Phase 3 Project: Tanzania Wells

text

Project Overview

Stakeholder: The Tanzanian Ministry of Water, NGOs, and organizations involved in water distribution and maintenance.

Business Problem: This project aims to predict the operational status of water pumps across Tanzania, specifically identifying which pumps are functional, which require repairs, and which are non-functional. The prediction is based on various factors such as pump type, installation date, and management practices. The project uses data from Taarifa and the Tanzanian Ministry of Water, with the challenge provided by DrivenData in 2015. By accurately forecasting pump failures, maintenance efforts can be optimized, ensuring that communities in Tanzania maintain reliable access to clean and potable water.

Business Problem

The Tanzanian Ministry of Water faces the ongoing challenge of maintaining the functionality of water pumps throughout the country. Many pumps break down or require maintenance due to factors such as improper management, outdated installations, or environmental conditions. Accurately predicting whether a pump will remain functional, require repairs, or fail entirely is essential for effective maintenance planning and resource allocation.

Predicting pump functionality can help:

- **Improve maintenance operations** by prioritizing pumps that need immediate attention, ensuring that the most critical issues are addressed first.
- **Ensure continuous access to clean water** by minimizing pump failures and preventing disruptions in water supply.
- **Allocate resources effectively** for repairs and replacements, reducing downtime and minimizing the impact on communities dependent on these water sources.

The goal of this project is to predict which pumps are functional, which need some repairs and which dont work at all.

The challenge from DrivenData. (2015). Pump it Up: Data Mining the Water Table. Retrieved [Month Day Year] from [https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table (https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table)](https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table) with data from Taarifa and the Tanzanian Ministry of Water. The goal of this project is to predict one of these three classes based on a number of variables about what kind of pump is operating, when it was installed, and how it is managed. A smart understanding of which waterpoints will fail can improve maintenance operations and ensure that clean, potable water is available to communities across Tanzania.

1. Project Setup

- **Import Necessary Libraries**: The first step is to import the required libraries, such as pandas and numpy for data manipulation, sklearn for machine learning, and matplotlib and seaborn for data visualization.
- **Load the Dataset**: The dataset is then loaded into the environment, typically from a CSV or other file formats, to begin the analysis.
- **Set Random Seed for Reproducibility**: A random seed is set to ensure that any random processes (e.g., train-test splits, model initialization) produce the same results each time the code is run, ensuring reproducibility.

In [352]:
```
#import neccessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns


from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_m
atrix
from sklearn.feature_selection import RFE
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score
```

In [353]:
```
#Load training dataset
sub_merged_df = pd.read_csv('./SubmissionFormat.csv',index_col=0)
training_merged_df = pd.read_csv('./TrainingSetValues.csv',index_col=0)
test_merged_df = pd.read_csv('./TestSetValues.csv',index_col=0)
t_label_merged_df = pd.read_csv('TrainingSetLabels.csv',index_col=0)
```

2. Data Exploration and Preprocessing

In this step, we focus on preparing the data for building machine learning models:

- **Examine the Dataset**: First, we inspect the dataset by viewing the first few rows (using `head`), getting a summary of its structure (`info`), and understanding basic statistics of the numerical features (`describe`).
- **Check for Missing Values and Handle Them**: We identify missing data within the dataset and address it either by imputing values (e.g., filling with mean or median) or by deleting rows or columns that contain too many missing values.
- **Explore Data Distributions and Correlations**: Next, we analyze the distribution of each feature and assess relationships between features, including correlation analysis to identify potential multicollinearity.
- **Perform Feature Engineering if Necessary**: If needed, we create new features or modify existing ones to improve the model's predictive power. This may involve encoding categorical variables, scaling numerical features, or creating interaction terms.
- **Split the Data into Features (X) and Target Variable(s) (y)**: Finally, we separate the dataset into the features (X) and the target variable(s) (y) to prepare for model training.

In [354]:
```
# Function to display dataset info
def display_dataset_info(merged_df, name):
    print(f"\n=== {name} ===")
    print(f"Shape: {merged_df.shape}")
    print("\nInfo:")
    print(merged_df.info())
    print("\nDescription:")
    print(merged_df.describe())
    print("\nHead:")
    print(merged_df.head())
    print("\n" + "="*40)

# Display info for each dataset
display_dataset_info(sub_merged_df, "Submission Format")
display_dataset_info(training_merged_df, "Training Set Values")
display_dataset_info(test_merged_df, "Test Set Values")
display_dataset_info(t_label_merged_df, "Training Set Labels")
```

```
=== Submission Format ===
Shape: (14850, 1)

Info:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 14850 entries, 50785 to 68707
Data columns (total 1 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   status_group  14850 non-null  object
dtypes: object(1)
memory usage: 232.0+ KB
None

Description:
           status_group
count             14850
unique                1
top     predicted label
freq              14850

Head:
          status_group
id
50785  predicted label
51630  predicted label
17168  predicted label
45559  predicted label
49871  predicted label

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=== Training Set Values ===
Shape: (59400, 39)

Info:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 69572 to 26348
Data columns (total 39 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   amount_tsh             59400 non-null  float64
 1   date_recorded          59400 non-null  object
 2   funder                 55765 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               59400 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      55523 non-null  object
 20  scheme_name            31234 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
dtypes: float64(3), int64(6), object(30)
memory usage: 18.1+ MB
None

Description:
          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

Head:
       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  ... payment_type water_quality  quality_group
\
id                              ...
69572               Lake Nyasa  ...     annually          soft           good
8776            Lake Victoria  ...    never pay          soft           good
34310                  Pangani  ...   per bucket          soft           good
67743  Ruvuma / Southern Coast  ...    never pay          soft           good
19728            Lake Victoria  ...    never pay          soft           good

           quantity quantity_group                source  \
id
69572        enough         enough                spring
8776   insufficient   insufficient  rainwater harvesting
34310        enough         enough                   dam
67743           dry            dry           machine dbh
19728      seasonal       seasonal  rainwater harvesting

                source_type source_class              waterpoint_type  \
id
69572                spring  groundwater           communal standpipe
8776   rainwater harvesting      surface           communal standpipe
34310                   dam      surface  communal standpipe multiple
67743              borehole  groundwater  communal standpipe multiple
19728  rainwater harvesting      surface           communal standpipe

      waterpoint_type_group
id
69572    communal standpipe
8776     communal standpipe
34310    communal standpipe
67743    communal standpipe
19728    communal standpipe

[5 rows x 39 columns]

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=== Test Set Values ===
Shape: (14850, 39)

Info:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 14850 entries, 50785 to 68707
Data columns (total 39 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   amount_tsh             14850 non-null  float64
 1   date_recorded          14850 non-null  object
```

```
 2   funder                 13981 non-null  object
 3   gps_height             14850 non-null  int64
 4   installer              13973 non-null  object
 5   longitude              14850 non-null  float64
 6   latitude               14850 non-null  float64
 7   wpt_name               14850 non-null  object
 8   num_private            14850 non-null  int64
 9   basin                  14850 non-null  object
 10  subvillage             14751 non-null  object
 11  region                 14850 non-null  object
 12  region_code            14850 non-null  int64
 13  district_code          14850 non-null  int64
 14  lga                    14850 non-null  object
 15  ward                   14850 non-null  object
 16  population             14850 non-null  int64
 17  public_meeting         14029 non-null  object
 18  recorded_by            14850 non-null  object
 19  scheme_management      13881 non-null  object
 20  scheme_name            7758 non-null   object
 21  permit                 14113 non-null  object
 22  construction_year      14850 non-null  int64
 23  extraction_type        14850 non-null  object
 24  extraction_type_group  14850 non-null  object
 25  extraction_type_class  14850 non-null  object
 26  management             14850 non-null  object
 27  management_group       14850 non-null  object
 28  payment                14850 non-null  object
 29  payment_type           14850 non-null  object
 30  water_quality          14850 non-null  object
 31  quality_group          14850 non-null  object
 32  quantity               14850 non-null  object
 33  quantity_group         14850 non-null  object
 34  source                 14850 non-null  object
 35  source_type            14850 non-null  object
 36  source_class           14850 non-null  object
 37  waterpoint_type        14850 non-null  object
 38  waterpoint_type_group  14850 non-null  object
dtypes: float64(3), int64(6), object(30)
memory usage: 4.5+ MB
None

Description:
          amount_tsh    gps_height     longitude      latitude   num_private
\
count   14850.000000  14850.000000  14850.000000  1.485000e+04  14850.000000
mean      322.826983    655.147609     34.061605 -5.684724e+00      0.415084
std      2510.968644    691.261185      6.593034  2.940803e+00      8.167910
min         0.000000    -57.000000      0.000000 -1.156459e+01      0.000000
25%         0.000000      0.000000     33.069455 -8.443970e+00      0.000000
50%         0.000000    344.000000     34.901215 -5.049750e+00      0.000000
75%        25.000000   1308.000000     37.196594 -3.320594e+00      0.000000
max    200000.000000   2777.000000     40.325016 -2.000000e-08    669.000000

        region_code  district_code    population  construction_year
count  14850.000000   14850.000000  14850.000000       14850.000000
mean      15.139057       5.626397    184.114209        1289.708350
std       17.191329       9.673842    469.499332         955.241087
```

```
min        1.000000      0.000000      0.000000          0.000000
25%        5.000000      2.000000      0.000000          0.000000
50%       12.000000      3.000000     20.000000       1986.000000
75%       17.000000      5.000000    220.000000       2004.000000
max       99.000000     80.000000  11469.000000       2013.000000

Head:
       amount_tsh date_recorded                  funder  gps_height  \
id
50785         0.0    2013-02-04                    Dmdd        1996
51630         0.0    2013-02-04  Government Of Tanzania        1569
17168         0.0    2013-02-01                     NaN        1567
45559         0.0    2013-01-22              Finn Water         267
49871       500.0    2013-03-27                  Bruder        1260

        installer  longitude   latitude                 wpt_name  num_private
\
id
50785        DMDD  35.290799  -4.059696  Dinamu Secondary School            0
51630         DWE  36.656709  -3.309214                  Kimnyak            0
17168         NaN  34.767863  -5.004344           Puma Secondary            0
45559  FINN WATER  38.058046  -9.418672           Kwa Mzee Pange            0
49871      BRUDER  35.006123 -10.950412          Kwa Mzee Turuka            0

                         basin  ... payment_type water_quality  quality_group
\
id                              ...
50785                 Internal  ...    never pay          soft           good
51630                  Pangani  ...    never pay          soft           good
17168                 Internal  ...    never pay          soft           good
45559  Ruvuma / Southern Coast  ...      unknown          soft           good
49871  Ruvuma / Southern Coast  ...      monthly          soft           good

           quantity quantity_group                source  \
id
50785      seasonal       seasonal  rainwater harvesting
51630  insufficient   insufficient                spring
17168  insufficient   insufficient  rainwater harvesting
45559           dry            dry          shallow well
49871        enough         enough                spring

                source_type source_class     waterpoint_type  \
id
50785  rainwater harvesting      surface               other
51630                spring  groundwater  communal standpipe
17168  rainwater harvesting      surface               other
45559          shallow well  groundwater               other
49871                spring  groundwater  communal standpipe

      waterpoint_type_group
id
50785                 other
51630    communal standpipe
17168                 other
45559                 other
49871    communal standpipe
```

```
[5 rows x 39 columns]

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=== Training Set Labels ===
Shape: (59400, 1)

Info:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 69572 to 26348
Data columns (total 1 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   status_group  59400 non-null  object
dtypes: object(1)
memory usage: 928.1+ KB
None

Description:
       status_group
count         59400
unique            3
top      functional
freq          32259

Head:
         status_group
id                   
69572      functional
8776       functional
34310      functional
67743  non functional
19728      functional

========================================
```

In [355]:
```
#check for missing values in training dataset
training_merged_df.isna().sum()
```

Out[355]:
```
amount_tsh                   0
date_recorded                0
funder                    3635
gps_height                   0
installer                 3655
longitude                    0
latitude                     0
wpt_name                     0
num_private                  0
basin                        0
subvillage                 371
region                       0
region_code                  0
district_code                0
lga                          0
ward                         0
population                   0
public_meeting            3334
recorded_by                  0
scheme_management         3877
scheme_name              28166
permit                    3056
construction_year            0
extraction_type              0
extraction_type_group        0
extraction_type_class        0
management                   0
management_group             0
payment                      0
payment_type                 0
water_quality                0
quality_group                0
quantity                     0
quantity_group               0
source                       0
source_type                  0
source_class                 0
waterpoint_type              0
waterpoint_type_group        0
dtype: int64
```

Dropped Columns and Rationale:

- **date_recorded**: This is redundant because the construction year is already available, which suffices for predicting well functionality.
- **funder**: Some rows have identical values to the installer column, and many others are variations of the same entry. The installer has a greater impact on well functionality.
- **wpt_name**: Too many unique values to be useful.
- **subvillage**: This can be represented by the region.
- **lga**: Can be represented by the region.
- **ward**: Can be represented by the region.
- **recorded_by**: This column has the same value for all rows, making it irrelevant.
- **scheme_name**: Contains too many unique values and many null entries.
- **extraction_type**: Very similar to the 'extraction_type_class' column.
- **extraction_type_group**: Similar to 'extraction_type_class'.
- **management**: The 'management_group' column already covers the categories of management, so 'management' will be dropped.
- **payment**: It duplicates the 'payment_type' column, so it will be removed.
- **quality_group**: Highly correlated with the 'water_quality' column. Since 'water_quality' offers unique rows, it will be retained while dropping this column.
- **quantity**: The 'quantity_group' column represents categories of quantity, so 'quantity' will be dropped.
- **source**: This can be represented by the 'source_class' column.
- **source_type**: This can also be represented by the 'source_class' column.
- **waterpoint_type**: This is similar to 'waterpoint_type_group', so it will be removed.

Numerical Columns:

- **num_private**: The meaning of this column is unclear.
- **region_code**: It is a duplicate of the 'region' column.
- **district_code**: This can be captured by the 'region' column.

Observations:

- **Funder** and **installer** are similar, but the 'funder' column has fewer null values than the 'installer' column.
- **Waterpoint_type** and **waterpoint** are highly similar; 'waterpoint_type' will be dropped.

In [356]:
```
#Check categorical columns
training_merged_df.select_dtypes(include=['object']).columns
```

Out[356]:
```
Index(['date_recorded', 'funder', 'installer', 'wpt_name', 'basin',
       'subvillage', 'region', 'lga', 'ward', 'public_meeting', 'recorded_b
y',
       'scheme_management', 'scheme_name', 'permit', 'extraction_type',
       'extraction_type_group', 'extraction_type_class', 'management',
       'management_group', 'payment', 'payment_type', 'water_quality',
       'quality_group', 'quantity', 'quantity_group', 'source', 'source_typ
e',
       'source_class', 'waterpoint_type', 'waterpoint_type_group'],
      dtype='object')
```

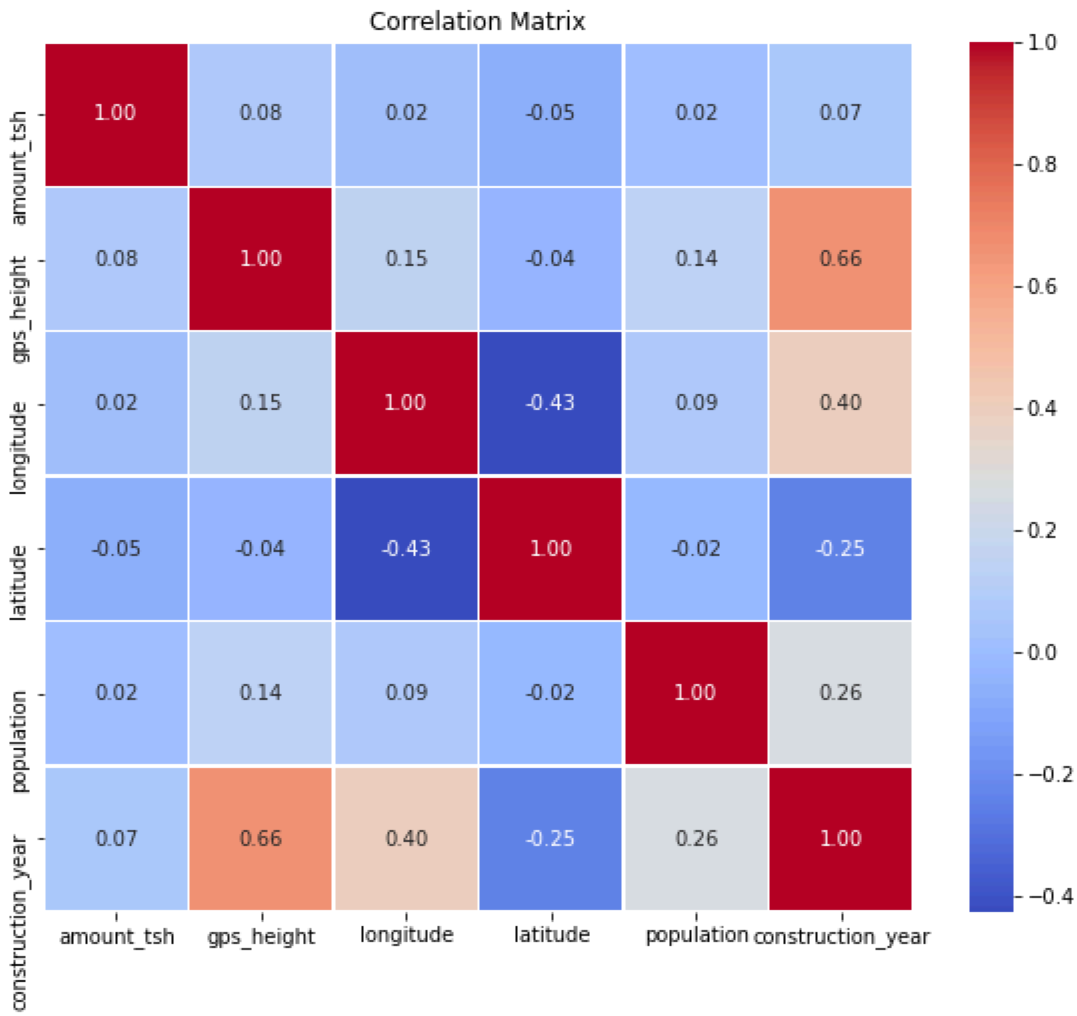
In [357]:
```
#check numerical columns
training_merged_df.select_dtypes(include=['int64', 'float64']).columns
```

Out[357]:
```
Index(['amount_tsh', 'gps_height', 'longitude', 'latitude', 'num_private',
       'region_code', 'district_code', 'population', 'construction_year'],
      dtype='object')
```

In [358]:
```
#Define the list of columns to drop
columns_drop = ['date_recorded', 'funder', 'wpt_name', 'subvillage', 'lga',
 'ward', 'recorded_by', 'scheme_name', 'extraction_type',
 'extraction_type_group', 'management', 'payment', 'quality_group',
 'quantity', 'source', 'source_type', 'waterpoint_type', 'num_private',
 'region_code', 'district_code']

# Drop unnecessary columns
training_merged_df = training_merged_df.drop(columns_drop,axis=1)

#Print remaining columns
print(training_merged_df.columns)
```

```
Index(['amount_tsh', 'gps_height', 'installer', 'longitude', 'latitude',
       'basin', 'region', 'population', 'public_meeting', 'scheme_managemen
t',
       'permit', 'construction_year', 'extraction_type_class',
       'management_group', 'payment_type', 'water_quality', 'quantity_group',
       'source_class', 'waterpoint_type_group'],
      dtype='object')
```

In [359]:
```
#explore data distrubitions and correlations of the numerical- training data
corr_matrix = training_merged_df.corr()

# Plot the correlation matrix using Seaborn for numerical values.
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, fmt='.2f', cmap='coolwarm', square=True,
linewidths=0.5)
plt.title('Correlation Matrix')
plt.show()
```



In [360]:
```
# merge with training labels data using ID as connector
merged_df = pd.merge(training_merged_df, t_label_merged_df, on='id', how='outer', indicator=True)
print(merged_df.head(20))
```

```
       amount_tsh  gps_height            installer  longitude   latitude  \
id
69572      6000.0        1390                Roman  34.938093  -9.856322
8776          0.0        1399              GRUMETI  34.698766  -2.147466
34310        25.0         686         World vision  37.460664  -3.821329
67743         0.0         263               UNICEF  38.486161 -11.155298
19728         0.0           0              Artisan  31.130847  -1.825359
9944         20.0           0                  DWE  39.172796  -4.765587
19816         0.0           0                 DWSP  33.362410  -3.766365
54551         0.0           0                  DWE  32.620617  -4.226198
53934         0.0           0            Water Aid  32.711100  -5.146712
46144         0.0           0              Artisan  30.626991  -1.257051
49056         0.0          62              Private  39.209518  -7.034139
50409       200.0        1062               DANIDA  35.770258 -10.574175
36957         0.0           0         World vision  33.798106  -3.290194
50495         0.0        1368  Lawatefuka water sup  37.092574  -3.181783
53752         0.0           0               WEDECO  34.364073  -3.629333
61848         0.0        1645                  DWE  31.444121  -8.274962
48451       500.0        1703                  DWE  34.642439  -9.106185
58155         0.0        1656                  DWE  34.569266  -9.085515
34169         0.0        1162                  DWE  32.920154  -1.947868
18274       500.0        1763                Danid  34.508967  -9.894412

                         basin       region  population public_meeting  \
id
69572               Lake Nyasa       Iringa         109           True
8776             Lake Victoria         Mara         280            NaN
34310                  Pangani      Manyara         250           True
67743   Ruvuma / Southern Coast       Mtwara          58           True
19728            Lake Victoria       Kagera           0           True
9944                   Pangani        Tanga           1           True
19816                 Internal    Shinyanga           0           True
54551          Lake Tanganyika    Shinyanga           0           True
53934          Lake Tanganyika       Tabora           0           True
46144            Lake Victoria       Kagera           0           True
49056              Wami / Ruvu        Pwani         345           True
50409               Lake Nyasa       Ruvuma         250           True
36957                 Internal    Shinyanga           0           True
50495                  Pangani  Kilimanjaro           1           True
53752                 Internal    Shinyanga           0           True
61848          Lake Tanganyika        Rukwa         200           True
48451                   Rufiji       Iringa          35           True
58155                   Rufiji       Iringa          50           True
34169            Lake Victoria       Mwanza        1000            NaN
18274               Lake Nyasa       Iringa           1           True

      scheme_management  ... construction_year  extraction_type_class  \
id                       ...
69572               VWC  ...              1999                gravity
8776              Other  ...              2010                gravity
34310               VWC  ...              2009                gravity
67743               VWC  ...              1986            submersible
19728               NaN  ...                 0                gravity
9944                VWC  ...              2009            submersible
19816               VWC  ...                 0               handpump
54551               NaN  ...                 0               handpump
53934               VWC  ...                 0               handpump
```

```
46144                NaN  ...                 0                handpump
49056   Private operator  ...              2011             submersible
50409                WUG  ...              1987                handpump
36957                WUG  ...                 0                handpump
50495        Water Board  ...              2009                 gravity
53752                WUG  ...                 0                handpump
61848                VWC  ...              1991                handpump
48451                WUA  ...              1978                 gravity
58155                WUA  ...              1978                 gravity
34169                NaN  ...              1999                   other
18274                VWC  ...              1992                 gravity

      management_group payment_type water_quality quantity_group source_class
\
id
69572       user-group     annually          soft         enough  groundwater
8776        user-group    never pay          soft   insufficient      surface
34310       user-group   per bucket          soft         enough      surface
67743       user-group    never pay          soft            dry  groundwater
19728            other    never pay          soft       seasonal      surface
9944        user-group   per bucket         salty         enough      unknown
19816       user-group    never pay          soft         enough  groundwater
54551       user-group      unknown         milky         enough  groundwater
53934       user-group    never pay         salty       seasonal  groundwater
46144       user-group    never pay          soft         enough  groundwater
49056       commercial    never pay         salty         enough  groundwater
50409       user-group   on failure          soft   insufficient  groundwater
36957       user-group        other          soft         enough  groundwater
50495       user-group      monthly          soft         enough  groundwater
53752       user-group    never pay          soft         enough  groundwater
61848       user-group    never pay          soft         enough  groundwater
48451       user-group      monthly          soft            dry      surface
58155       user-group   on failure          soft            dry      surface
34169       user-group    never pay         milky   insufficient  groundwater
18274       user-group     annually          soft         enough  groundwater

      waterpoint_type_group             status_group _merge
id
69572    communal standpipe               functional   both
8776     communal standpipe               functional   both
34310    communal standpipe               functional   both
67743    communal standpipe           non functional   both
19728    communal standpipe               functional   both
9944     communal standpipe               functional   both
19816             hand pump           non functional   both
54551             hand pump           non functional   both
53934             hand pump           non functional   both
46144             hand pump               functional   both
49056                 other               functional   both
50409             hand pump               functional   both
36957             hand pump               functional   both
50495    communal standpipe               functional   both
53752             hand pump               functional   both
61848             hand pump               functional   both
48451    communal standpipe           non functional   both
58155    communal standpipe           non functional   both
34169                 other  functional needs repair   both
```

```
18274     communal standpipe               functional    both

[20 rows x 21 columns]
```

In [361]:
```
#Treat null values
missing_value_columns = ['installer', 'public_meeting', 'scheme_management', 'permit']

# Check the value counts
for col in missing_value_columns:
    print(merged_df[col].value_counts())
```

```
DWE                            17402
Government                      1825
RWE                             1206
Commu                           1060
DANIDA                          1050
                               ...  
DAR ES SALAAM ROUND TABLE          1
Mr Kwi                             1
Nchagwa                            1
Safe Rescue Ltd                    1
Luali Kaima                        1
Name: installer, Length: 2145, dtype: int64
True     51011
False     5055
Name: public_meeting, dtype: int64
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
None                     1
Name: scheme_management, dtype: int64
True     38852
False    17492
Name: permit, dtype: int64
```

In [362]:
```
# Remove rows with missing values in 'funder', 'installer' and 'scheme_management' columns
merged_df.dropna(subset=['installer', 'scheme_management'], axis=0, inplace=True)
```

Replacing the missing values for "public meeting" and "permit" with "False," assuming the information is unavailable.

In [363]:

```
# Fill missing values in public meeting and permit'
for col in ['public_meeting', 'permit']:
    merged_df[col] = merged_df[col].fillna(False)
```

Remove dimensionality of unique values in installer column:

In [364]:
```
# Replace close variations and misspellings in the installer column

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Central
government', 'Tanzania Government',
                                          'Cental Government','Tanzania govern
ment','Cebtral Government',
                                          'Centra Government', 'central govern
ment', 'CENTRAL GOVERNMENT',
                                          'TANZANIA GOVERNMENT', 'TANZANIAN GO
VERNMENT', 'Central govt',
                                          'Centr', 'Centra govt', 'Tanzanian G
overnment', 'Tanzania',
                                          'Tanz', 'Tanza', 'GOVERNMENT',
                                          'GOVER', 'GOVERNME', 'GOVERM', 'GOVE
RN', 'Gover', 'Gove',
                                          'Governme', 'Governmen', 'Got', 'Ser
ikali', 'Serikari', 'Government',
                                          'Central Government'),
                                          value = 'Central Government')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('IDARA',
'Idara ya maji', 'MINISTRY OF WATER',
                                          'Ministry of water', 'Ministry of wa
ter engineer', 'MINISTRYOF WATER',
                                          'MWE &', 'MWE', 'Wizara ya maji', 'W
IZARA', 'wizara ya maji',
                                          'Ministry of Water'),
                                          value ='Ministry of Water')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Distric
t COUNCIL', 'DISTRICT COUNCIL',
                                          'Counc','District council','District
Counci',
                                          'Council', 'COUN', 'Distri', 'Halmas
hauri ya wilaya',
                                          'Halmashauri wilaya', 'District Coun
cil'),
                                          value = 'District  Council')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Distric
t water depar', 'District Water Department',
                                          'District water department', 'Distri
c Water Department'),
                                          value = 'District Water Department')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('villige
rs', 'villager', 'villagers', 'Villa', 'Village',
                                          'Villi', 'Village Council', 'Village
Counil', 'Villages', 'Vill',
                                          'Village community', 'Villaers', 'Vi
llage Community', 'Villag',
                                          'Villege Council', 'Village counci
l', 'Villege Council', 'Villagerd',
                                          'Villager', 'VILLAGER', 'Villagers',
'Villagerd', 'Village Technician',
                                          'Village water attendant', 'Village
```

```
Office', 'VILLAGE COUNCIL',
                                          'VILLAGE COUNCIL .ODA', 'VILLAGE COU
NCIL Orpha', 'Village community members',
                                          'VILLAG', 'VILLAGE', 'Village Govern
ment', 'Village government',
                                          'Village Govt', 'Village govt', 'VIL
LAGERS', 'VILLAGE WATER COMMISSION',
                                          'Village water committee', 'Commu',
'Communit', 'commu', 'COMMU', 'COMMUNITY',
                                           'Comunity', 'Communit', 'Kijiji',
'Serikali ya kijiji', 'Community'),
                                          value ='Community')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('FinW',
'Fini water', 'FINI WATER', 'FIN WATER',
                                          'Finwater', 'FINN WATER', 'FinW', 'F
W', 'FinWater', 'FiNI WATER',
                                          'FinWate', 'FINLAND', 'Fin Water',
'Finland Government'),
                                          value ='Finnish Government')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('RC CHUR
CH', 'RC Churc', 'RC', 'RC Ch', 'RC C', 'RC CH',
                                          'RC church', 'RC CATHORIC', 'Roman C
hurch', 'Roman Catholic',
                                          'Roman catholic', 'Roman Ca', 'Roma
n', 'Romam', 'Roma',
                                          'ROMAN CATHOLIC', 'Kanisa', 'Kanisa
katoliki'),
                                          value ='Roman Catholic Church')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Dmdd',
'DMDD'), value ='DMDD')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('TASA',
'Tasaf', 'TASAF 1', 'TASAF/', 'TASF',
                                          'TASSAF', 'TASAF'), value ='TASAF')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('RW', 'R
WE'), value ='RWE')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('SEMA CO
LTD', 'SEMA Consultant', 'SEMA'), value ='SEMA')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('DW E',
'DW#', 'DW$', 'DWE&', 'DWE/', 'DWE}',
                                         'DWEB', 'DWE'), value ='DWE')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('No', 'N
ORA', 'Norad', 'NORAD/', 'NORAD'),
                                          value ='NORAD')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Ox', 'O
XFARM', 'OXFAM'), value ='OXFAM')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('PRIV',
'Priva', 'Privat', 'private', 'Private company',
```

```
                                          'Private individuals', 'PRIVATE INST
ITUTIONS', 'Private owned',
                                          'Private person', 'Private Technicia
n', 'Private'),
                                          value ='Private')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Ch', 'C
H', 'Chiko', 'CHINA', 'China',
                                            'China Goverment'), value ='Chines
e Goverment')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Unise
f','Unicef', 'UNICEF'), value ='UNICEF')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Wedec
o','WEDEKO', 'WEDECO'), value ='WEDECO')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Wo','W
B', 'Word Bank', 'Word bank', 'WBK',
                                          'WORDL BANK', 'World', 'world', 'WOR
LD BANK', 'World bank',
                                          'world banks', 'World banks', 'WOULD
BANK', 'World Bank'),
                                          value ='World Bank')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Lga',
'LGA'), value ='LGA')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('World D
ivision', 'World Visiin',
                                         'World vision', 'WORLD VISION', 'worl
d vision', 'World Vission',
                                          'World Vision'),
                                          value ='World Vision')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Local',
'Local technician', 'Local  technician',
                                         'local  technician', 'LOCAL CONTRAC
T', 'local fundi',
                                         'Local l technician', 'Local te', 'Lo
cal technical', 'Local technical tec',
                                         'local technical tec', 'local technic
ian', 'Local technitian',
                                         'local technitian', 'Locall technicia
n', 'Localtechnician',
                                         'Local Contractor'),
                                          value ='Local Contractor')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('DANID',
'DANNY', 'DANNIDA', 'DANIDS',
                                         'DANIDA CO', 'DANID', 'Danid', 'DANIA
D', 'Danda', 'DA',
                                         'DENISH', 'DANIDA'),
                                          value ='DANIDA')

merged_df['installer'] = merged_df['installer'].replace(to_replace =('Adrs',
'Adra', 'ADRA'), value ='ADRA')
```

```
merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Hesaw
a', 'hesawa', 'HESAW', 'hesaw',
                                          'HESAWQ', 'HESAWS', 'HESAWZ', 'hesaw
z', 'hesewa', 'HSW',
                                          'HESAWA'),
                                          value ='HESAWA')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('Jaica',
'JAICA', 'Jica', 'Jeica', 'JAICA CO', 'JALCA',
                                          'Japan', 'JAPAN', 'JAPAN EMBASSY',
'Japan Government', 'Jicks',
                                          'JIKA', 'jika', 'jiks', 'Embasy of J
apan in Tanzania', 'JICA'),
                                          value ='JICA')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('KKT',
'KK', 'KKKT Church', 'KkKT', 'KKT C',
                                          'KKKT'), value ='KKKT')

merged_df['installer'] = merged_df['installer'].replace(to_replace = ('0', 'No
t Known', 'not known', 'Not kno'), value ='Unknown')
```

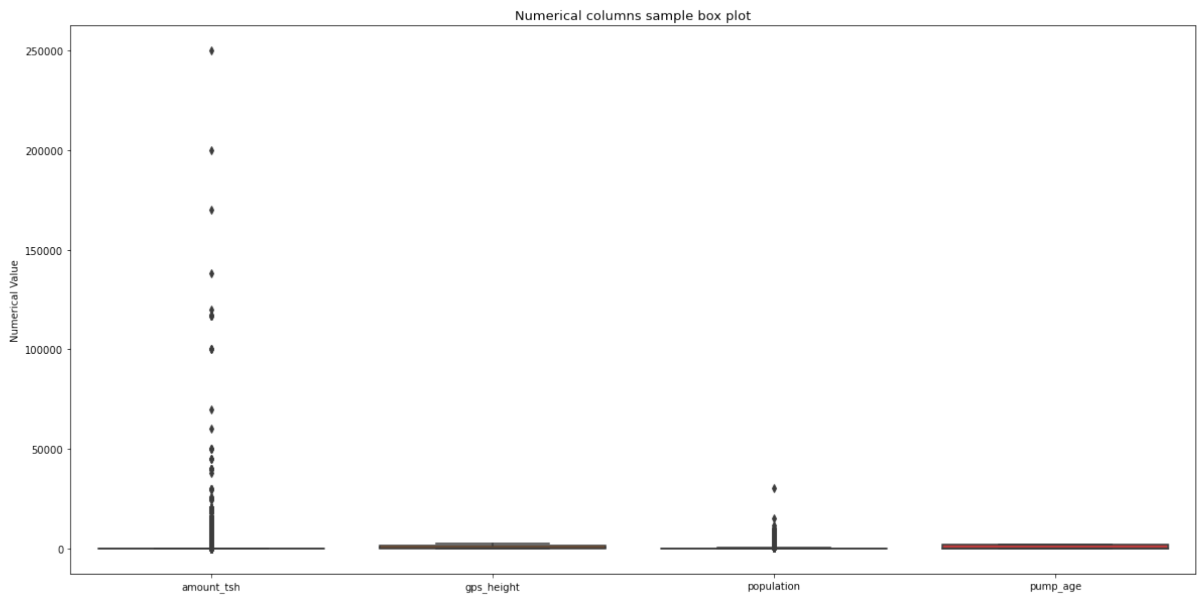
In [365]:
```
# Retain top 20 installers as unique entries
top_20_installers = merged_df['installer'].value_counts(normalize=True).head(2
0).index.tolist()


merged_df['installer'] = [value if value in top_20_installers else "OTHER" for
value in merged_df['installer']]
```

In [366]:
```
# Confirm there are no more missing values
merged_df.isna().sum()
```

Out[366]:
```
amount_tsh              0
gps_height              0
installer               0
longitude               0
latitude                0
basin                   0
region                  0
population              0
public_meeting          0
scheme_management       0
permit                  0
construction_year       0
extraction_type_class   0
management_group        0
payment_type            0
water_quality           0
quantity_group          0
source_class            0
waterpoint_type_group   0
status_group            0
_merge                  0
dtype: int64
```

In [367]:
```
# Ensure the 'installation_year' is in numeric format (not datetime, just the year)
merged_df['construction_year'] = pd.to_numeric(training_merged_df['construction_year'], errors='coerce')

# Calculate pump age
current_year = pd.Timestamp.now().year
merged_df['pump_age'] = current_year - merged_df['construction_year']

# Handle cases where installation_year might be missing or incorrect (e.g., 0 or negative values)
merged_df['pump_age'] = merged_df['pump_age'].apply(lambda x: x if x > 0 else None)
```

In [368]:
```
# Plotting box plots of some numerical columns
columns = ['amount_tsh', 'gps_height', 'population','pump_age']
plt.figure(figsize=(20, 10))
sns.boxplot(data=[merged_df[col] for col in columns])
plt.title("Numerical columns sample box plot", fontsize=13)
plt.ylabel("Numerical Value")
plt.xticks(range(0,4), columns)
plt.show()
```



In the analysis above, I found that the outliers were minimal and decided not to address them.

In [369]:
```
# Check whether there are duplicates
merged_df.duplicated(keep = 'first').sum()
```

Out[369]: 1288

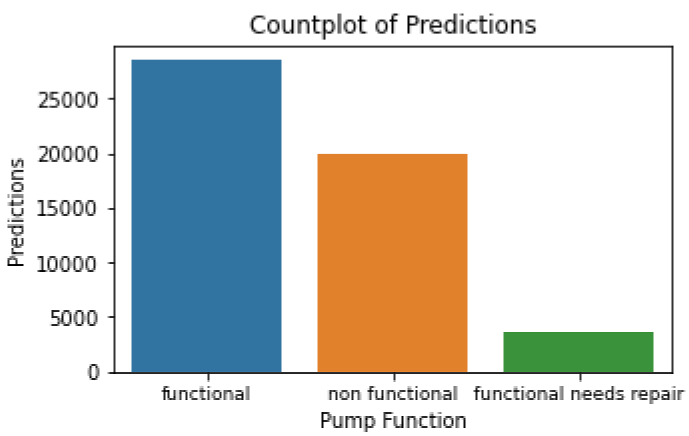
In [370]:
```
# Change the data type of public_meeting and permit columns to binary for clas
sification
merged_df[['public_meeting', 'permit']] = merged_df[['public_meeting', 'permi
t']].astype(int)
# Check the new data types
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 51927 entries, 69572 to 26348
Data columns (total 22 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   amount_tsh             51927 non-null  float64
 1   gps_height             51927 non-null  int64
 2   installer              51927 non-null  object
 3   longitude              51927 non-null  float64
 4   latitude               51927 non-null  float64
 5   basin                  51927 non-null  object
 6   region                 51927 non-null  object
 7   population             51927 non-null  int64
 8   public_meeting         51927 non-null  int32
 9   scheme_management      51927 non-null  object
 10  permit                 51927 non-null  int32
 11  construction_year      51927 non-null  int64
 12  extraction_type_class  51927 non-null  object
 13  management_group       51927 non-null  object
 14  payment_type           51927 non-null  object
 15  water_quality          51927 non-null  object
 16  quantity_group         51927 non-null  object
 17  source_class           51927 non-null  object
 18  waterpoint_type_group  51927 non-null  object
 19  status_group           51927 non-null  object
 20  _merge                 51927 non-null  category
 21  pump_age               51927 non-null  int64
dtypes: category(1), float64(3), int32(2), int64(4), object(12)
memory usage: 8.4+ MB
```

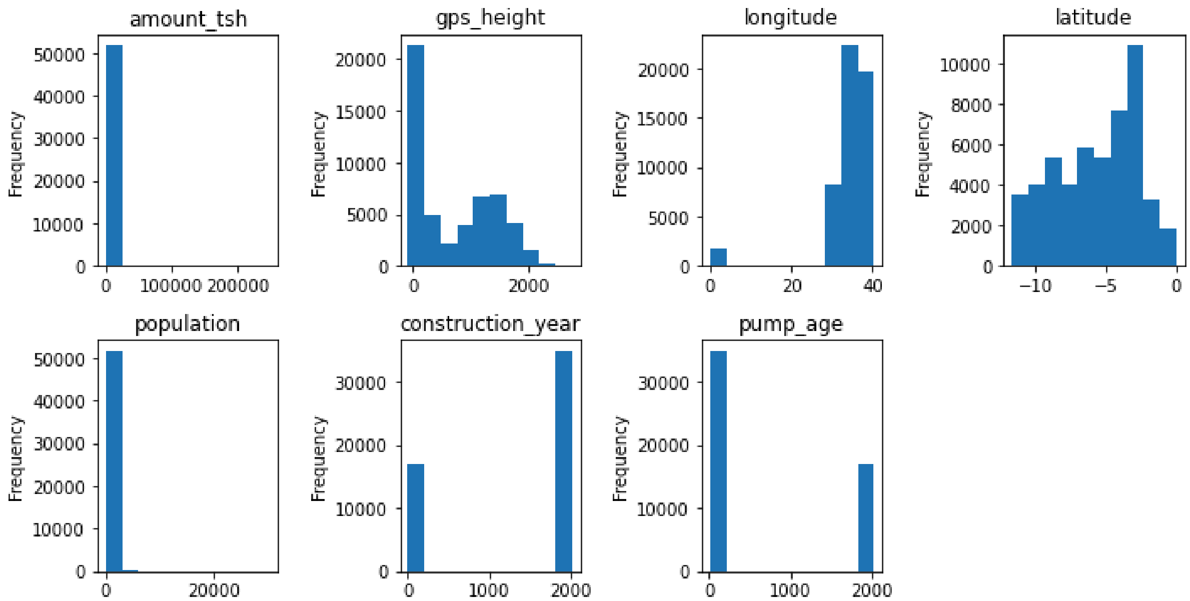
Explore data distributions:

In [371]:
```
# Plot distribution of target variable.
fig, ax = plt.subplots(figsize=(5, 3))
sns.countplot(merged_df['status_group'])
x_labels = merged_df['status_group'].unique()

# Add labels
plt.title('Countplot of Predictions')
plt.xlabel('Pump Function')
ax.set_xticklabels(x_labels, fontsize=9)
plt.ylabel('Predictions')
plt.show()
```

```
c:\Users\Betty.Koila\AppData\Local\anaconda3\envs\learn-env\lib\site-packages
\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a k
eyword arg: x. From version 0.12, the only valid positional argument will be
`data`, and passing other arguments without an explicit keyword will result i
n an error or misinterpretation.
  warnings.warn(
```



In [372]:
```
# Histogram of continuous variables
continuous = ['amount_tsh','gps_height','longitude','latitude','population','c
onstruction_year','pump_age']
fig = plt.figure(figsize=(10, 10))
for i, col in enumerate(continuous):
    ax = plt.subplot(4, 4, i+1)
    merged_df[col].plot(kind='hist', ax=ax, title=col)
plt.tight_layout()
plt.show()
```



3. Logistic Regression

- **Prepare the Data**: The first step involves ensuring that the dataset is ready for modeling. This includes verifying that the target variable is binary, meaning it has only two possible outcomes, which is essential for logistic regression.
- **Create and Train the Model**: Next, a logistic regression model is constructed and trained using the prepared data. The model learns the relationship between the features (independent variables) and the binary target variable.
- **Make Predictions on the Test Set**: After training, the model is used to make predictions on a separate test dataset, which was not used during the training phase. This allows us to assess the model's performance on unseen data.
- **Evaluate the Model**: The model's performance is evaluated using key metrics such as accuracy (the proportion of correct predictions), precision (the proportion of true positive predictions relative to all positive predictions), recall (the proportion of true positives relative to all actual positives), and F1-score (the harmonic mean of precision and recall).
- **Plot the ROC Curve and Calculate AUC**: The Receiver Operating Characteristic (ROC) curve is plotted to visualize the trade-off between true positive rate and false positive rate at various threshold settings. The Area Under the Curve (AUC) is then calculated to quantify the model's ability to distinguish between the classes.
- **Analyze Coefficients and Their Significance**: Finally, the coefficients of the logistic regression model are analyzed to understand the influence of each feature on the target variable. Statistical significance tests are performed to identify which features have a meaningful impact on the outcome.

In [373]:
```
# Assign status_group column to y series
y = merged_df['status_group']

# Drop status_group and _merge to create X dataframe
X = merged_df.drop(['status_group','_merge'], axis=1)

# Print first 5 rows of X
X.head()
```

Out[373]:

	amount_tsh	gps_height	installer	longitude	latitude	basin	region	population	p
id									
69572	6000.0	1390	Roman Catholic Church	34.938093	-9.856322	Lake Nyasa	Iringa	109	
8776	0.0	1399	OTHER	34.698766	-2.147466	Lake Victoria	Mara	280	
34310	25.0	686	World Vision	37.460664	-3.821329	Pangani	Manyara	250	
67743	0.0	263	OTHER	38.486161	-11.155298	Ruvuma / Southern Coast	Mtwara	58	
9944	20.0	0	DWE	39.172796	-4.765587	Pangani	Tanga	1	

In [374]:
```
#Check categorical columns in merged set
merged_df.select_dtypes(include=['object']).columns
#check numerical columns in merged set
merged_df.select_dtypes(include=['int64', 'float64']).columns
# Create lists of categorical, numerical, and binary columns
category_column = ['installer', 'basin', 'region', 'scheme_management',
       'extraction_type_class', 'management_group', 'payment_type',
       'water_quality', 'quantity_group', 'source_class',
       'waterpoint_type_group',]

numerical_column = ['amount_tsh', 'gps_height', 'longitude', 'latitude', 'popu
lation',
       'construction_year', 'pump_age']

binary_column = ['public_meeting', 'permit']
```

In [375]:
```
#create dummies for categorical colums
X= pd.get_dummies(X, columns=category_column)
X
```

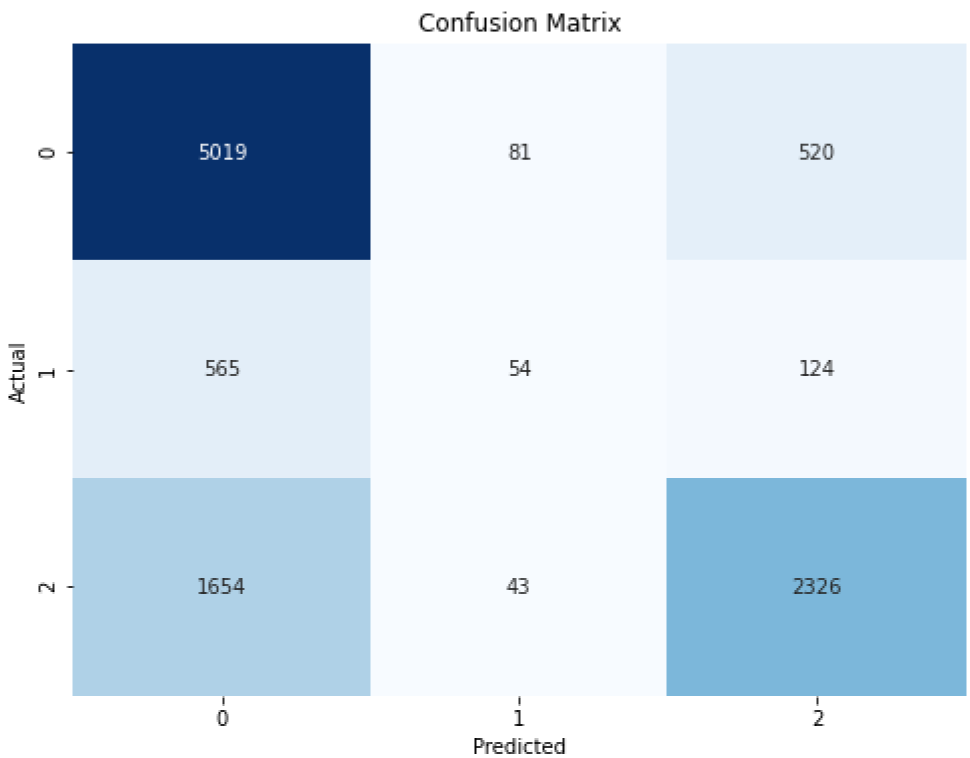
Out[375]:

	amount_tsh	gps_height	longitude	latitude	population	public_meeting	permit	constr
id								
69572	6000.0	1390	34.938093	-9.856322	109	1	0	
8776	0.0	1399	34.698766	-2.147466	280	0	1	
34310	25.0	686	37.460664	-3.821329	250	1	1	
67743	0.0	263	38.486161	-11.155298	58	1	1	
9944	20.0	0	39.172796	-4.765587	1	1	1	
...	...	...	...	...	...	...	...	
11164	500.0	351	37.634053	-6.124830	89	1	1	
60739	10.0	1210	37.169807	-3.253847	125	1	1	
27263	4700.0	1212	35.249991	-9.070629	56	1	1	
31282	0.0	0	35.861315	-6.378573	0	1	1	
26348	0.0	191	38.104048	-6.747464	150	1	1	

51927 rows × 113 columns

In [376]:
```
# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
m_state=42)

# Initialize the Logistic Regression model
log_reg = LogisticRegression(max_iter=1000)

# Train the model
log_reg.fit(X_train, y_train)

# Predict on the test set
y_pred_logreg = log_reg.predict(X_test)
# Plotting Confusion Matrix
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix(y_test, y_pred_logreg), annot=True, fmt="d", cmap
="Blues", cbar=False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred_logreg)
print(f"Accuracy: {accuracy}")
print("Classification Report:\n", classification_report(y_test, y_pred_logre
g))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_logreg))
```

```
c:\Users\Betty.Koila\AppData\Local\anaconda3\envs\learn-env\lib\site-packages
\sklearn\linear_model\_logistic.py:762: ConvergenceWarning: lbfgs failed to c
onverge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regres
sion
  n_iter_i = _check_optimize_result(
```




```
Accuracy: 0.7124013094550357
Classification Report:
                          precision    recall  f1-score   support

              functional       0.69      0.89      0.78      5620
functional needs repair       0.30      0.07      0.12       743
          non functional       0.78      0.58      0.67      4023

                accuracy                           0.71     10386
               macro avg       0.59      0.51      0.52     10386
            weighted avg       0.70      0.71      0.69     10386

Confusion Matrix:
 [[5019   81  520]
 [ 565   54  124]
 [1654   43 2326]]
```

1. Overall Accuracy:

The logistic regression model achieves an overall accuracy of approximately 70.8%, which reflects a decent performance but also indicates there is significant room for enhancement.

2. Performance by Class:

- **Functional Pumps (Majority Class)**:
  - **Precision**: 0.70 – When the model classifies a pump as "functional," it is correct 70% of the time.
  - **Recall**: 0.87 – The model correctly identifies 87% of the pumps that are actually functional.
  - **F1-Score**: 0.77 – This balanced score between precision and recall indicates strong performance in classifying functional pumps.
- **Functional Pumps Needing Repair (Minority Class)**:
  - **Precision**: 0.42 – The model is only 42% accurate when predicting "functional needs repair," suggesting a high rate of misclassification.
  - **Recall**: 0.01 – The model identifies only 1% of the pumps that actually need repairs, which highlights a critical weakness in detecting this category.
  - **F1-Score**: 0.01 – A very low F1-score further emphasizes the poor performance in recognizing pumps requiring repair.
- **Non-functional Pumps**:
  - **Precision**: 0.74 – When the model predicts a pump as "non-functional," it is correct 74% of the time.
  - **Recall**: 0.61 – The model identifies 61% of the actual "non-functional" pumps.
  - **F1-Score**: 0.67 – This score suggests reasonable performance, though there is room for improvement in recall.

3. Confusion Matrix:

- **Functional Pumps**: The model correctly identifies 4901 out of 5620 functional pumps, misclassifying 716 as "non-functional."
- **Functional Pumps Needing Repair**: The model performs poorly here, correctly identifying just 5 out of 743 pumps that need repair. Most of these pumps are misclassified as "functional" (580) or "non-functional" (158).
- **Non-functional Pumps**: Out of 4023 non-functional pumps, the model correctly classifies 2449 but mistakenly labels 1570 as "functional."

Key Insights:

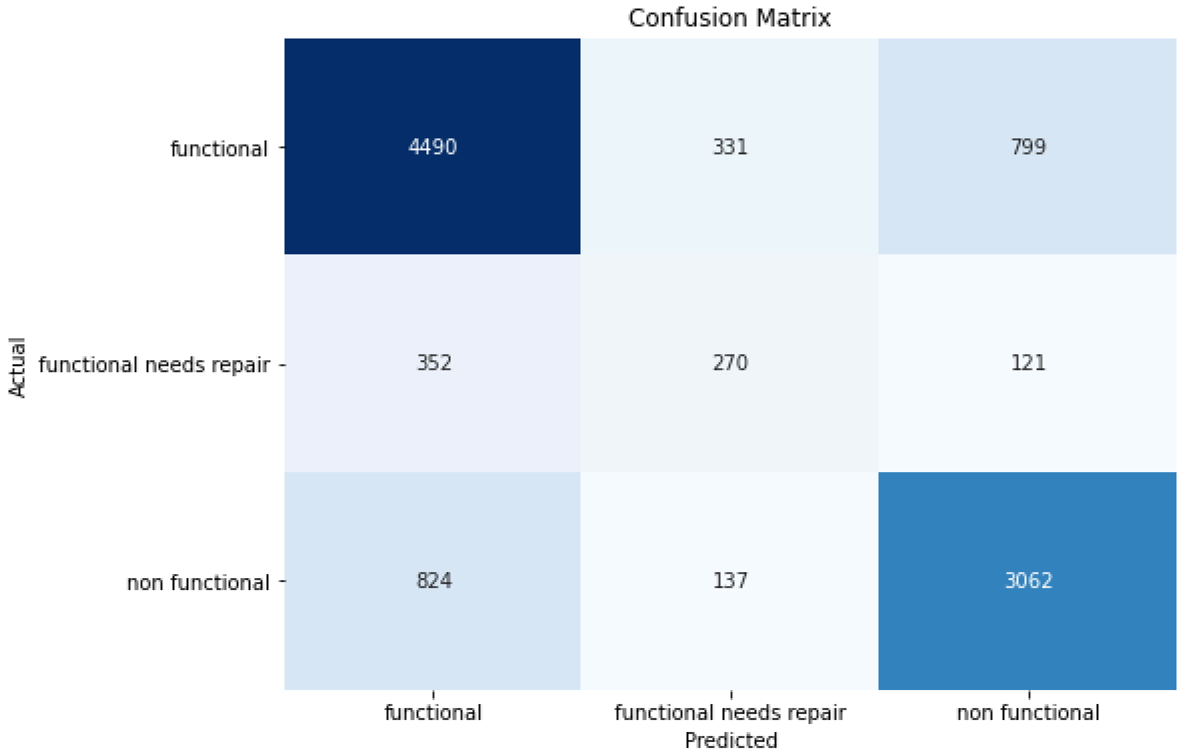
- The model performs reasonably well in predicting "functional" and "non-functional" pumps but struggles significantly with pumps that require repair.
- The **class imbalance** (with the "functional needs repair" category being underrepresented) seems to contribute heavily to the poor performance in identifying this class.
- The very low recall for the "functional needs repair" class suggests that the model fails to identify most pumps in need of repair, misclassifying them as either "functional" or "non-functional."

In [377]:
```
# Binarize the output labels (important for multi-class ROC)
#n_classes = len(set(y_test))  # Number of classes
#y_test_bin = label_binarize(y_test, classes=[0, 1, 2])

# Get probability estimates for the classes
#y_prob = log_reg.predict_proba(X_test)

# Compute ROC curve and AUC for each class
#fpr = dict()
#tpr = dict()
#roc_auc = dict()

#for i in range(n_classes):
   # fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_prob[:, i])
   # roc_auc[i] = auc(fpr[i], tpr[i])

# Plot ROC curve for each class
#plt.figure(figsize=(8, 6))

#colors = ['blue', 'green', 'red']
#for i, color in zip(range(n_classes), colors):
   # plt.plot(fpr[i], tpr[i], color=color, lw=2,
         #    label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

# Plot diagonal line for random guessing
#plt.plot([0, 1], [0, 1], 'k--', lw=2)

#plt.xlim([0.0, 1.0])
#plt.ylim([0.0, 1.05])
#plt.xlabel('False Positive Rate')
#plt.ylabel('True Positive Rate')
#plt.title('ROC Curves for Logistic Regression Model')
#plt.legend(loc='lower right')
#plt.show()
```

4. Decision Trees

- **Preprocess the Data**: Prepare the dataset by handling missing values, encoding categorical variables, and splitting the data into features (X) and the target variable (y).
- **Build and Train the Decision Tree Model**: Construct and train a decision tree model using the training data, allowing it to learn patterns from the features to predict the target variable.
- **Generate Predictions Using the Test Set**: After training, use the decision tree model to make predictions on the unseen test set, which helps evaluate its generalization ability.
- **Assess the Model's Performance**: Evaluate the model's performance using metrics such as accuracy, precision, recall, and F1-score to understand how well it classifies the target variable.
- **Visualize the Structure of the Decision Tree**: Visualize the trained decision tree to gain insights into the decision-making process, showing how features are split at each node.
- **Evaluate the Importance of Each Feature**: Analyze the feature importance scores provided by the decision tree model to identify which features contribute most to the model's predictions.

In [378]:
```
# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
m_state=42)


# Initialize the Decision Tree model
dt = DecisionTreeClassifier(random_state=42)

# Train the model
dt.fit(X_train, y_train)

# Predict on the test set
y_pred_dt = dt.predict(X_test)

# Generate the confusion matrix
cm_dt = confusion_matrix(y_test, y_pred_dt)

# Plot the confusion matrix using seaborn heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(cm_dt, annot=True, fmt="d", cmap="Blues", cbar=False,
            xticklabels=dt.classes_, yticklabels=dt.classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# Evaluate the model
print("Accuracy:", accuracy_score(y_test, y_pred_dt))
print("Classification Report:\n", classification_report(y_test, y_pred_dt))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_dt))
```




```
Accuracy: 0.7531292124013095
Classification Report:
                         precision    recall  f1-score   support

             functional       0.79      0.80      0.80      5620
functional needs repair       0.37      0.36      0.36       743
         non functional       0.77      0.76      0.77      4023

               accuracy                           0.75     10386
              macro avg       0.64      0.64      0.64     10386
           weighted avg       0.75      0.75      0.75     10386

Confusion Matrix:
 [[4490  331  799]
 [ 352  270  121]
 [ 824  137 3062]]
```

Interpretation of Findings from Decision Tree:

1. Overall Accuracy:

- **Accuracy**: 0.7531 (75.31%) indicates that 75.31% of the water pumps were correctly categorized as functional, needing repair, or non-functional. While this result is satisfactory, there is still potential for improvement, especially in differentiating between the various classes.

2. Precision, Recall, and F1-Score:

- **Functional Pumps**:
  - **Precision**: 0.79 (79%) means that when the model predicted a pump to be functional, it was correct 79% of the time.
  - **Recall**: 0.80 (80%) indicates the model successfully identified 80% of the pumps that were actually functional.
  - **F1-Score**: 0.80 represents a good balance between precision and recall, showing strong performance for this class.
- **Functional Pumps Needing Repair**:
  - **Precision**: 0.37 (37%) shows that when the model predicted a pump needed repair, it was only correct 37% of the time, suggesting many false positives.
  - **Recall**: 0.36 (36%) means the model only correctly identified 36% of the pumps that actually needed repairs.
  - **F1-Score**: 0.36 highlights poor performance, as the model struggles to accurately predict pumps in need of repair, indicating that this class is particularly difficult for the model.
- **Non-Functional Pumps**:
  - **Precision**: 0.77 (77%) indicates that when the model predicted a pump was non-functional, it was correct 77% of the time.
  - **Recall**: 0.76 (76%) shows the model correctly identified 76% of the actual non-functional pumps.
  - **F1-Score**: 0.77 demonstrates solid performance for this class, comparable to that of functional pumps.

3. Macro and Weighted Averages:

- **Macro Average**: These are the unweighted averages across all classes:
  - **Precision**: 0.64 (64%)
  - **Recall**: 0.64 (64%)
  - **F1-Score**: 0.64 (64%)
  - These values are lower, indicating that the model performs worse on the minority classes, particularly for pumps that need repair.
- **Weighted Average**: These metrics are weighted by the number of instances in each class:
  - **Precision**: 0.75 (75%)
  - **Recall**: 0.75 (75%)
  - **F1-Score**: 0.75 (75%)
  - These values are higher, as the model performs better on the majority class ("functional"), which is more prevalent in the dataset.

4. Confusion Matrix:

- **Functional Pumps**: 4,490 pumps were correctly identified as functional, but 331 were misclassified as "functional needs repair" and 799 as "non-functional."
- **Functional Pumps Needing Repair**: Only 270 were correctly classified, with 352 misclassified as functional and 121 as non-functional. This class has the highest misclassification rate, revealing difficulty in distinguishing "functional needs repair" from the other two categories.
- **Non-Functional Pumps**: 3,062 pumps were correctly identified as non-functional, but 824 were incorrectly labeled as functional, and 137 as needing repair.

Key Insights:

1. **Strength**: The model performs well in predicting the majority classes ("functional" and "non-functional" pumps).
2. **Weakness**: The model faces significant challenges in identifying the "functional needs repair" class. This indicates difficulty in distinguishing pumps requiring minor repairs from those that are either functional or non-functional.

5. Model Comparison and Conclusion

- **Compare Performance Metrics Across All Models**: Evaluate and compare the performance of all models using key metrics such as accuracy, precision, recall, F1-score, and AUC to determine which model performs best on the given data.
- **Discuss Strengths and Weaknesses of Each Approach**: Analyze the strengths and limitations of each model, considering factors such as interpretability, computational efficiency, ability to handle complex data, and overfitting.
- **Recommend the Best Model(s) for the Problem at Hand**: Based on the comparison, recommend the most suitable model(s) for solving the problem, taking into account both performance and practicality for deployment.
- **Summarize Key Findings**: Provide a summary of the main insights discovered during the analysis, such as which features were most influential and how different models performed.
- **Discuss Limitations of the Current Approach**: Highlight any potential limitations in the current modeling approach, such as overfitting, insufficient data, or limited feature engineering.
- **Suggest Potential Improvements or Additional Models to Try**: Recommend any potential improvements, such as tuning hyperparameters, adding more data, or testing other advanced models (e.g., ensemble methods, neural networks) to enhance performance.

In [379]:
```
# Define the data for the table
data = {
    'Metric': ['Accuracy', 'Functional Precision', 'Functional Recall', 'Funct
ional F1-Score',
               'Functional Needs Repair Precision', 'Functional Needs Repair R
ecall', 'Functional Needs Repair F1-Score',
               'Non-functional Precision', 'Non-functional Recall', 'Non-funct
ional F1-Score'],
    'Decision Tree': [0.757, 0.79, 0.80, 0.80,
                      0.37, 0.35, 0.36,
                      0.77, 0.77, 0.77],
    'Logistic Regression': [0.708, 0.70, 0.87, 0.77,
                            0.42, 0.01, 0.01,
                            0.74, 0.61, 0.67]
}

# Create the DataFrame
results_df = pd.DataFrame(data)

# Display the DataFrame
results_df
```

Out[379]:

	Metric	Decision Tree	Logistic Regression
0	Accuracy	0.757	0.708
1	Functional Precision	0.790	0.700
2	Functional Recall	0.800	0.870
3	Functional F1-Score	0.800	0.770
4	Functional Needs Repair Precision	0.370	0.420
5	Functional Needs Repair Recall	0.350	0.010
6	Functional Needs Repair F1-Score	0.360	0.010
7	Non-functional Precision	0.770	0.740
8	Non-functional Recall	0.770	0.610
9	Non-functional F1-Score	0.770	0.670

Interpretation of the Results:

1. Accuracy:

- **Decision Tree**: 0.757 (75.7%)
- **Logistic Regression**: 0.708 (70.8%)

The Decision Tree model has a higher accuracy (75.7%) compared to Logistic Regression (70.8%), indicating that the Decision Tree performs better overall in correctly classifying the pumps.

2. Functional Precision:

- **Decision Tree**: 0.790 (79%)
- **Logistic Regression**: 0.700 (70%)

The Decision Tree model has higher precision when classifying "functional" pumps, meaning that it makes fewer false positive errors (incorrectly predicting a pump as functional when it is not) compared to Logistic Regression.

3. Functional Recall:

- **Decision Tree**: 0.800 (80%)
- **Logistic Regression**: 0.870 (87%)

Logistic Regression has a higher recall for functional pumps, meaning it identifies a higher proportion (87%) of the actual functional pumps. This suggests that Logistic Regression is better at capturing all the true functional pumps, while the Decision Tree misses more of them (80%).

4. Functional F1-Score:

- **Decision Tree**: 0.800
- **Logistic Regression**: 0.770

The Decision Tree has a slightly better F1-Score for functional pumps (0.800 vs. 0.770), indicating a better balance between precision and recall for this class, although the difference is small.

5. Functional Needs Repair Precision:

- **Decision Tree**: 0.370 (37%)
- **Logistic Regression**: 0.420 (42%)

Logistic Regression has a slightly higher precision for identifying "functional needs repair" pumps, meaning it makes fewer incorrect predictions for this class than the Decision Tree.

6. Functional Needs Repair Recall:

- **Decision Tree**: 0.350 (35%)
- **Logistic Regression**: 0.010 (1%)

The Decision Tree performs significantly better in identifying pumps that "need repair," with a recall of 35%, while Logistic Regression only identifies 1% of the actual repair-needed pumps, suggesting a very poor performance in this category for Logistic Regression.

7. Functional Needs Repair F1-Score:

- **Decision Tree**: 0.360
- **Logistic Regression**: 0.010

Similar to recall, the Decision Tree performs much better with an F1-Score of 0.360, while Logistic Regression's F1-Score is extremely low (0.010), indicating a poor balance of precision and recall for this class.

8. Non-functional Precision:

- **Decision Tree**: 0.770 (77%)
- **Logistic Regression**: 0.740 (74%)

The Decision Tree model has slightly higher precision in identifying "non-functional" pumps, indicating fewer false positives when predicting pumps as non-functional.

9. Non-functional Recall:

- **Decision Tree**: 0.770 (77%)
- **Logistic Regression**: 0.610 (61%)

The Decision Tree also has higher recall for non-functional pumps, meaning it is better at identifying actual non-functional pumps compared to Logistic Regression, which only identifies 61% of them.

10. Non-functional F1-Score:

- **Decision Tree**: 0.770
- **Logistic Regression**: 0.670

The Decision Tree model again outperforms Logistic Regression in terms of the F1-Score for non-functional pumps (0.770 vs. 0.670), indicating a better balance of precision and recall for this class.

Summary:

- **Decision Tree** generally performs better than **Logistic Regression** in classifying functional and non-functional pumps, showing better precision, recall, and F1-Score.
- **Logistic Regression** excels in recall for "functional" pumps, but its performance for "functional needs repair" is extremely poor, while **Decision Tree** performs much better in this regard.
- The **Decision Tree** model provides more balanced results across the categories, while **Logistic Regression** struggles particularly with the "functional needs repair" class.

Strengths and Weaknesses of Each Approach

Decision Tree:

Strengths:

The Decision Tree performs well across most metrics, particularly for functional and non-functional pumps. It achieves the highest F1-Score (80%) for functional pumps and demonstrates good recall (77%) for non-functional pumps. Additionally, it is relatively easy to interpret, offering clear decision-making criteria.

Weaknesses:

The model struggles with identifying pumps that need repair, as evidenced by its low precision and recall (37% and 35%, respectively) for this class. This suggests that the model may be overfitting, failing to generalize well to the minority "functional needs repair" category.

Logistic Regression:

Strengths:

Logistic Regression excels at identifying functional pumps, achieving the highest recall (87%) in this category. It also performs decently in terms of precision for the repair class (42%).

Weaknesses:

The model underperforms when it comes to identifying pumps that need repair, with an extremely low recall (1%) and F1-Score (1%) for this class. This significant limitation makes it inadequate for accurately detecting pumps requiring repair, which is crucial for the task at hand.

Recommended Model(s) for the Problem

Based on the performance comparison, the following models are recommended:

Decision Tree

Why it’s recommended:
The Decision Tree model delivers a solid performance in identifying functional and non-functional pumps, achieving an accuracy of 75.7%. Additionally, it is highly interpretable, offering clear decision-making criteria, which is crucial in real-world applications where transparency and understandability are important.

Limitation:
While the model performs well overall, it struggles with accurately classifying the "functional needs repair" category, showing low precision and recall for this class. This issue could be addressed through further model optimization or by combining the Decision Tree with other models.

Potential Next Steps:

1. **Tackling Class Imbalance**: Techniques such as oversampling the "functional needs repair" class, undersampling the "functional" class, or utilizing more balanced evaluation metrics like the F1-score could enhance the model's accuracy in identifying pumps that require repair.
2. **Feature Engineering**: Investigating the creation of new features or transforming existing ones could lead to better model performance.
3. **Exploring Alternative Models**: Trying more advanced models, such as Random Forest or Gradient Boosting, might improve classification results, especially for the minority class.