany Republi            610
Tcrs                       602
Ministry Of Water          590
Water                      583
Dwe                        484
Name: funder, dtype: int64
```

We see that DWE (District Water Engineering) and Govt are the major installers which is similar to our funders.

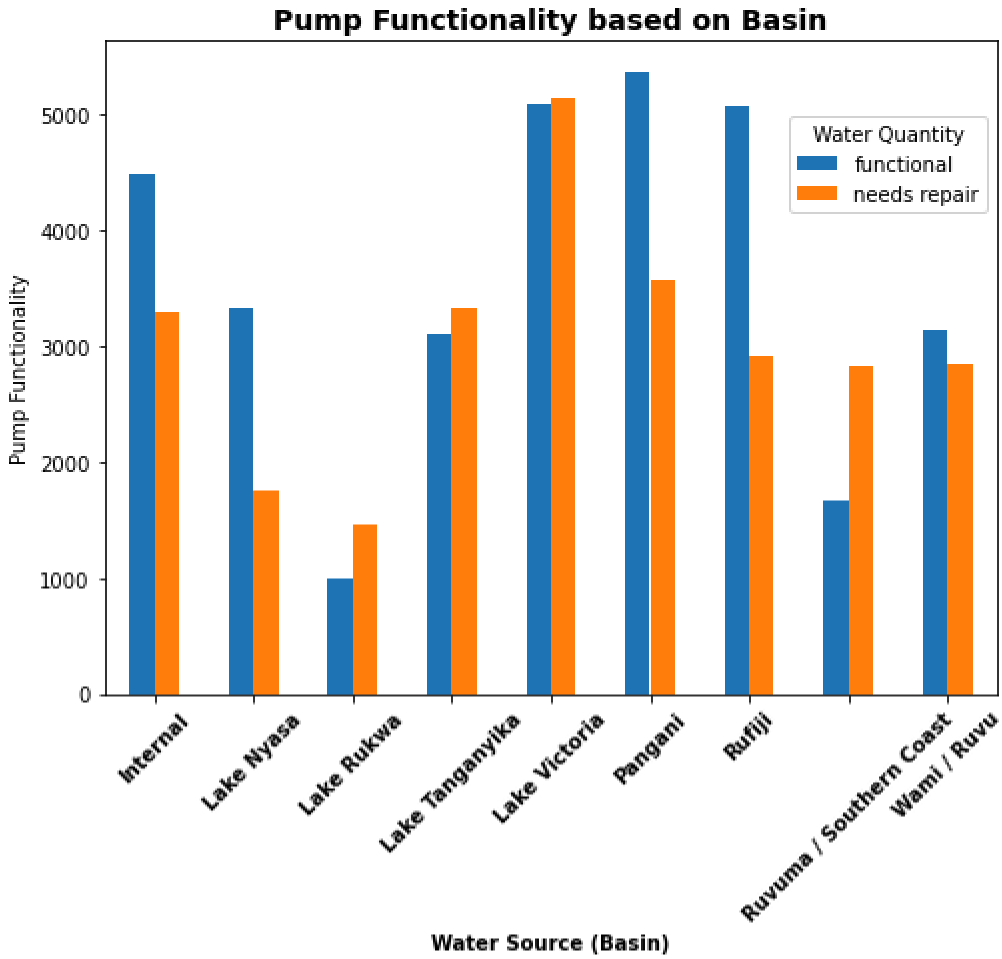
In [20]:
```
# Grouping the data by multiple categorical variables and performing a
data.groupby(['basin', 'region', 'region_code', 'district_code', 'lga'
    ['functional', 'needs repair']].agg(['mean','sum']).head()
```

Out[20]:

							functional		
							mean	sum	mea
basin	region	region_code	district_code	lga	ward	subvillage			
Internal	Arusha	2	1	Monduli	Engaruka	Hyhh	0.0	0	1.
						Madukani	0.0	0	1.
						Mkaoo	0.0	0	1.
						Mula	0.0	0	1.
						Mwembeni	0.0	0	1.

For this group, the mean and sum of the 'functional' variable are 0.0 and 0, respectively, indicating that none of the water pumps in this group are functional. Similarly, the mean and sum of the 'needs repair' variable are 1.0 and 1, respectively, indicating that all water pumps in this group need repair.

In [21]:
```
ed grouping the data by 'basin' and 'status_group', and then unstackin
oupby('basin')['status_group'].value_counts(ascending=True).unstack()

ataFrame using a bar plot
='bar', figsize=(8,6))

to the x-axis, y-axis, and title
r Source (Basin)", fontweight='bold')
ion=45, fontweight='bold')
 Functionality")
Functionality based on Basin', fontsize=14, fontweight='bold')

d with a custom location and title
to_anchor=(1.0, 0.9), title='Water Quantity');
```

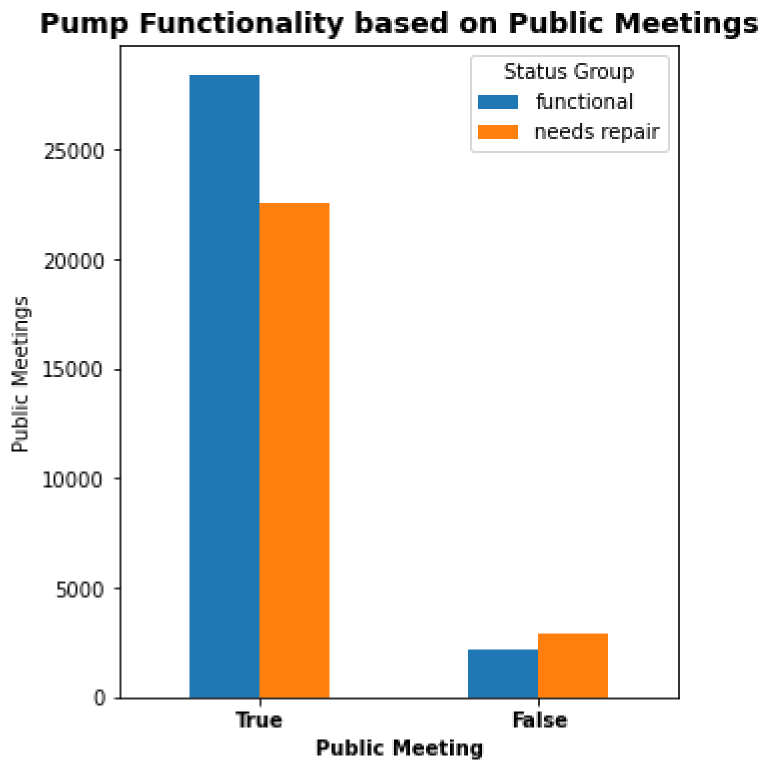


The basins that seem to be more reliable are Rufiji, Pangani and Nyasa this is because they seem to have a higher number of functional water sources compared to the non-functional.

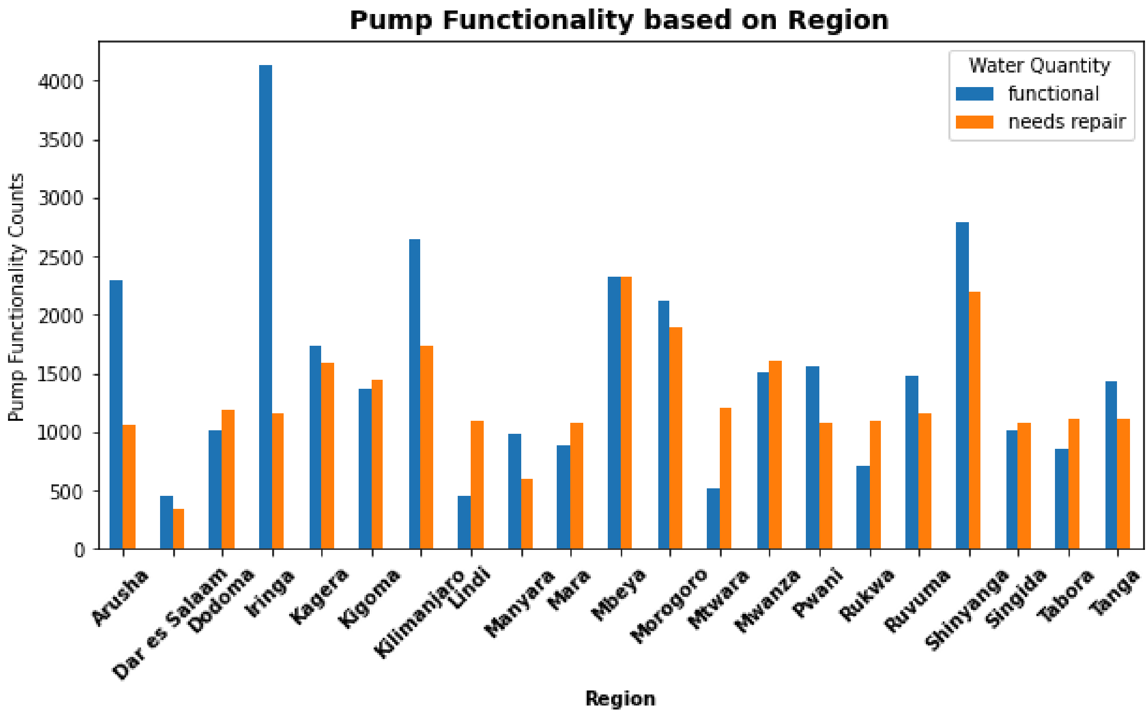
In [22]:
```
#let's analyze the public meeting
analyze_column(data, 'public_meeting')
```

```
Missing Values: 3334/59400

Number of Unique Values in 'public_meeting': 2

Count of '0' as Placeholder for Missing Values in 'public_meeting':
0

Top 20 Most Frequent Values in 'public_meeting':
True     51011
False     5055
Name: public_meeting, dtype: int64
```

In [23]:
```
#let's group the data by public meeting and status group and then unst
sub_df = data.groupby('public_meeting')['status_group'].value_counts(a

sub_df.sort_values(by='public_meeting', ascending=False).plot(kind='ba


# Adding labels to the x-axis, y-axis, and a title
plt.xlabel("Public Meeting", fontweight='bold')
plt.xticks(rotation=0, fontweight='bold')  # Rotating x-axis labels fo
plt.ylabel("Public Meetings")
plt.title('Pump Functionality based on Public Meetings', fontsize=14,

# Adding a legend with a custom location and title
plt.legend(bbox_to_anchor=(1.0, 1.0), title='Status Group');
```



In [24]:
```
# Grouping the data by 'region' and 'status_group', and then unstackir
sub_df = data.groupby('region')['status_group'].value_counts(ascending

# Plotting the DataFrame using a bar plot
sub_df.plot(kind='bar', figsize=(10,5))

# Adding labels to the x-axis, y-axis, and a title
plt.xlabel("Region", fontweight='bold')
plt.xticks(rotation=45, fontweight='bold')  # Rotating x-axis labels 1
plt.ylabel("Pump Functionality Counts")
plt.title('Pump Functionality based on Region', fontsize=14, fontweigh

# Adding a legend with a custom location and title
plt.legend(bbox_to_anchor=(1.0, 1.0), title='Water Quantity');
```



Iringa region seems to have a good number of functioning pumps compared to the other regions.

In [25]:
```
# Analyzing the 'management' variable
analyze_column(data, 'management')
```

```
Missing Values: 0/59400

Number of Unique Values in 'management': 12

Count of '0' as Placeholder for Missing Values in 'management': 0

Top 20 Most Frequent Values in '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: management, dtype: int64
```

In [26]:
```
# Grouping the data by 'management_group' and 'management', and then c
data.groupby(['management_group', 'management'])[['functional', 'needs
```

Out[26]:

management_group	management	functional	needs repair
commercial	company	0.389781	0.610219
	private operator	0.748858	0.251142
	trust	0.589744	0.410256
	water authority	0.493363	0.506637
other	other	0.598341	0.401659
	other - school	0.232323	0.767677
parastatal	parastatal	0.576923	0.423077
unknown	unknown	0.399287	0.600713
user-group	vwc	0.504234	0.495766
	water board	0.739857	0.260143
	wua	0.690730	0.309270
	wug	0.599540	0.400460

"Pumps managed by private operators and the water board have a good percentage of functioning, which is approximately 74.88% and 73.98%, respectively, whereas other pumps need repair."

In [27]:
```
# Analysis of the 'payment' variable
analyze_column(data, 'payment')
# Analysis of the 'payment_type' variable
analyze_column(data, 'payment_type')
```

```
Missing Values: 0/59400

Number of Unique Values in 'payment': 7

Count of '0' as Placeholder for Missing Values in 'payment': 0

Top 20 Most Frequent Values in 'payment':
never pay                25348
pay per bucket            8985
pay monthly               8300
unknown                   8157
pay when scheme fails     3914
pay annually              3642
other                     1054
Name: payment, dtype: int64
Missing Values: 0/59400

Number of Unique Values in 'payment_type': 7

Count of '0' as Placeholder for Missing Values in 'payment_type': 0

Top 20 Most Frequent Values in 'payment_type':
never pay     25348
per bucket     8985
monthly        8300
unknown        8157
on failure     3914
annually       3642
other          1054
Name: payment_type, dtype: int64
```

The analysis reveals that both the 'payment' and 'payment_type' variables have seven unique values, with no missing values or occurrences of '0' as a placeholder. The most common payment methods include 'never pay', 'per bucket', 'monthly', and 'unknown', indicating varied payment structures within the dataset, with 'never pay' being the most prevalent method across both variables.

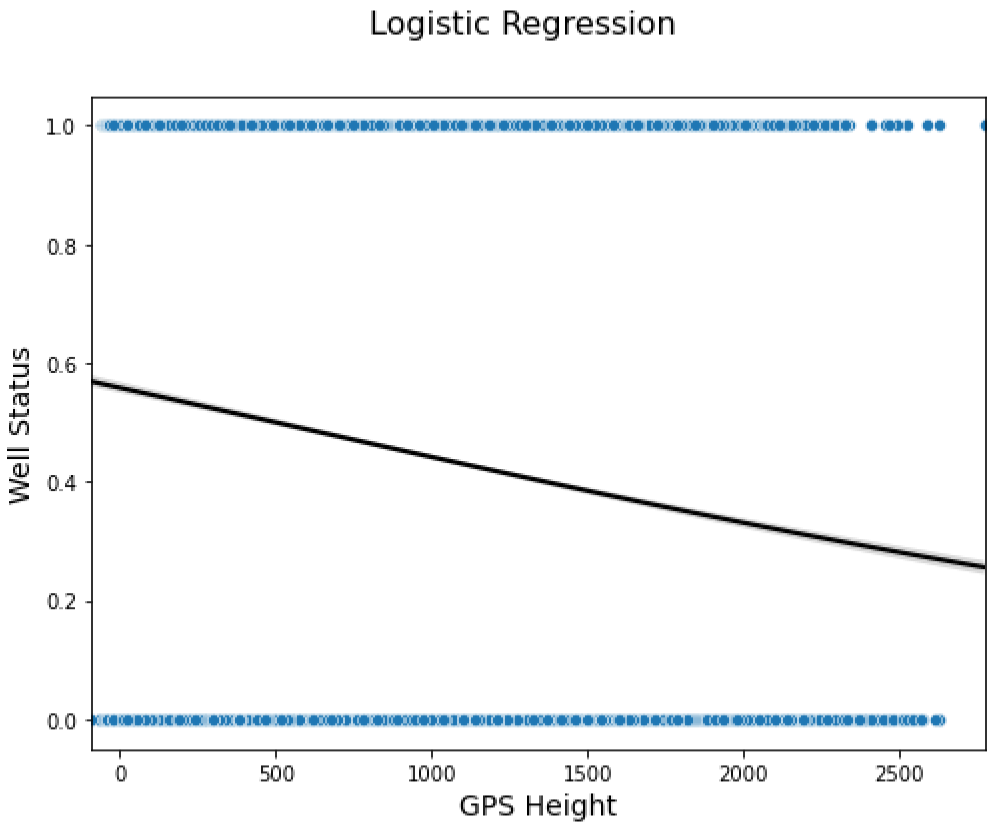
Numeric variables

In [28]:
```
#Let's now analyze some nureoc variables
analyze_column(data,'gps_height')
```

```
Missing Values: 0/59400

Number of Unique Values in 'gps_height': 2428

Count of '0' as Placeholder for Missing Values in 'gps_height': 0

Top 20 Most Frequent Values in 'gps_height':
 0       20438
-15         60
-16         55
-13         55
-20         52
 1290       52
-14         51
 303        51
-18         49
-19         47
 1269       46
 1295       46
 1304       45
-23         45
 280        44
 1538       44
 1286       44
-8          44
-17         44
 1332       43
Name: gps_height, dtype: int64
```

The analysis of the 'gps_height' variable indicates a diverse range of altitude values with no missing or potentially missing data, with the most frequent altitude recorded at 0 meters and a variety of other altitudes present in the dataset.

In [29]:
```
ig, ax = plt.subplots(figsize=(8, 6))  # Create a figure and axes obje
ig.suptitle('Logistic Regression', fontsize=16)  # Add a title to the 
ns.scatterplot(x='gps_height', y='target', data=data[(data['gps_height
ns.regplot(x='gps_height', y='target', data=data[(data['gps_height'] !
x.set_xlabel('GPS Height', fontsize=14)  # Set x-axis label
x.set_ylabel('Well Status', fontsize=14)  # Set y-axis label
lt.show()  # Show the plot
```



In [30]:
```
# CONSTRUCTION YEAR
analyze_column(data, 'construction_year')
```

```
Missing Values: 0/59400

Number of Unique Values in 'construction_year': 55

Count of '0' as Placeholder for Missing Values in 'construction_yea
r': 0

Top 20 Most Frequent Values in 'construction_year':
0       20709
2010     2645
2008     2613
2009     2533
2000     2091
2007     1587
2006     1471
2003     1286
2011     1256
2004     1123
2012     1084
2002     1075
1978     1037
1995     1014
2005     1011
1999      979
1998      966
1990      954
1985      945
1980      811
Name: construction_year, dtype: int64
```

In [31]:
```
from datetime import datetime
data['age_of_well']=datetime.now().year - data['construction_year']

data['age_of_well'].value_counts()
```

Out[31]:
```
2024    20709
14       2645
16       2613
15       2533
24       2091
17       1587
18       1471
21       1286
13       1256
20       1123
12       1084
22       1075
46       1037
29       1014
19       1011
25        979
26        966
34        954
39        945
44        811
28        811
40        779
42        744
30        738
52        708
50        676
27        644
32        640
31        608
23        540
36        521
41        488
49        437
38        434
48        414
54        411
33        324
35        316
37        302
43        238
47        202
45        192
51        184
11        176
53        145
64        102
57         88
61         85
56         77
55         59
60         40
62         30
63         21
59         19
58         17
Name: age_of_well, dtype: int64
```

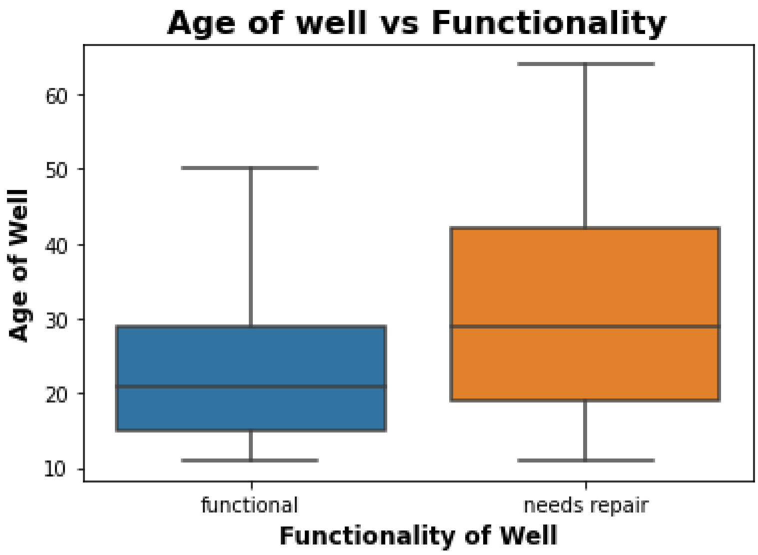
In [32]:
```
# Filtering the DataFrame 'data' to include only rows where 'construct
data = data[(data['construction_year'] > 0) & (data['population'] > 0)
data.head()
```

Out[32]:

	id	status_group	amount_tsh	date_recorded	funder	gps_height	installer	longitude
0	69572	functional	6000.0	2011-03-14	Roman	1390	Roman	34.93809
1	8776	functional	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.69876
2	34310	functional	25.0	2013-02-25	Lottery Club	686	World vision	37.46066
3	67743	needs repair	0.0	2013-01-28	Unicef	263	UNICEF	38.48616
10	49056	functional	0.0	2011-02-20	Private	62	Private	39.20951

5 rows × 45 columns

In [33]:
```
sns.boxplot(x='status_group',y='age_of_well', data=data, showfliers=Fa
plt.xlabel('Functionality of Well', fontsize=12, fontweight='bold');
plt.ylabel('Age of Well', fontsize=12, fontweight='bold');
plt.title('Age of well vs Functionality', fontsize=16, fontweight='bol
```



It is clear that the newer the well the more functional and the older the well the more repairs it needs

In [34]:
```
data= data.drop_duplicates()
```

In [35]:
```
#Now we can drop the columnsn not needed
to_be_dropped = ['wpt_name','id','date_recorded','recorded_by','region
           'lga','scheme_name','funder','subvillage','latitude',
           'longitude','extraction_type_class','extraction_type',
           'payment_type','quantity_group','source_type','waterpoint_t
           'district_code','amount_tsh','num_private','construction_ye
           'status_group','population','functional','needs repair','ma
          ]
```

In [36]:
```
#try to drop the columns not needed and also the null values
data = data.drop(to_be_dropped, axis=1)
data = data.dropna()
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 29361 entries, 0 to 59399
Data columns (total 19 columns):
 #   Column                 Non-Null Count  Dtype 
---  ------                 --------------  ----- 
 0   gps_height             29361 non-null  int64 
 1   installer              29361 non-null  object
 2   basin                  29361 non-null  object
 3   region                 29361 non-null  object
 4   ward                   29361 non-null  object
 5   public_meeting         29361 non-null  object
 6   scheme_management      29361 non-null  object
 7   permit                 29361 non-null  object
 8   extraction_type_group  29361 non-null  object
 9   management_group       29361 non-null  object
 10  payment                29361 non-null  object
 11  water_quality          29361 non-null  object
 12  quality_group          29361 non-null  object
 13  quantity               29361 non-null  object
 14  source                 29361 non-null  object
 15  source_class           29361 non-null  object
 16  waterpoint_type        29361 non-null  object
 17  target                 29361 non-null  int8  
 18  age_of_well            29361 non-null  int64 
dtypes: int64(2), int8(1), object(16)
memory usage: 4.3+ MB
```

Modeling

In [37]:
```
X = data.drop(['target'], axis=1)  # Assigning features to X by droppi
y = data['target']  # Assigning the 'target' variable to y
```

In [38]:
```
# Extracting numerical columns from the feature dataset 'X' and conver
numerical_cols = list(X.select_dtypes(include=np.number).columns)

# Extracting categorical columns from the feature dataset 'X' and conv
categorical_cols = list(X.select_dtypes(exclude=np.number).columns)
print(numerical_cols, categorical_cols)
```

```
['gps_height', 'age_of_well'] ['installer', 'basin', 'region', 'war
d', 'public_meeting', 'scheme_management', 'permit', 'extraction_typ
e_group', 'management_group', 'payment', 'water_quality', 'quality_g
roup', 'quantity', 'source', 'source_class', 'waterpoint_type']
```

Preporcessing of data

In [39]:
```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, StandardScaler

# Preprocessing for numerical data
numerical_transformer = Pipeline(steps=[
    ('scale', StandardScaler())
])

# Preprocessing for categorical data
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Bundle preprocessing for numerical and categorical data
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_cols),
        ('cat', categorical_transformer, categorical_cols)
    ])
```

In [40]:
```
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import GridSearchCV
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline
from sklearn.decomposition import TruncatedSVD
import xgboost as xgboost

def fit_predict(model, X_train, X_test, y_train, y_test):
    '''fit pipeline using given model, and return predictions'''

    param_grid = model['params']
    model = model['model']


    my_pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                                  ('model', model)
                                 ])

    search = GridSearchCV(estimator=my_pipeline,
             param_grid=param_grid, n_jobs=-1, verbose=2, cv=10)

    search.fit(X_train, y_train)

    best_estimator = search.best_estimator_._final_estimator

    print("Best parameter (CV score=%0.3f):" % search.best_score_)
    print(search.best_params_)

    # Preprocessing of validation data, get predictions
    test_preds = search.predict(X_test)
    train_preds = search.predict(X_train)

    return test_preds, train_preds, search
```

In [41]:
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
import itertools
import matplotlib.pyplot as plt
%matplotlib inline

def plot_confusion_matrix(y_true, y_preds):
    # Printing the  confusion matrix
    cnf_matrix = confusion_matrix(y_true, y_preds)
    # Create the basic matrix
    plt.imshow(cnf_matrix,  cmap=plt.cm.Blues)
    # Add title and axis labels
    plt.title('Confusion Matrix')
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

    class_names = set(y)
    tick_marks = np.arange(len(class_names))
    plt.xticks(tick_marks, class_names, rotation=0)
    plt.yticks(tick_marks, class_names)
    # Add labels to each cell
    thresh = cnf_matrix.max() / 2. # Used for text coloring below
    # Here we iterate through the confusion matrix and append labels t
    for i, j in itertools.product(range(cnf_matrix.shape[0]), range(cr
            plt.text(j, i, cnf_matrix[i, j],
                     horizontalalignment='center',
                     color='white' if cnf_matrix[i, j] > thresh else '
    # Add a legend
    plt.colorbar();
    plt.show();

def metrics(model_name, y_train, y_test, y_train_pred, y_test_pred):
    '''Print out the evaluation metrics for a given models predictions
    print(f'Model: {model_name}', )
    print('-'*60)
    plot_confusion_matrix(y_test,y_test_pred)
    print(f'test accuracy: {accuracy_score(y_test, y_test_pred)}')
    print(f'train accuracy: {accuracy_score(y_train, y_train_pred)}')
    print('-'*60)
    print('\ntest report:\n' + classification_report(y_test, y_test_pr
    print('~'*60)
    print('\ntrain report:\n' + classification_report(y_train, y_trair
    print('-'*60)
```

In [42]:
```
# Calculate the smallest number of samples among the two classes
smallest_num = data['target'].value_counts().sort_values().values[0]

# Randomly sample the subset of data where the target label is 0 to ma
target_0 = data[data['target'] == 0].sample(smallest_num)

# Randomly sample the subset of data where the target label is 1 to ma
target_1 = data[data['target'] == 1].sample(smallest_num)

# Concatenate the sampled subsets for both target labels to create a b
sampled_df = pd.concat([target_0, target_1])
```

In [43]:
```
roc(X_test, y_test, pred_y, model):
# Extracting the name of the model from the pipeline
name = str(model.best_estimator_.named_steps["model"])[:str(model.bes

# Predicting probabilities for positive class
y_pred_proba = model.predict_proba(X_test)[:,1]

# Calculating true positive rate (TPR) and false positive rate (FPR)
fpr, tpr, threshold = roc_curve(y_test, y_pred_proba)

# Plotting ROC curve
plt.plot(fpr, tpr, label=model)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title(f'ROC curve for {name}')
plt.show()
```

In [44]:
```
# Display the count of each class (0 and 1) in the 'target' column of
sampled_df['target'].value_counts()
```

Out[44]:
```
1    12664
0    12664
Name: target, dtype: int64
```

In [45]:
```
# Separate the features and the target variable from the 'sampled_df'
X_sampled_df = sampled_df.drop('target', axis=1)
y_sampled_df = sampled_df['target']
```

In [46]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_sampled_df, y_sa

X_sampled_df.head()
```

Out[46]:

	gps_height	installer	basin	region	ward	public_meeting	scheme_manag
42518	1327	Magadini-Makiwaru wa	Pangani	Kilimanjaro	Siha Kati	True	Wate
58602	895	Government	Pangani	Kilimanjaro	Makuyuni	True	
47597	1380	DWE	Lake Victoria	Shinyanga	Mhunze	True	
20290	1522	wanan	Lake Nyasa	Iringa	Ibumi	True	
9032	271	District Council	Ruvuma / Southern Coast	Lindi	Milola	False	

Classification algorithms

1) Logistic regression

In [47]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, roc_auc_score

# Define logistic regression model
logistic_regression = LogisticRegression(random_state=42)

# Define hyperparameters to tune
param_grid = {
    'model__C': [0.001, 0.01, 0.1, 1, 10, 100]  # regularization paran
}

# Create a pipeline
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),  # assuming you have defined prepr
    ('model', logistic_regression)
])

# Grid search for hyperparameter tuning
grid_search = GridSearchCV(estimator=pipeline,
                           param_grid=param_grid,
                           cv=5,  # cross-validation folds
                           scoring='accuracy',  # evaluation metric
                           n_jobs=-1  # use all available CPU cores
                          )

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Make predictions on the test data
y_pred = grid_search.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print(f"ROC AUC: {roc_auc}")

# Best hyperparameters
print("Best hyperparameters:", grid_search.best_params_)
```

```
Accuracy: 0.7866824582181866
ROC AUC: 0.7865869143527149
Best hyperparameters: {'model__C': 10}
```

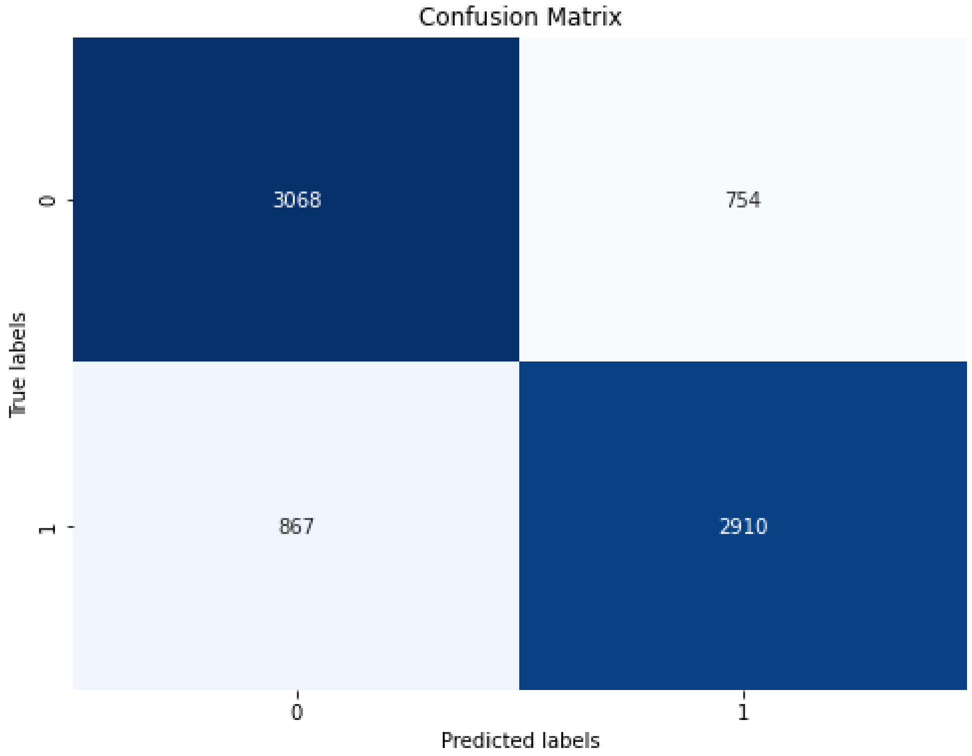
```
/Users/myraminayokadenge/anaconda3/envs/learn-env/lib/python3.8/site
-packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning:
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as sh
own in:
    https://scikit-learn.org/stable/modules/preprocessing.html (http
s://scikit-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver option
s:
    https://scikit-learn.org/stable/modules/linear_model.html#logist
ic-regression (https://scikit-learn.org/stable/modules/linear_model.
html#logistic-regression)
  n_iter_i = _check_optimize_result(
```

In [48]:

```
from sklearn.metrics import confusion_matrix

# Calculate confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Print confusion matrix
print("Confusion Matrix:")
print(conf_matrix)
```

```
Confusion Matrix:
[[3068  754]
 [ 867 2910]]
```

In [49]:
```
import matplotlib.pyplot as plt
import seaborn as sns

#we can now try plot the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, cmap='Blues', fmt='d', cbar=False
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show();
```



2) XG Boost

In [50]:

```
from scipy import stats
import math

#Sklearn
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier as KNN
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, accuracy_score, roc

from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

#Visual/Graphs
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
plt.style.use('seaborn')



#Import warnings
import warnings
warnings.filterwarnings("ignore")

import pandas.util.testing as tm
```

In [51]:
```
function finds the top features of a model using eli5 library
o_feat(model_pipe):
'This function is used to find the best features of our models

gs:
  model_pipe (GridSearchCV): model_pipe is a pipeline

turns:
  the top features of the model
'

Extracting the one-hot encoded column names
ehot_columns = list(model_pipe.best_estimator_.named_steps['preprocess
                    .named_transformers_['cat']
                    .named_steps['onehot']
                    .get_feature_names(input_features=categorical_cols

Combining numerical and one-hot encoded column names
neric_features_list = list(numerical_cols)
neric_features_list.extend(onehot_columns)

Returning the top features using eli5 library
turn eli5.explain_weights(model_pipe.best_estimator_.named_steps['mode
```

In [52]:
```
xgb_param = {
    'model__eta': [.3, .2, .1, .05, .01, .005], #Learning rate
    'model__max_depth': [10], #The maximum depth of a tree.Used to cor
    'model__min_child_weight': [6], # minimum sum of weights of all ob
    'model__subsample': [0.8]      # Subsample ratio of the training i
}
```

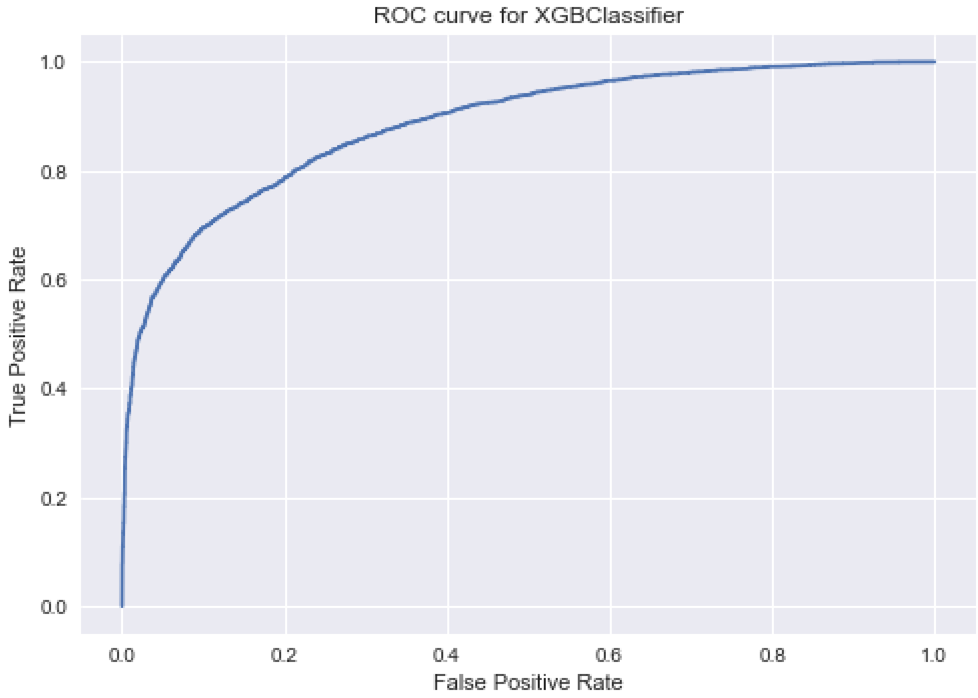
In [53]:
```
# Importing XGBClassifier from xgboost library
from xgboost import XGBClassifier

# Defining the XGBClassifier model and its parameters
xgb = { 'model': XGBClassifier(random_state=42), 'params': xgb_param }

# Fitting and predicting using the XGBClassifier model
xgb_test_preds, xgb_train_preds, xgb_pipeline = fit_predict(xgb, X_tra
```

```
Fitting 10 folds for each of 6 candidates, totalling 60 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent w
orkers.
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:   51.5s
[Parallel(n_jobs=-1)]: Done  60 out of  60 | elapsed:  1.7min finish
ed

Best parameter (CV score=0.798):
{'model__eta': 0.2, 'model__max_depth': 10, 'model__min_child_weigh
t': 6, 'model__subsample': 0.8}
```

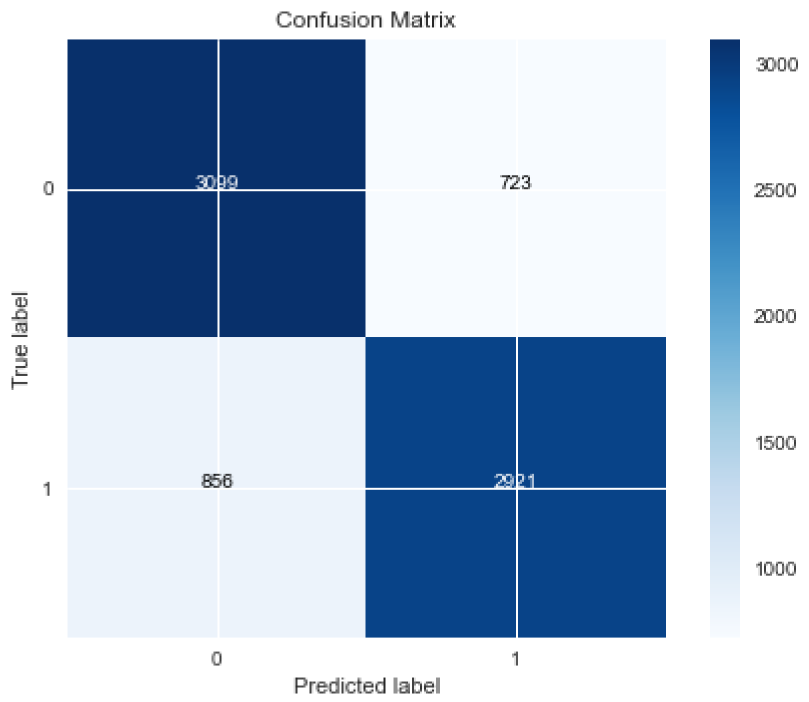
In [54]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_sc

# Calculate and print various metrics using the same data provided to
XGBoost_accuracy = accuracy_score(y_test, xgb_test_preds)
XGBoost_precision = precision_score(y_test, xgb_test_preds)
XGBoost_recall = recall_score(y_test, xgb_test_preds)
XGBoost_f1 = f1_score(y_test, xgb_test_preds)

# Printing the calculated metrics for XGBoost
print(f"XGBoost Accuracy: {XGBoost_accuracy}")
print(f"XGBoost Precision: {XGBoost_precision}")
print(f"XGBoost Recall: {XGBoost_recall}")
print(f"XGBoost F1-score: {XGBoost_f1}")
```

```
XGBoost Accuracy: 0.7922095012501645
XGBoost Precision: 0.8015916575192097
XGBoost Recall: 0.7733651045803548
XGBoost F1-score: 0.7872254413151866
```

In [55]:
```
# Now we can Plot the ROC curve
roc(X_test, y_test, xgb_test_preds, xgb_pipeline)
```



In [56]:
```
plot_confusion_matrix(y_test, xgb_test_preds);
```



3) Random forest classifier

A random forest is also a machine learning technique that is used to solve classification problems. It utilizes ensemble learning,which is a technique that combines many classifiers to provide solution to complex problems.

In [57]:
```
n sklearn.tree import DecisionTreeClassifier
n sklearn.ensemble import BaggingClassifier, RandomForestClassifier

est_params = {'model__n_estimators' : [500,1000],  # number of decision
              'model__criterion' : ['gini','entropy'], # function that
              'model__max_depth': [10],          # maximum depth of the
              'model__min_samples_split' : [10], # minimum number of sa
              'model__min_samples_leaf' : [5]} # minimum number of samp
                                      # Smaller leaf size makes the
= { 'model': RandomForestClassifier(random_state=42), 'params': forest

_test_preds, rfc_train_preds,rfc_pipeline = fit_predict(rfc, X_train, X
```

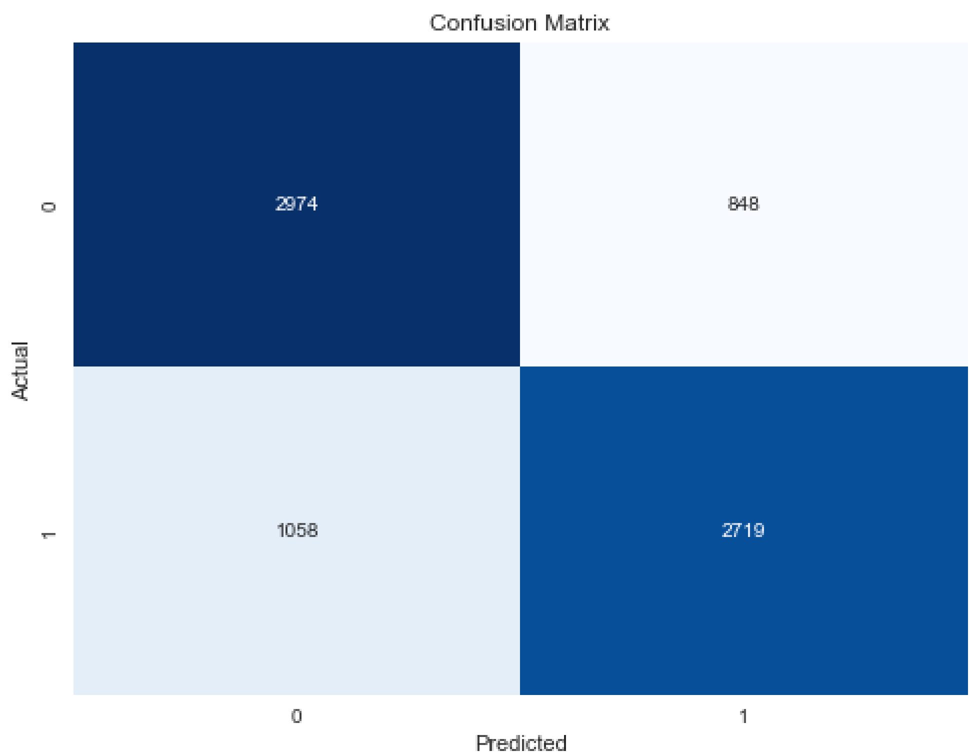
```
Fitting 10 folds for each of 4 candidates, totalling 40 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent w
orkers.
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:   42.2s
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:  1.1min finish
ed

Best parameter (CV score=0.749):
{'model__criterion': 'gini', 'model__max_depth': 10, 'model__min_sam
ples_leaf': 5, 'model__min_samples_split': 10, 'model__n_estimator
s': 500}
```

In [58]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_sc

rfc_test_preds, rfc_train_preds, rfc_pipeline = fit_predict(rfc, X_tra

random_forest_accuracy = accuracy_score(y_test, rfc_test_preds)
random_forest_precision = precision_score(y_test, rfc_test_preds)
# ... calculate other metrics

print(f"Random Forest Accuracy: {random_forest_accuracy}")
print(f"Random Forest Precision: {random_forest_precision}")
# ... print other metric values
```

```
Fitting 10 folds for each of 4 candidates, totalling 40 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent w
orkers.
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:   41.9s
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:  3.5min finish
ed

Best parameter (CV score=0.749):
{'model__criterion': 'gini', 'model__max_depth': 10, 'model__min_sam
ples_leaf': 5, 'model__min_samples_split': 10, 'model__n_estimator
s': 500}
Random Forest Accuracy: 0.7491775233583367
Random Forest Precision: 0.7622652088589852
```

In [59]:
```
# Calculate accuracy
accuracy = accuracy_score(y_test, rfc_test_preds)
print(f'Accuracy: {accuracy}')

# Generate and print classification report
print('Classification Report:')
print(classification_report(y_test, rfc_test_preds))

# Generate confusion matrix
cm = confusion_matrix(y_test, rfc_test_preds)

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show();
```

```
Accuracy: 0.7491775233583367
Classification Report:
              precision    recall  f1-score   support

           0       0.74      0.78      0.76      3822
           1       0.76      0.72      0.74      3777

    accuracy                           0.75      7599
   macro avg       0.75      0.75      0.75      7599
weighted avg       0.75      0.75      0.75      7599
```



4) Support vector machine

This is where the machine learning model kind of learns from the past input data and now predicts whatever output.

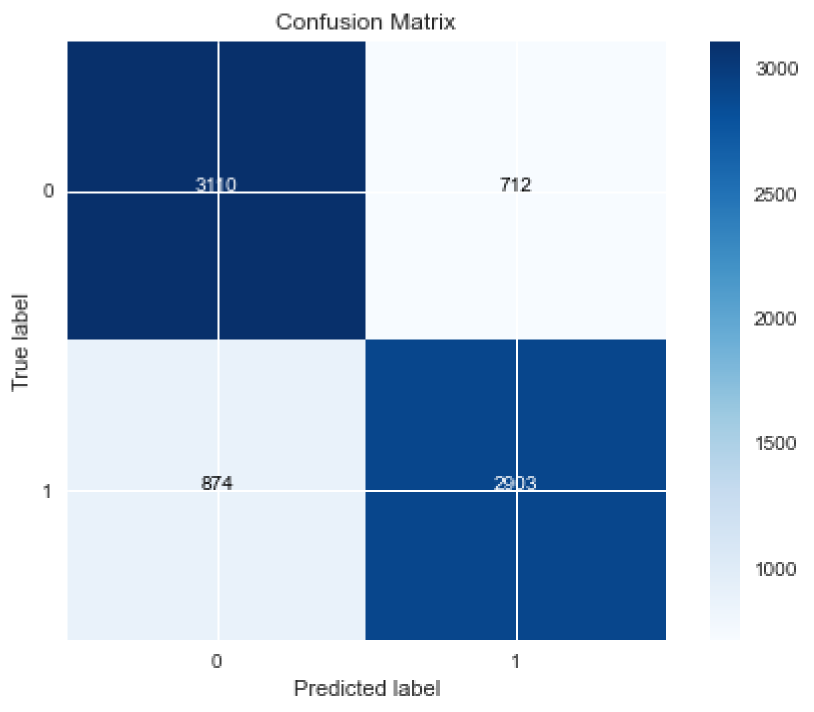
In [60]:
```
lsvc_parameter = { 'model__C': [1, 10],
    'model__max_iter': [10000], # maximum number of iterations to be r
    'model__dual':[False],  # dual=False when n_samples > n_features.
    'model__penalty': ['l1','l2'],
    }
```

In [61]:
```
from sklearn.svm import LinearSVC
lsvc = { 'model': LinearSVC(random_state=42), 'params': lsvc_parameter

lsvc_test_preds, lsvc_train_preds,lsvc_pipeline = fit_predict(lsvc, X_
```

```
Fitting 10 folds for each of 4 candidates, totalling 40 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent w
orkers.
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:  1.8min finish
ed

Best parameter (CV score=0.789):
{'model__C': 1, 'model__dual': False, 'model__max_iter': 10000, 'mod
el__penalty': 'l1'}
```

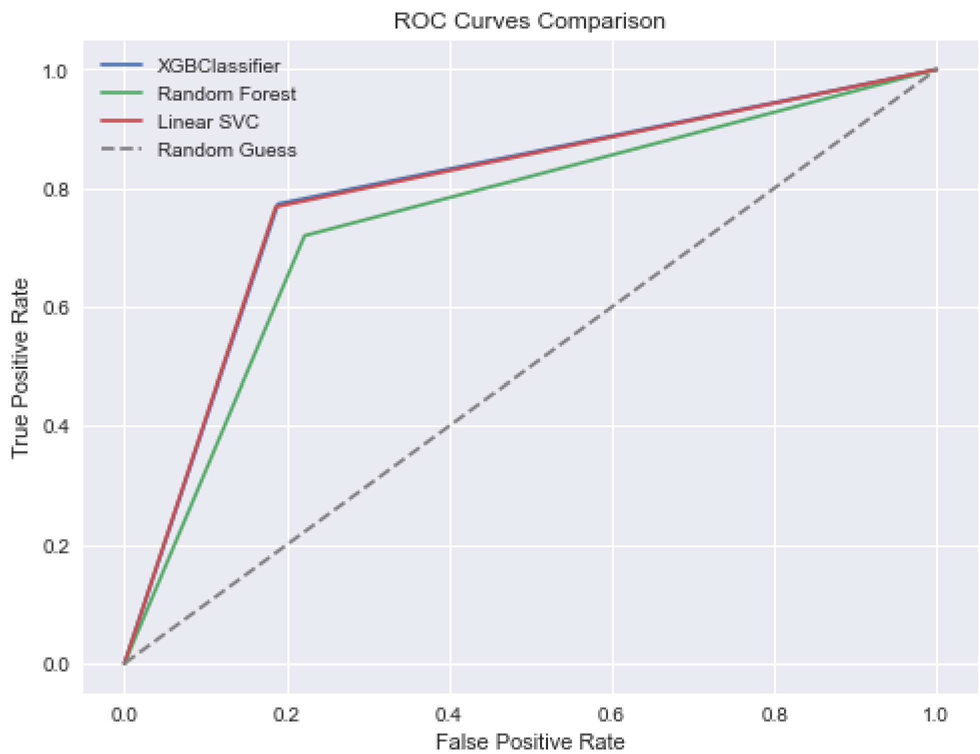
In [62]:
```
from sklearn.metrics import accuracy_score, classification_report, cor
import itertools
import matplotlib.pyplot as plt

def plot_confusion_matrix(y_true, y_pred):
    cm = confusion_matrix(y_true, y_pred)
    plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
    plt.title('Confusion Matrix')
    plt.colorbar()
    plt.xlabel('Predicted label')
    plt.ylabel('True label')
    tick_marks = range(len(set(y_true)))
    plt.xticks(tick_marks, tick_marks)
    plt.yticks(tick_marks, tick_marks)
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1
        plt.text(j, i, cm[i, j], horizontalalignment='center', color='
    plt.show()

def evaluate_model(model_name, y_train, y_test, y_train_pred, y_test_p
    print(f'Model: {model_name}')
    print('-' * 60)
    plot_confusion_matrix(y_test, y_test_pred)
    print(f'Test accuracy: {accuracy_score(y_test, y_test_pred)}')
    print(f'Train accuracy: {accuracy_score(y_train, y_train_pred)}')
    print('-' * 60)
    print('\nTest report:\n' + classification_report(y_test, y_test_pr
    print('~' * 60)
    print('\nTrain report:\n' + classification_report(y_train, y_trair
    print('-' * 60)

# Assuming you have trained a model and made predictions
# Replace lsvc_train_preds and lsvc_test_preds with your actual predic
# Call the evaluate_model function
evaluate_model('LinearSVC', y_train, y_test, lsvc_train_preds, lsvc_te
```

```
Model: LinearSVC
------------------------------------------------------------
```



```
Test accuracy: 0.7912883274115016
Train accuracy: 0.8344520277511422
------------------------------------------------------------

Test report:
              precision    recall  f1-score   support

           0       0.78      0.81      0.80      3822
           1       0.80      0.77      0.79      3777

    accuracy                           0.79      7599
   macro avg       0.79      0.79      0.79      7599
weighted avg       0.79      0.79      0.79      7599

~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~

Train report:
              precision    recall  f1-score   support

           0       0.82      0.86      0.84      8842
           1       0.85      0.81      0.83      8887

    accuracy                           0.83     17729
   macro avg       0.84      0.83      0.83     17729
weighted avg       0.84      0.83      0.83     17729

------------------------------------------------------------
```

In [63]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve

def plot_roc_curves(models, X_test, y_test):
    plt.figure(figsize=(8, 6))
    for model_name, y_pred_proba in models.items():
        # Calculating true positive rate (TPR) and false positive rate
        fpr, tpr, _ = roc_curve(y_test, y_pred_proba)

        # Plotting ROC curve for each model
        plt.plot(fpr, tpr, label=model_name)

    # Plotting the random guess line
    plt.plot([0, 1], [0, 1], linestyle='--', color='grey', label='Ranc

    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curves Comparison')
    plt.legend()
    plt.grid(True)
    plt.show()

# Define the models and their corresponding predicted probabilities
models = {'XGBClassifier': xgb_test_preds,
          'Random Forest': rfc_test_preds,
          'Linear SVC': lsvc_test_preds
          }

# Plot ROC curves for the models
plot_roc_curves(models, X_test, y_test)
```



Evaluation

For the random forest classifier the model achieved an accuracy of 74.5% indicating that it correctly classified about three quarter of the instances.

For class 0 (Positive class): Precision was 74% and recall was 77%, indicating that the model correctly identified 77% of the actual positive instances, and when it predicted a positive instance, it was correct about 74% of the time. For class 1 (Negative class): Precision was 76% and recall was 72%, suggesting that the model correctly identified 72% of the actual negative instances, and when it predicted a negative instance, it was correct about 76% of the time.

It seems like our XGboost model is the most accurate with an accuracy of 80%

Conclusion and Recommendation

Payment methods seem to be an important factor in maintenance of the wells. From the analysis it is noted that payments 'never pay', 'per bucket', and 'monthly' with 'never pay' being the most prevalent method help lead to better maintenance of the wells.

The age of the wells seems to be a contributing factor to the functionality. The older wells seem to be in need of more repairs compared to the new wells.

Groundwater is very important to maintain the functionality of the wells. Almost, the entire water supply to the wells is dependent on groundwater. Hence we would look into different methods such as rainwater harvesting and soil conservation which would also help sustain more water in the lakes.

It is also clear that private operations and waterboards seem to have credible management of the wells as they have the highest number of functional wells and relatively lowest number of wells that need to be repaired.

We can see that having a public meeting helps in functioning of the wells. More than 50% wells are functional when there is a public meeting held for the same. Thus, Public meeting is an important factor for the functioning of wells.

Further send out designated people to inspect the pumps detected by the model and assess what needs to be done.

Type *Markdown* and LaTeX: α^2