Business Understanding

This notebook presents our approach to addressing water access challenges in Tanzania through predictive modeling. We build a classification model to identify which water wells require repairs, enabling proactive maintenance and ensuring reliable access to clean drinking water.

Problem Statement

This problem we intend to solve is addressing water access challenges in Tanzania through predictive modeling. We build a classification model to identify which water wells require repairs, enabling proactive maintenance and ensuring reliable access to clean drinking water. By leveraging multiple machine learning techniques to provide governmental agencies and other interested agencies with data-driven insights to improve resource allocation and infrastructure planning.

Objectives

1. **Optimize Predictive Accuracy for Water Pump Failures**
2. **Prioritize Repairs for High-Risk & Functional-But-Vulnerable Wells**
3. **Identify Key Factors Influencing Water Pump Failures**
4. **Enhance Data Quality & Model Improvement Strategy**
5. **Support Government & Stakeholders in Water Crisis Management**

Data Understanding

The target variable categorizes water points into three groups:

1. **Functional – The water point is fully operational with no repairs needed.**
2. **Functional but needs repair – The water point is working but requires maintenance.**
3. **Non-functional – The water point is not operational.**

The raw data is originally sourced from the Tanzanian Ministry of Water and supplied by Taarifa.

Data Cleaning

Libraries

In [1]:

```
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, GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.metrics import confusion_matrix, accuracy_score
```

Import Datasets

In [2]:

```
# Load datasets
train_values = pd.read_csv("/content/training_set_values.csv")
train_labels = pd.read_csv("/content/training_set_labels.csv")
test_values = pd.read_csv("/content/test_set_values.csv")

data = train_values.merge(train_labels, on='id')
```

In [3]:

```
# Data Overview
def data_summary(df):
    print(df.info())
    print(df.describe())
    print(df.isnull().sum())

data_summary(data)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 41 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     59400 non-null  int64
 1   amount_tsh             59400 non-null  float64
 2   date_recorded          59400 non-null  object
 3   funder                 55763 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               59398 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      55522 non-null  object
 21  scheme_name            30590 non-null  object
 22  permit                 56344 non-null  object
 23  construction_year      59400 non-null  int64
 24  extraction_type        59400 non-null  object
 25  extraction_type_group  59400 non-null  object
 26  extraction_type_class  59400 non-null  object
 27  management             59400 non-null  object
 28  management_group       59400 non-null  object
 29  payment                59400 non-null  object
 30  payment_type           59400 non-null  object
 31  water_quality          59400 non-null  object
 32  quality_group          59400 non-null  object
 33  quantity               59400 non-null  object
 34  quantity_group         59400 non-null  object
 35  source                 59400 non-null  object
 36  source_type            59400 non-null  object
 37  source_class           59400 non-null  object
 38  waterpoint_type        59400 non-null  object
 39  waterpoint_type_group  59400 non-null  object
 40  status_group           59400 non-null  object
dtypes: float64(3), int64(7), object(31)
memory usage: 18.6+ MB
None
```

```
None
                 id     amount_tsh    gps_height     longitude      latitude  \
count  59400.000000   59400.000000  59400.000000  59400.000000  5.940000e+04
mean   37115.131768     317.650385    668.297239     34.077427 -5.706033e+00
std    21453.128371    2997.574558    693.116350      6.567432  2.946019e+00
min        0.000000       0.000000    -90.000000      0.000000 -1.164944e+01
25%    18519.750000       0.000000      0.000000     33.090347 -8.540621e+00
50%    37061.500000       0.000000    369.000000     34.908743 -5.021597e+00
75%    55656.500000      20.000000   1319.250000     37.178387 -3.326156e+00
max    74247.000000  350000.000000   2770.000000     40.345193 -2.000000e-08

        num_private   region_code  district_code    population  \
count  59400.000000  59400.000000   59400.000000  59400.000000
mean       0.474141     15.297003       5.629747    179.909983
std       12.236230     17.587406       9.633649    471.482176
min        0.000000      1.000000       0.000000      0.000000
25%        0.000000      5.000000       2.000000      0.000000
50%        0.000000     12.000000       3.000000     25.000000
75%        0.000000     17.000000       5.000000    215.000000
max     1776.000000     99.000000      80.000000  30500.000000

       construction_year
count       59400.000000
mean         1300.652475
std           951.620547
min             0.000000
25%             0.000000
50%          1986.000000
75%          2004.000000
max          2013.000000
id                           0
amount_tsh                   0
date_recorded                0
funder                    3637
gps_height                   0
installer                 3655
longitude                    0
latitude                     0
wpt_name                     2
num_private                  0
basin                        0
subvillage                 371
region                       0
region_code                  0
district_code                0
lga                          0
ward                         0
population                   0
public_meeting            3334
recorded_by                  0
scheme_management         3878
scheme_name              28810
permit                    3056
construction_year            0
extraction_type              0
extraction_type_group        0
extraction_type_class        0
management                   0
management_group             0
payment                      0
payment_type                 0
water_quality                0
quality_group                0
quantity                     0
quantity_group               0
source                       0
source_type                  0
source_class                 0
waterpoint_type              0
waterpoint_type_group        0
status_group                 0
dtype: int64
```

In [4]:

```
data_summary(data)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 41 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     59400 non-null  int64  
 1   amount_tsh             59400 non-null  float64
 2   date_recorded          59400 non-null  object 
 3   funder                 55763 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               59398 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      55522 non-null  object 
 21  scheme_name            30590 non-null  object 
 22  permit                 56344 non-null  object 
 23  construction_year      59400 non-null  int64  
 24  extraction_type        59400 non-null  object 
 25  extraction_type_group  59400 non-null  object 
 26  extraction_type_class  59400 non-null  object 
 27  management             59400 non-null  object 
 28  management_group       59400 non-null  object 
 29  payment                59400 non-null  object 
 30  payment_type           59400 non-null  object 
 31  water_quality          59400 non-null  object 
 32  quality_group          59400 non-null  object 
 33  quantity               59400 non-null  object 
 34  quantity_group         59400 non-null  object 
 35  source                 59400 non-null  object 
 36  source_type            59400 non-null  object 
 37  source_class           59400 non-null  object 
 38  waterpoint_type        59400 non-null  object 
 39  waterpoint_type_group  59400 non-null  object 
 40  status_group           59400 non-null  object 
dtypes: float64(3), int64(7), object(31)
memory usage: 18.6+ MB
None
                 id     amount_tsh    gps_height     longitude      latitude  \
count  59400.000000   59400.000000  59400.000000  59400.000000  5.940000e+04   
mean   37115.131768     317.650385    668.297239     34.077427 -5.706033e+00   
std    21453.128371    2997.574558    693.116350      6.567432  2.946019e+00   
min        0.000000       0.000000    -90.000000      0.000000 -1.164944e+01   
25%    18519.750000       0.000000      0.000000     33.090347 -8.540621e+00   
50%    37061.500000       0.000000    369.000000     34.908743 -5.021597e+00   
75%    55656.500000      20.000000   1319.250000     37.178387 -3.326156e+00   
max    74247.000000  350000.000000   2770.000000     40.345193 -2.000000e-08   

        num_private   region_code  district_code    population  \
count  59400.000000  59400.000000   59400.000000  59400.000000   
mean       0.474141     15.297003       5.629747    179.909983   
std       12.236230     17.587406       9.633649    471.482176   
min        0.000000      1.000000       0.000000      0.000000   
25%        0.000000      5.000000       2.000000      0.000000   
50%        0.000000     12.000000       3.000000     25.000000   
75%        0.000000     17.000000       5.000000    215.000000   
max     1776.000000     99.000000      80.000000  30500.000000   
```

```
max      2770.000000     99.000000       80.000000   30500.000000

       construction_year
count       59400.000000
mean         1300.652475
std           951.620547
min             0.000000
25%             0.000000
50%          1986.000000
75%          2004.000000
max          2013.000000
id                           0
amount_tsh                   0
date_recorded                0
funder                    3637
gps_height                   0
installer                 3655
longitude                    0
latitude                     0
wpt_name                     2
num_private                  0
basin                        0
subvillage                 371
region                       0
region_code                  0
district_code                0
lga                          0
ward                         0
population                   0
public_meeting            3334
recorded_by                  0
scheme_management         3878
scheme_name              28810
permit                    3056
construction_year            0
extraction_type              0
extraction_type_group        0
extraction_type_class        0
management                   0
management_group             0
payment                      0
payment_type                 0
water_quality                0
quality_group                0
quantity                     0
quantity_group               0
source                       0
source_type                  0
source_class                 0
waterpoint_type              0
waterpoint_type_group        0
status_group                 0
dtype: int64
```

In [5]:

```
print(data.isnull().sum())
```

```
id                           0
amount_tsh                   0
date_recorded                0
funder                    3637
gps_height                   0
installer                 3655
longitude                    0
latitude                     0
wpt_name                     2
num_private                  0
basin                        0
subvillage                 371
region                       0
region_code                  0
district_code                0
```

```
district_code              0
lga                        0
ward                       0
population                 0
public_meeting          3334
recorded_by                0
scheme_management       3878
scheme_name            28810
permit                  3056
construction_year          0
extraction_type            0
extraction_type_group      0
extraction_type_class      0
management                 0
management_group           0
payment                    0
payment_type               0
water_quality              0
quality_group              0
quantity                   0
quantity_group             0
source                     0
source_type                0
source_class               0
waterpoint_type            0
waterpoint_type_group      0
status_group               0
dtype: int64
```

Correct formats

Handling NAs

In [6]:

```
# Handle missing values
data.fillna(method='ffill', inplace=True)
```

```
<ipython-input-6-4ffc19450609>:2: FutureWarning: DataFrame.fillna with 'method' is deprec
ated and will raise in a future version. Use obj.ffill() or obj.bfill() instead.
  data.fillna(method='ffill', inplace=True)
<ipython-input-6-4ffc19450609>:2: FutureWarning: Downcasting object dtype arrays on .fill
na, .ffill, .bfill is deprecated and will change in a future version. Call result.infer_o
bjects(copy=False) instead. To opt-in to the future behavior, set `pd.set_option('future.
no_silent_downcasting', True)`
  data.fillna(method='ffill', inplace=True)
```

In [7]:

```
#Check to see that it worked
data.isna().sum()
```

Out[7]:

	0
id	0
amount_tsh	0
date_recorded	0
funder	0
gps_height	0
installer	0
longitude	0
latitude	0

wpt_name	0
num_private	0
basin	0
subvillage	0
region	0
region_code	0
district_code	0
lga	0
ward	0
population	0
public_meeting	0
recorded_by	0
scheme_management	0
scheme_name	0
permit	0
construction_year	0
extraction_type	0
extraction_type_group	0
extraction_type_class	0
management	0
management_group	0
payment	0
payment_type	0
water_quality	0
quality_group	0
quantity	0
quantity_group	0
source	0
source_type	0
source_class	0
waterpoint_type	0
waterpoint_type_group	0
status_group	0

dtype: int64

In [9]:

```
drop_columns = ["quantity_group", "source_type", "num_private", "waterpoint_type"]
data = data.drop(drop_columns, axis =1)
```

In [10]:

```
#Get number of unique values for each column
unique_counts = data.nunique()
```

In [11]:

```
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
```

```
Data columns (total 37 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                 59400 non-null  object 
 4   gps_height             59400 non-null  int64  
 5   installer              59400 non-null  object 
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   wpt_name               59400 non-null  object 
 9   basin                  59400 non-null  object 
 10  subvillage             59400 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         59400 non-null  bool   
 18  recorded_by            59400 non-null  object 
 19  scheme_management      59400 non-null  object 
 20  scheme_name            59400 non-null  object 
 21  permit                 59400 non-null  bool   
 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  source                 59400 non-null  object 
 34  source_class           59400 non-null  object 
 35  waterpoint_type_group  59400 non-null  object 
 36  status_group           59400 non-null  object 
dtypes: bool(2), float64(3), int64(6), object(26)
memory usage: 16.0+ MB
None
```

EDA

Univariate Analysis

In [12]:

```
# brief description of the data

data.describe()
```

Out[12]:

	id	amount_tsh	gps_height	longitude	latitude	region_code	district_code	population	co
count	59400.000000	59400.000000	59400.000000	59400.000000	5.940000e+04	59400.000000	59400.000000	59400.000000	
mean	37115.131768	317.650385	668.297239	34.077427	-5.706033e+00	15.297003	5.629747	179.909983	
std	21453.128371	2997.574558	693.116350	6.567432	2.946019e+00	17.587406	9.633649	471.482176	
min	0.000000	0.000000	-90.000000	0.000000	-1.164944e+01	1.000000	0.000000	0.000000	
25%	18519.750000	0.000000	0.000000	33.090347	-8.540621e+00	5.000000	2.000000	0.000000	

	id	amount_tsh	gps_height	longitude	latitude	region_code	district_code	population	co
50%	37061.500000	0.000000	369.000000	34.908743	-5.021597e+00	12.000000	3.000000	25.000000	
75%	55656.500000	20.000000	1319.250000	37.178387	-3.326156e+00	17.000000	5.000000	215.000000	
max	74247.000000	350000.000000	2770.000000	40.345193	-2.000000e-08	99.000000	80.000000	30500.000000	

In [13]:

```
#Get unique values for status group of the pumps

label_vc = data['status_group'].value_counts()
label_vc
```

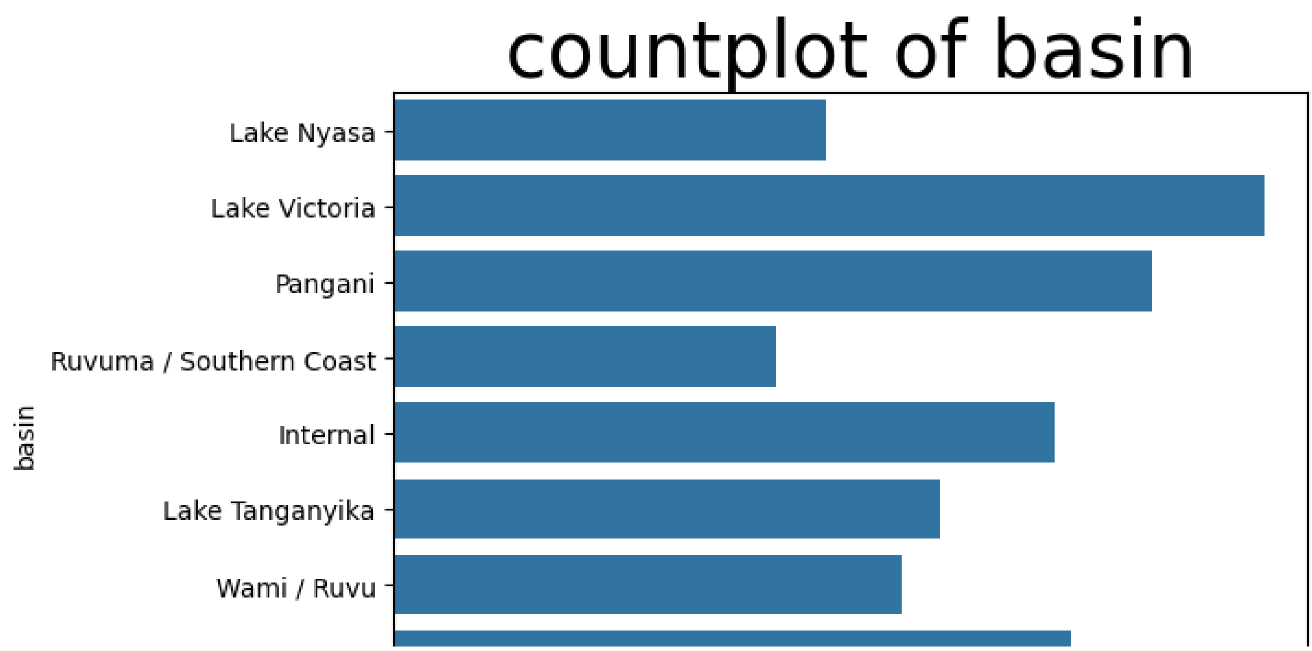
Out[13]:

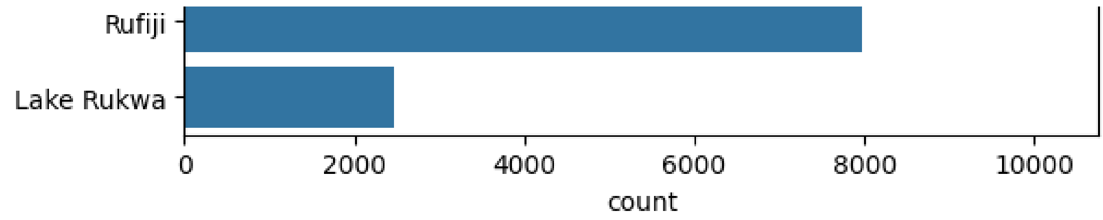
status_group	count
functional	32259
non functional	22824
functional needs repair	4317

dtype: int64

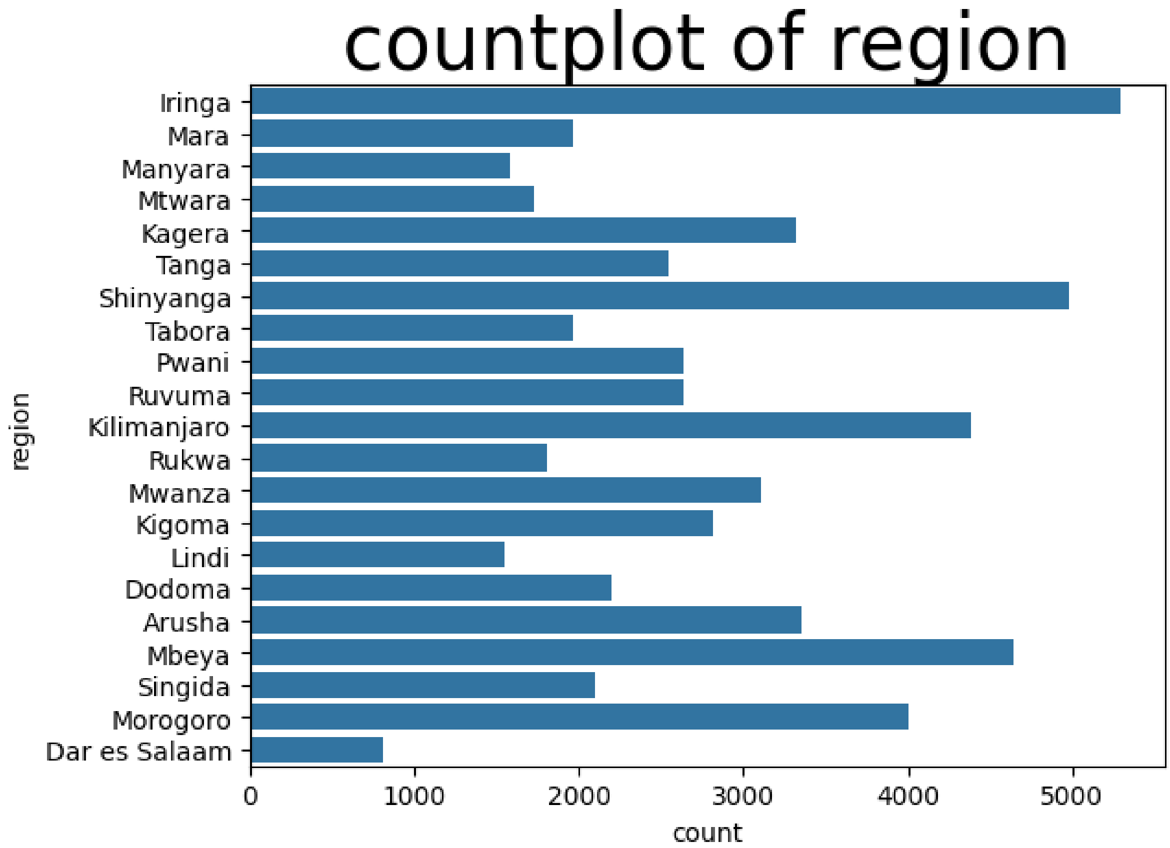
In [14]:

```
# selecting object datatypes columns

categorical = ['basin', 'region',
         'public_meeting', 'recorded_by',
       'scheme_management', 'permit',
       'extraction_type_group', 'extraction_type_class',
       'management', 'management_group',  'payment_type',
        'quality_group',
       'source', 'source_class',
       'waterpoint_type_group']
categorical

# lets make a for loop to make countplots for our categorical variables.
for col in categorical:
  ax=sns.countplot(y=col,data=data)
  plt.title(f"countplot of {col}", fontsize = 30)
  plt.show(plt.figure(figsize=(4, 4)))
```

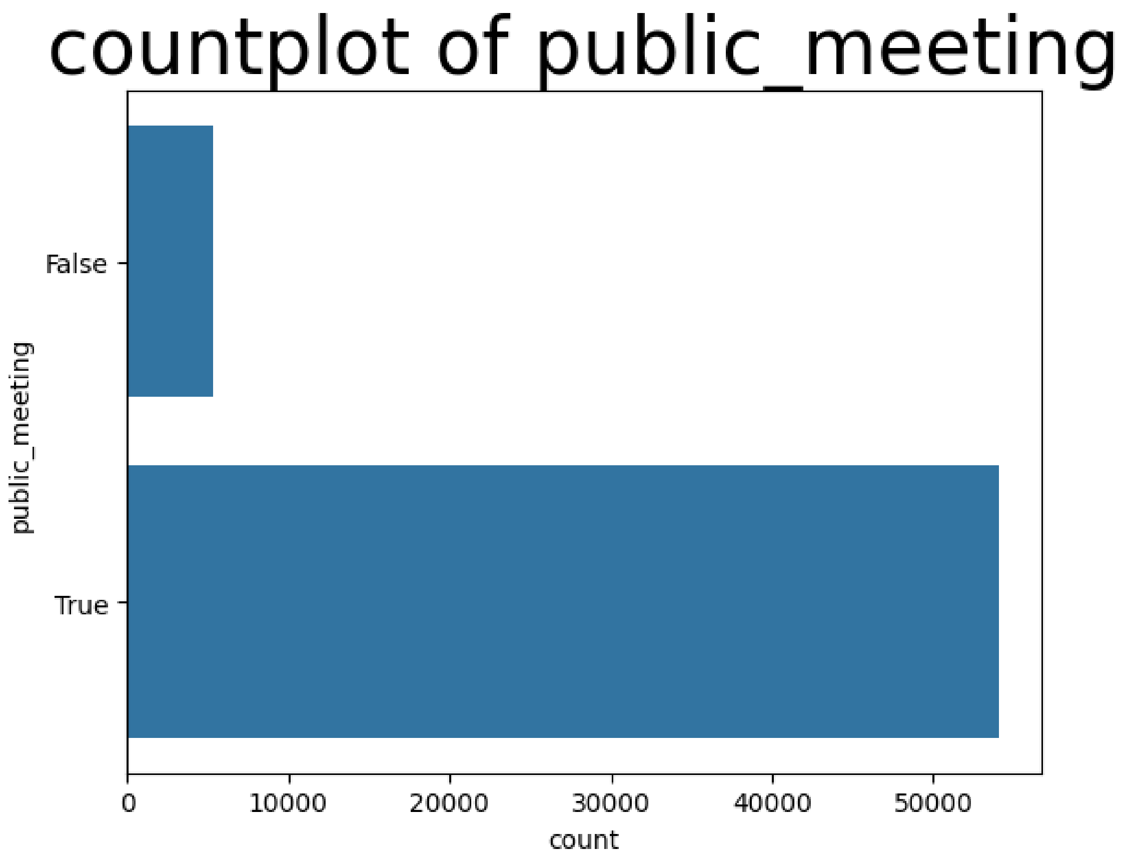




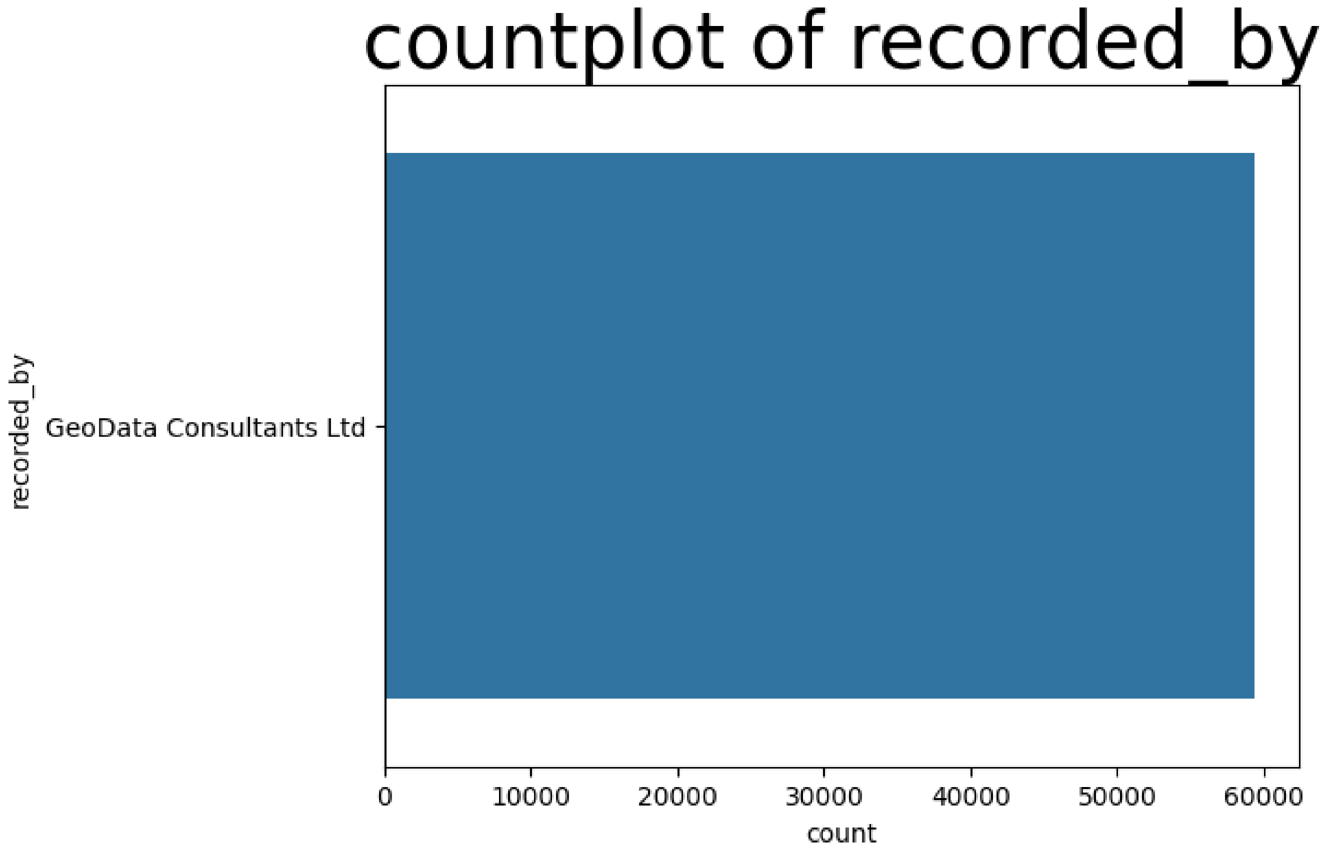
<Figure size 400x400 with 0 Axes>



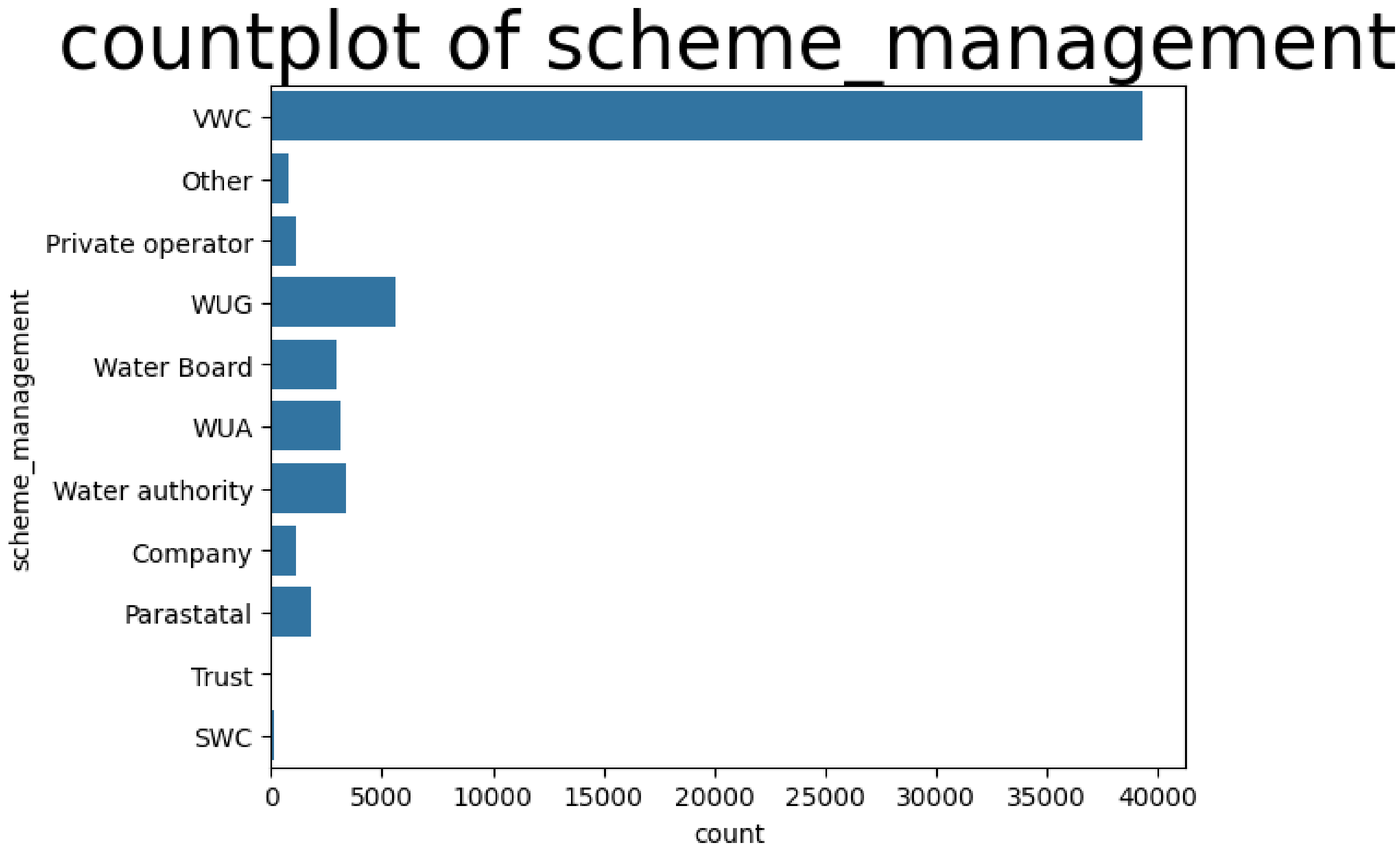
<Figure size 400x400 with 0 Axes>



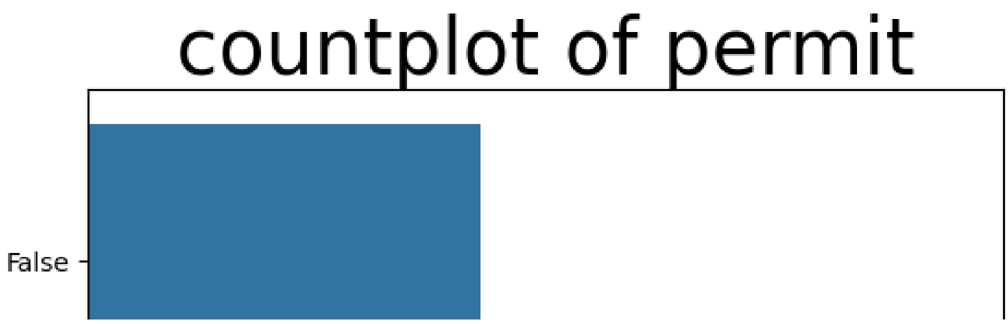
<Figure size 400x400 with 0 Axes>

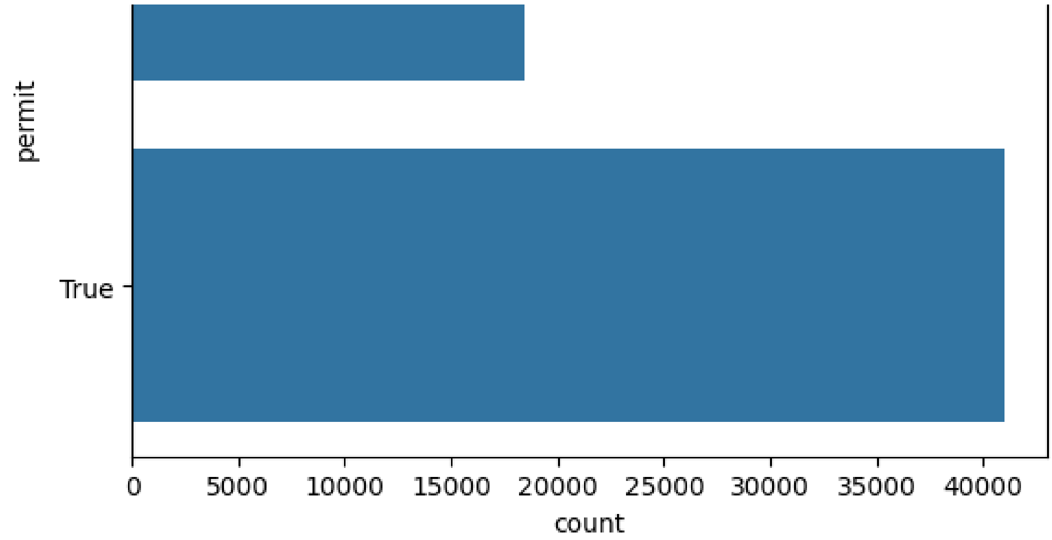


<Figure size 400x400 with 0 Axes>

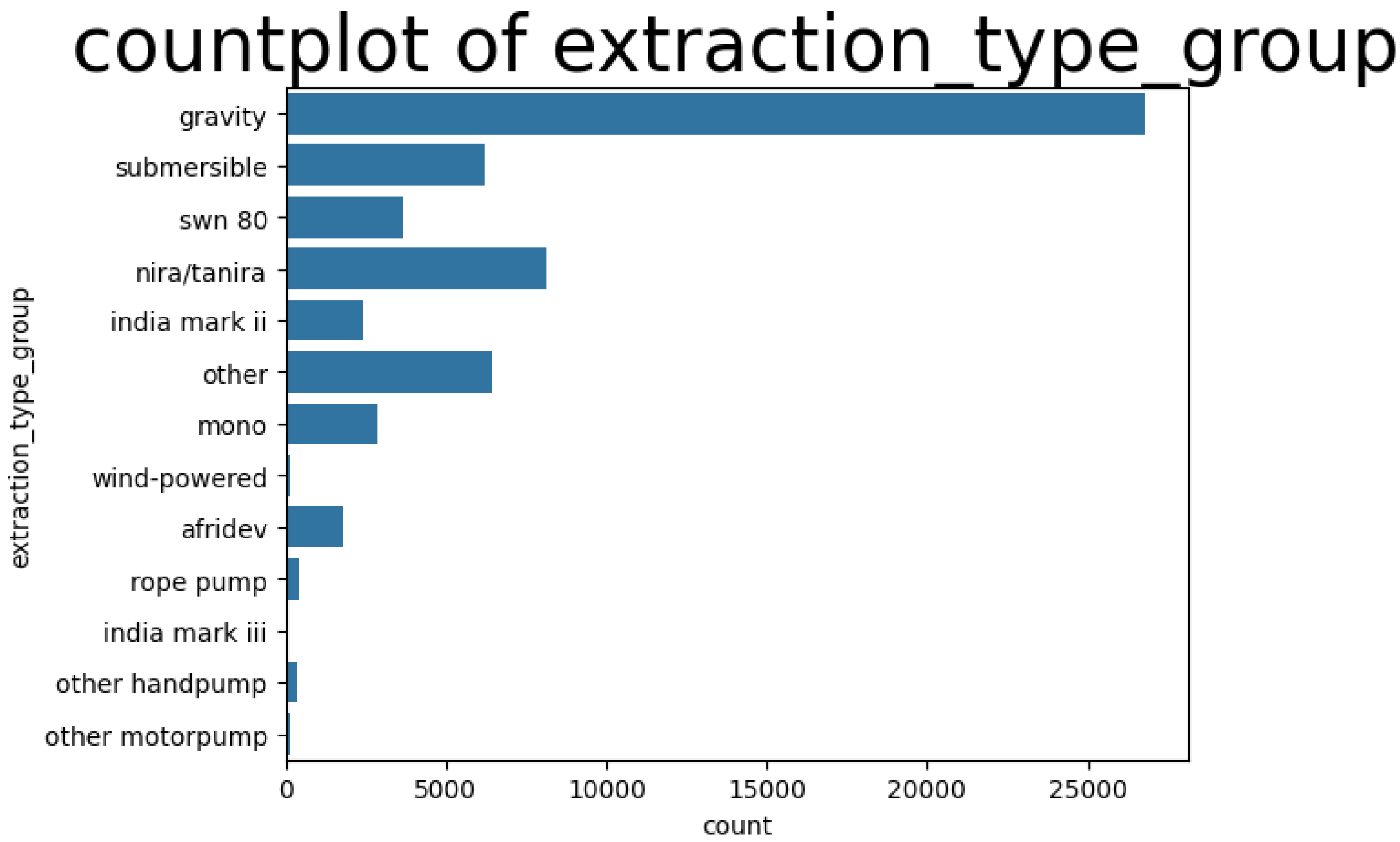


<Figure size 400x400 with 0 Axes>

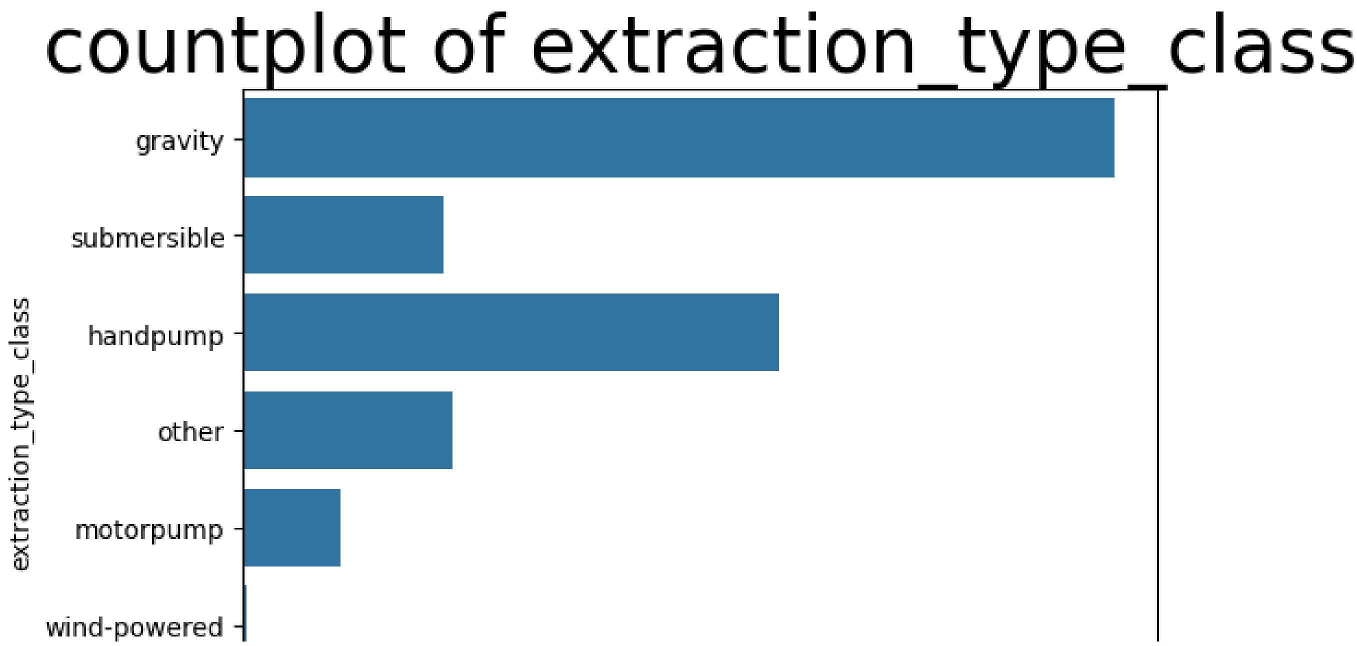


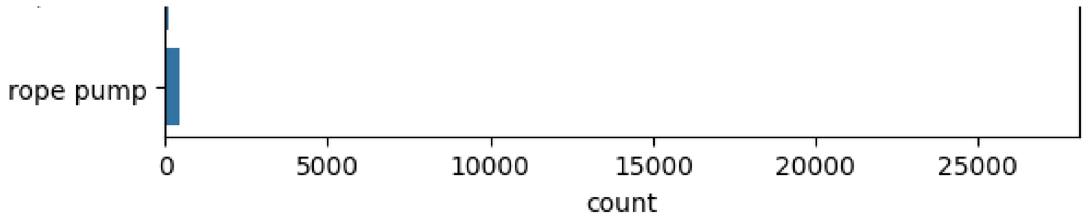



```
<Figure size 400x400 with 0 Axes>
```

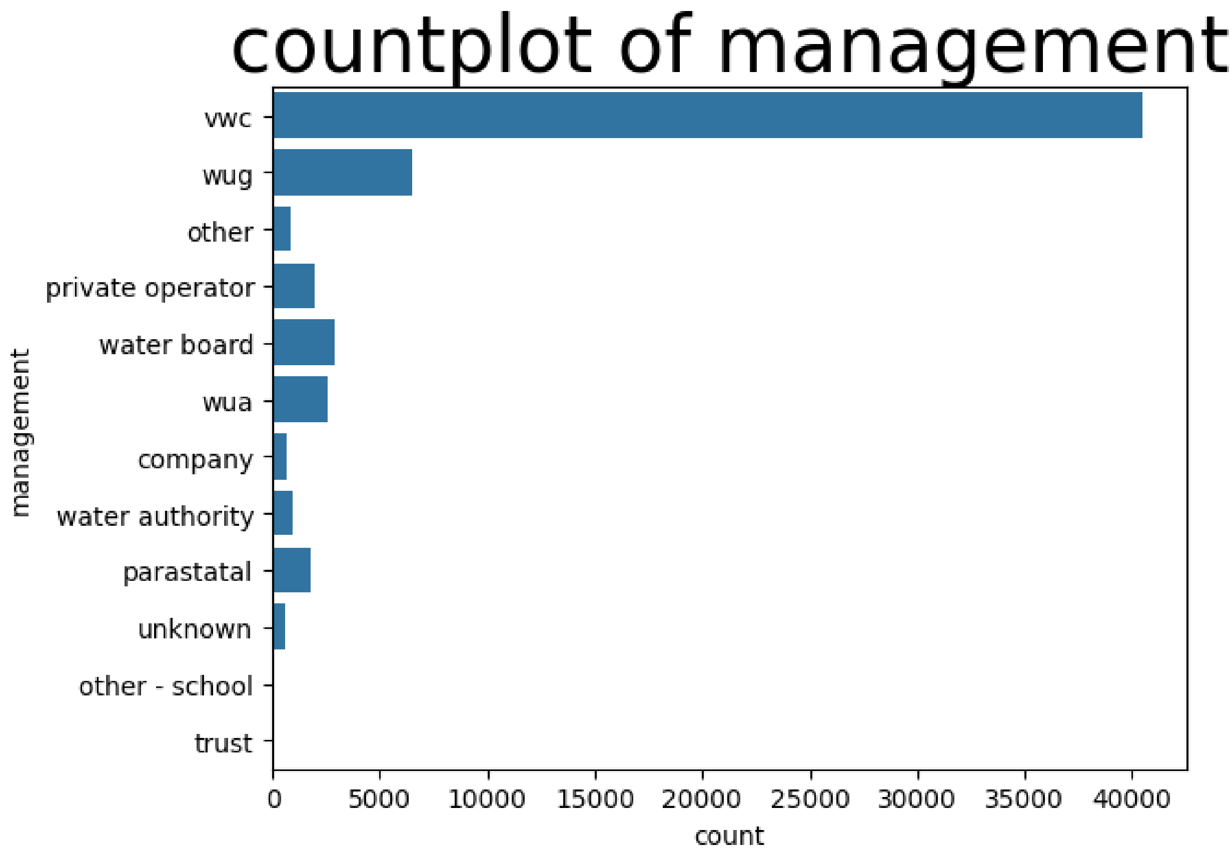



```
<Figure size 400x400 with 0 Axes>
```

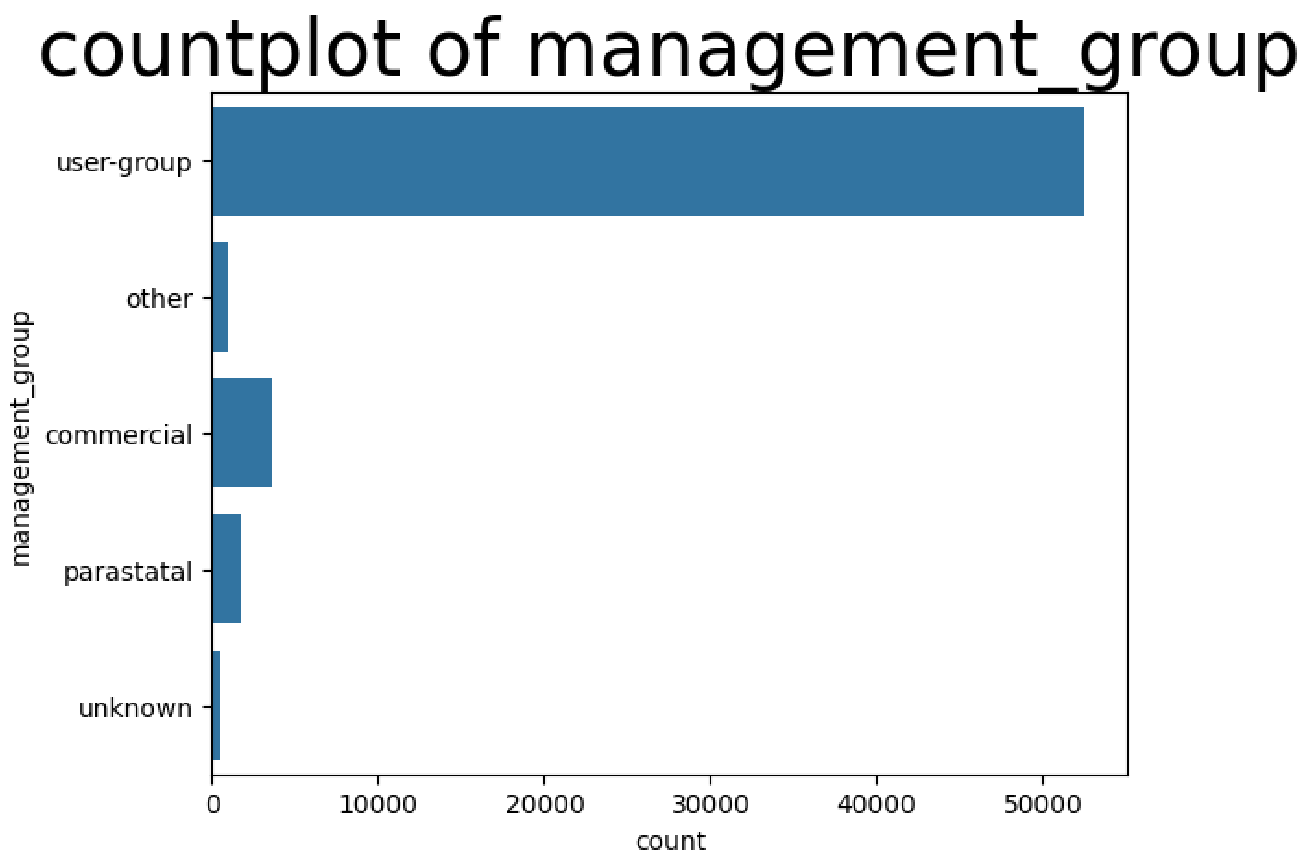




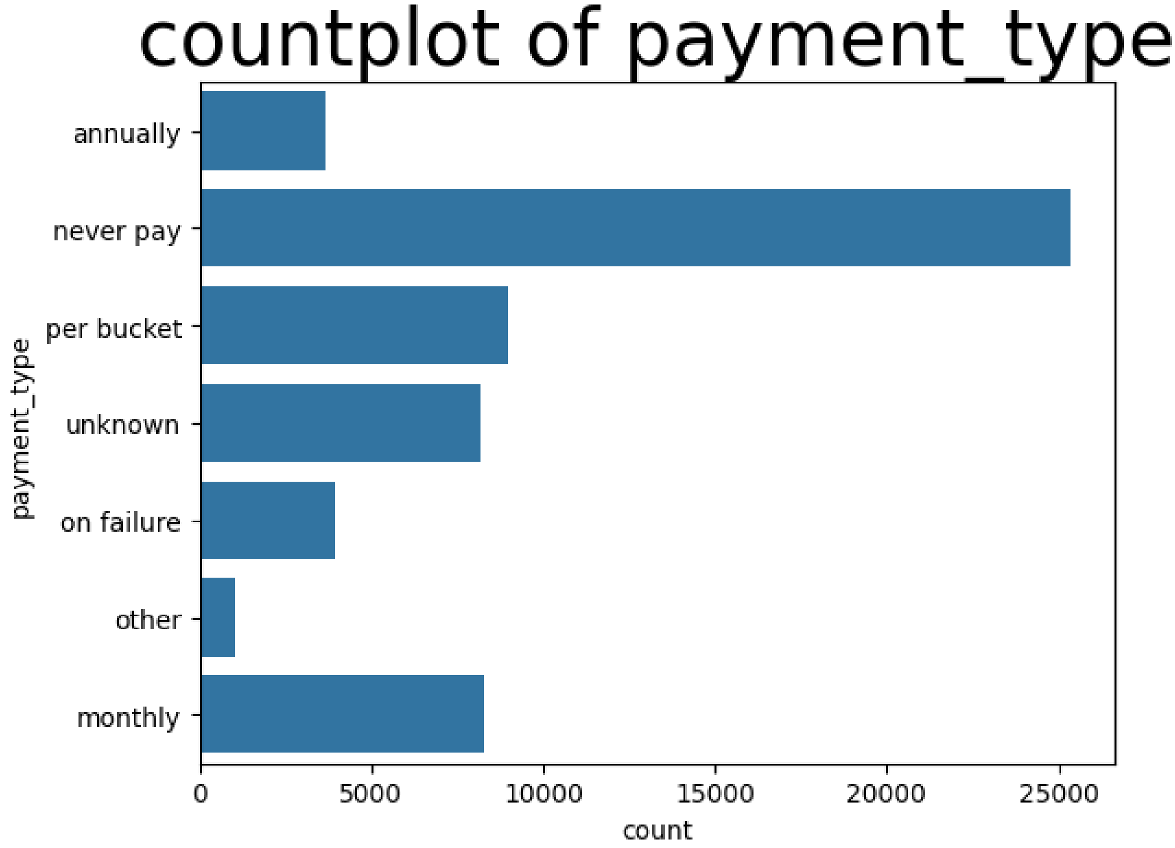
<Figure size 400x400 with 0 Axes>



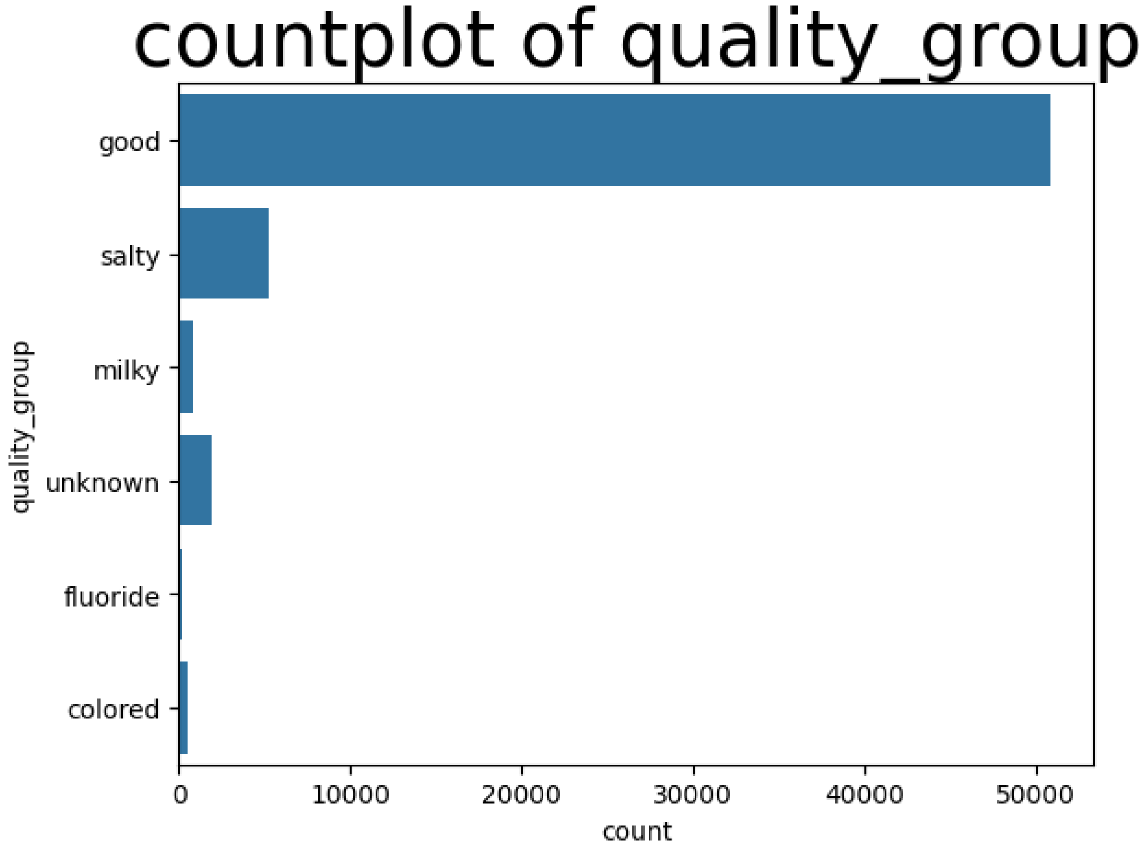
<Figure size 400x400 with 0 Axes>



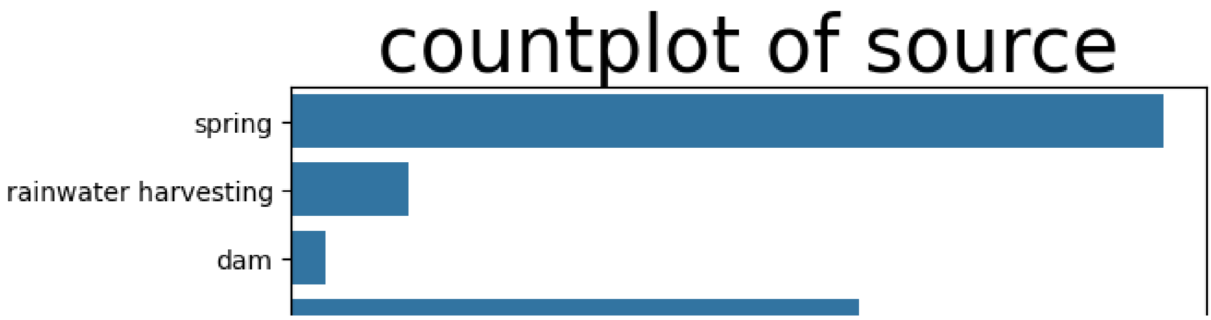
<Figure size 400x400 with 0 Axes>

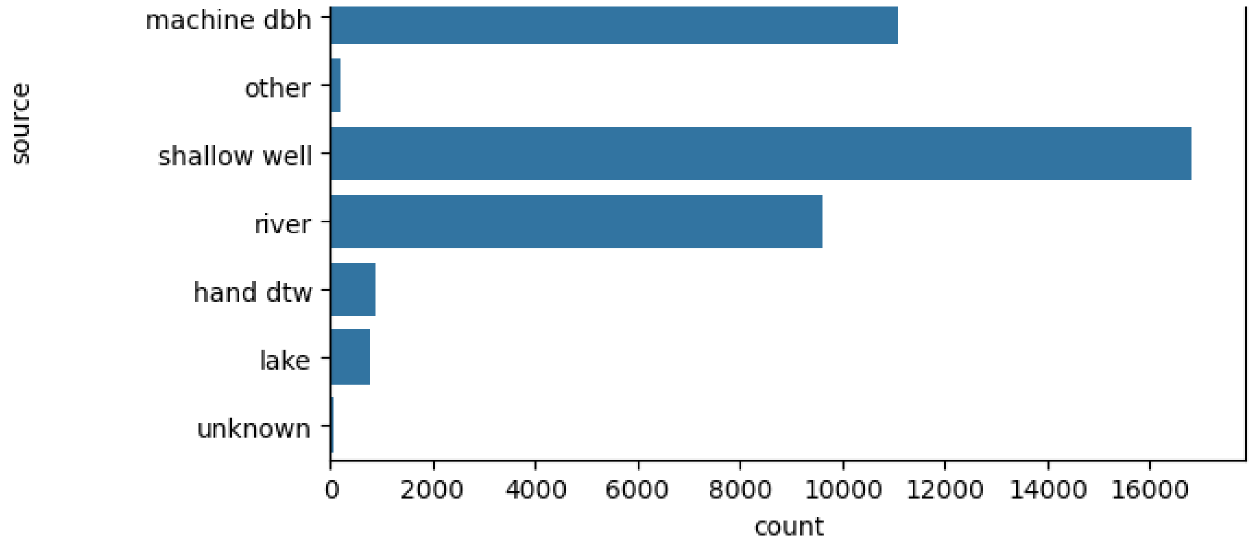


<Figure size 400x400 with 0 Axes>

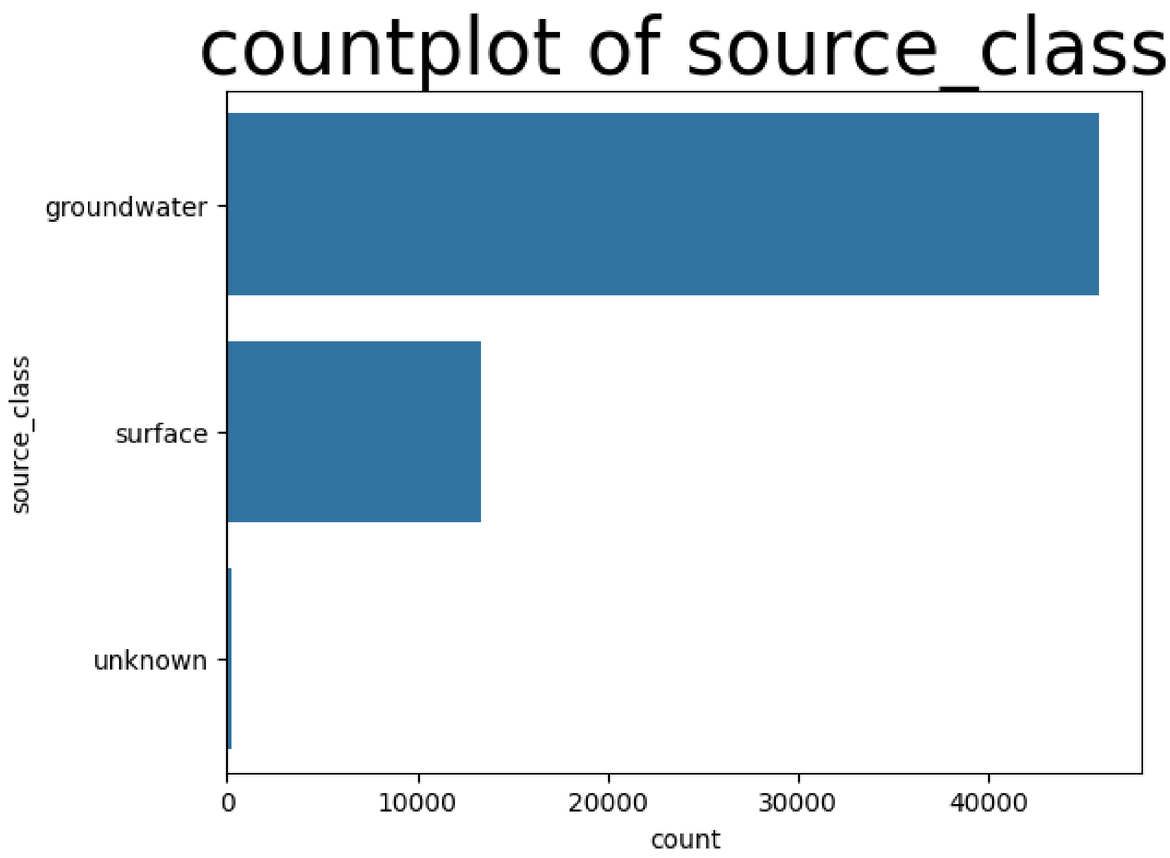


<Figure size 400x400 with 0 Axes>

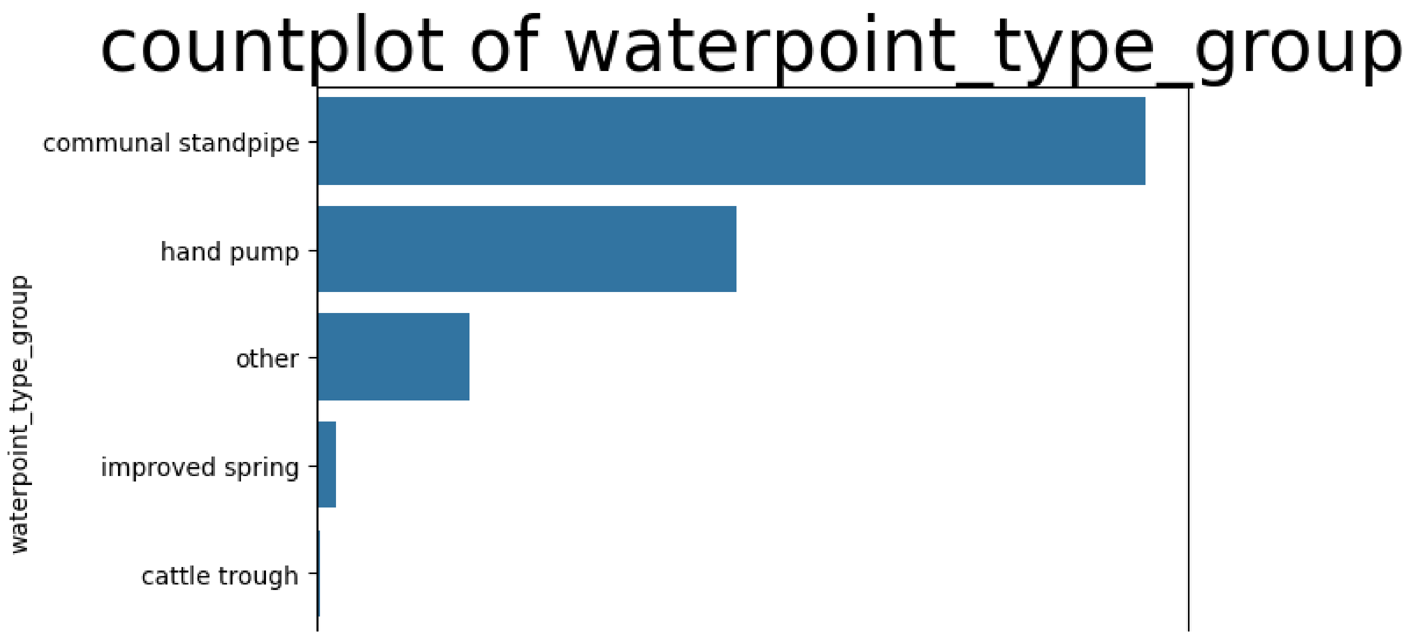


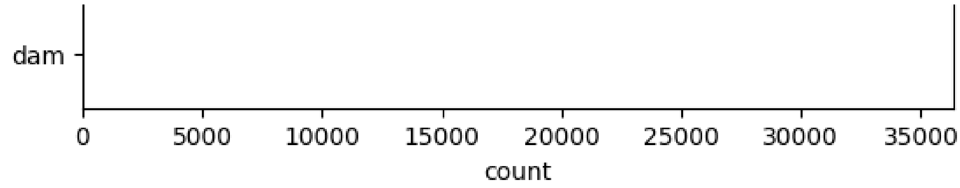



```
<Figure size 400x400 with 0 Axes>
```




```
<Figure size 400x400 with 0 Axes>
```






```
<Figure size 400x400 with 0 Axes>
```

Bivariate Analysis

In [15]:

```
# let's get maximum and minimum values for latitude and longitude
BBox = ((
    data[data['longitude']!=0].longitude.min(),
    data.longitude.max(),
    data.latitude.min(),
    data.latitude.max()
))
BBox
```

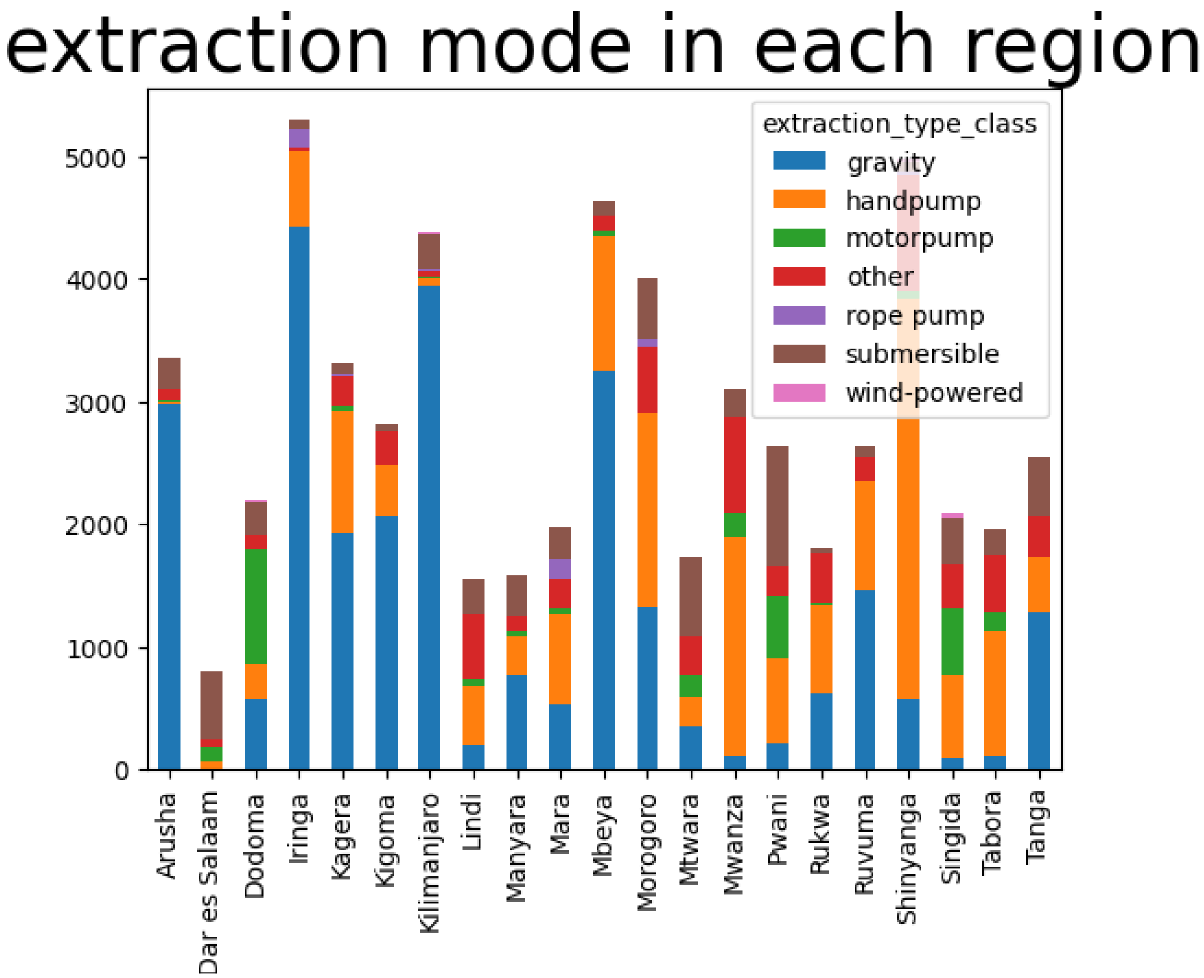
Out[15]:

```
(29.6071219, 40.34519307, -11.64944018, -2e-08)
```

In [16]:

```
#creating a crosstab
crosstb=pd.crosstab(data.region,data.extraction_type_class)

#creating a bar plot
plt.figure(figsize=(30,25))
pl=crosstb.plot(kind="bar",stacked=True,rot=90)
plt.title("extraction mode in each region", fontsize=30)
plt.show(plt.figure(figsize=(2, 2)))
```

```
<Figure size 3000x2500 with 0 Axes>
```



region

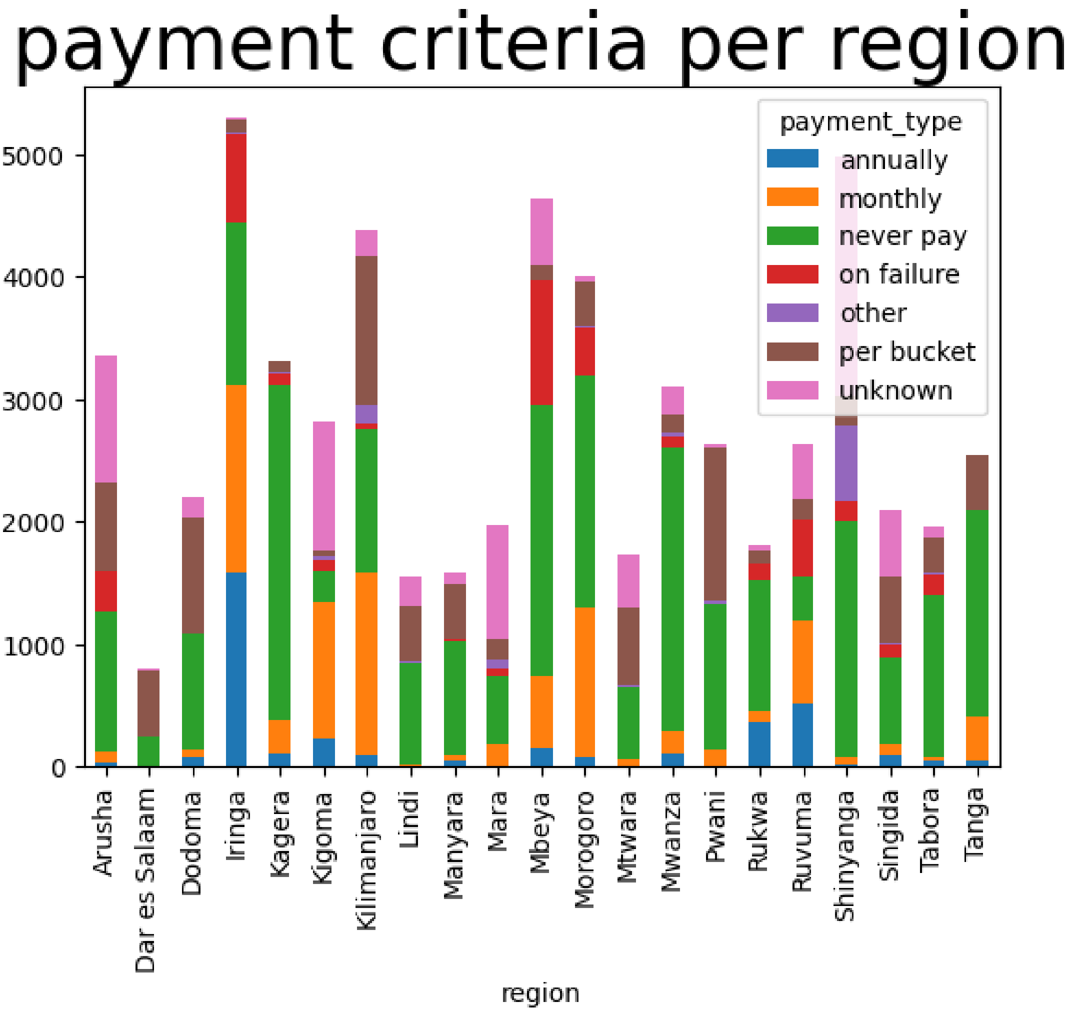
<Figure size 200x200 with 0 Axes>

Plot above shows region and most used mode of extraction on the water pumps

In [17]:

```
#creating a crosstab
crosstb=pd.crosstab(data.region,data.payment_type)

#creating a bar plot
plt.figure(figsize=(30,25))
pl=crosstb.plot(kind="bar",stacked=True,rot=90)
plt.title("payment criteria per region", fontsize=30)
plt.show(plt.figure(figsize=(4, 4)))
```

<Figure size 3000x2500 with 0 Axes>



<Figure size 400x400 with 0 Axes>

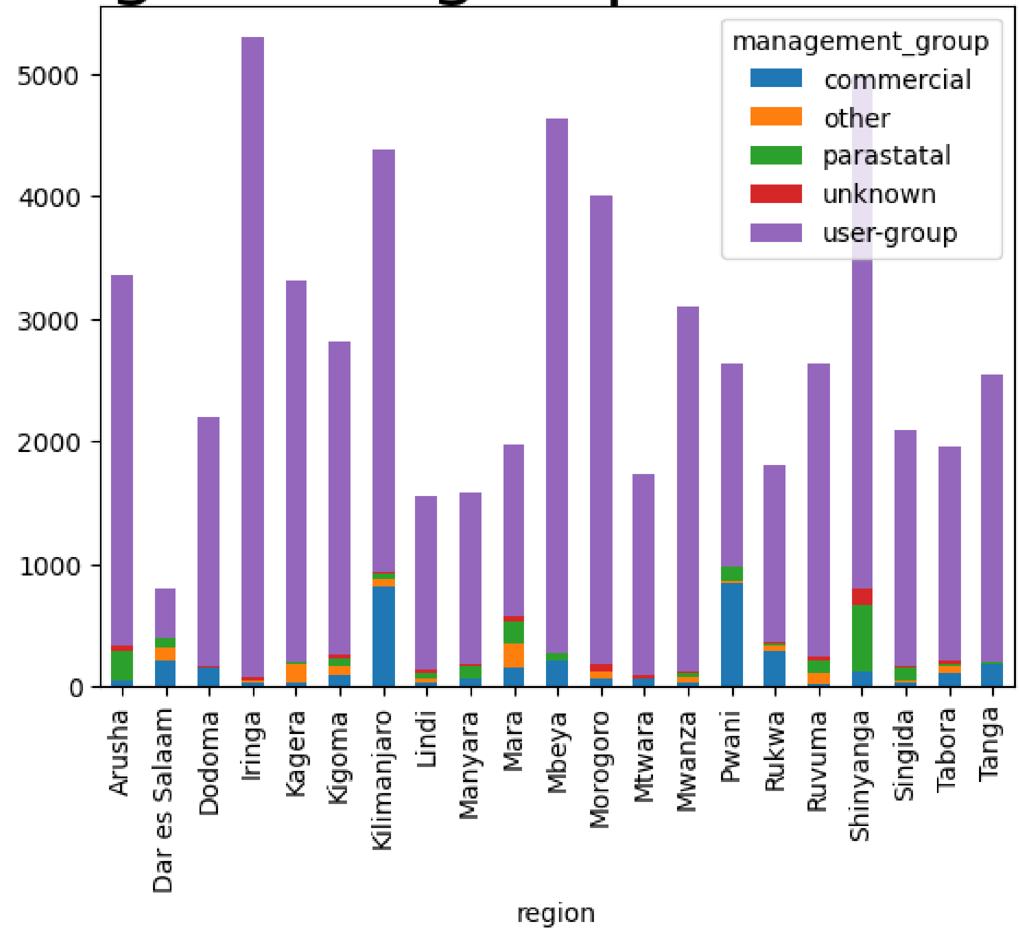
Plot above shows how pple pay for their water. We still have a substantial number getting them for free.

In [18]:

```
#df.sort_values('arrival_date_month',ascending=False)
#creating a crosstab
crosstb=pd.crosstab(data.region,data.management_group)
#creating a bar plot
plt.figure(figsize=(34,30))
pl=crosstb.plot(kind="bar",stacked=True,rot=90)
plt.title("management group in each region", fontsize=30)
plt.show(plt.figure(figsize=(4, 4)))
```

<Figure size 3400x3000 with 0 Axes>

management group in each region




```
<Figure size 400x400 with 0 Axes>
```

Majority of the water wells are managed by communities

Preprocessing

Encoding

In [19]:

```
# Encode categorical variables
encoder = LabelEncoder()
categorical_columns = data.select_dtypes(include=['object']).columns
for col in categorical_columns:
    data[col] = encoder.fit_transform(data[col])
```

In [20]:

```
# Splitting features and target
X = data.drop(columns=['id', 'status_group'])
y = data['status_group']
```

In [21]:

```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
)
```

In [22]:

```
for col in categorical_columns:
    print(f"Column: {col}")
    print(data[col].unique())
```

```
    print()
```

```
Column: date_recorded
[171 216 144  21 268 169  35  71  84 320 133 128  41 174  49 324 290 351
 278 137 147 115  64  85  13   7 266 213 176 191 175 182 165 139 202 271
 199 116  61 167 294   6 180  51 155 283 243 136 307 289 298 269 138 287
 321  14 189 254  10 159  27 154 212 209 148 327 207  52 183 210 172  45
 328 352 226   8  11  20 130  67 118 146 124 126 277 217 267 272 248 225
  58 143  37 120  66 274 230 177  18  68 141 188 309 151  16  50 231 152
 142 235  46  25 205 306 201 279 156 300 221 179 218 303 350 123 241 296
 227 229 163 196 150   9  36 286 325 276 170 173 273 206  91 244  43 192
 242 158 187 246  42 181 260 204  57 270  38 285 326  39 184 117  22  28
  54  76 114 299 178 288 135 125 308 122 132  19 247 312 194  48 224 140
 134 249 203 195 162 256  89 193 185 211  55 262 311 157 280 281 190 310
 284 168 208 111 197 219  15  88  47  69 233  78 301 314  70 145 198 161
 101 119   5  65 282  56  44 341  60 186  93 121  53 164 293 295 100 316
 297 250  63 215 275  75 149 131  26 265 232 292 261 313  23   4  94   2
  32 291 127 302  90 259   3 220  95 103 228  72 200 110  33 234 102  62
 305  31  24 252 304 129  83 238   1  73 112  74  59 317 239 329 263  40
 222 153  34  99  77  98 237 105 318 106  81 347 315 349  82 340 107  80
 166  79 253  97  87 251 245 104  92  86 258 257 108 355 109 255 240 236
 113 339 353 342 160 338   0  30 264 332 323 343 322 319 331 348 337 334
 354 344  29 335 214  12  17 336 345 330 223 346 333  96]

Column: funder
[1368  469  825 ...  298  133 1439]

Column: installer
[1518  545 2048 ...  415 2067 1566]

Column: wpt_name
[37398 37194 14572 ... 24074 29693 18700]

Column: basin
[1 4 5 7 0 3 8 6 2]

Column: subvillage
[11807 15838  9074 ...  3974  9632  5892]

Column: region
[ 3  9  8 12  4 20 17 19 14 16  6 15 13  5  7  2  0 10 18 11  1]

Column: lga
[ 51 103 108  87  26  68 104  25 115  69  86  58 106  64 113  91 121   5
 101  31  73  47  96  11   3  53   0  46  42  34  30  55 109  57 100  74
  15  63   7  80  52  65  23  35  59  28   8  44   9  71  40  82 102  24
  81  14  98  17  66  67 111 117 120  16  84  12   6  21  76  83  10  41
  50 123  62 107  20 118 119  60  54  56  19  36   2  13  79  77  89  27
  75  29 110  88  94  92   4  61 122 114  72 116  39  78  37  49  43 124
  99  45  70 105  90  18  97  95  48  85  38  32  22  33   1 112  93]

Column: ward
[1426 1576 1624 ...  180 1715  708]

Column: recorded_by
[0]

Column: scheme_management
[ 6  1  3  8  9  7 10  0  2  5  4]

Column: scheme_name
[2244 2120 2621 ...  111 1174 1748]

Column: extraction_type
[ 3 14 15  8  4  9  6  7 17  0 12  5 13 11  1  2 16 10]

Column: extraction_type_group
[ 1 10 11  5  2  6  4 12  0  9  3  7  8]

Column: extraction_type_class
[0 5 1 3 2 6 4]
```

```
Column: management
[ 7 11  1  4  9 10  0  8  3  6  2  5]

Column: management_group
[4 1 0 2 3]

Column: payment
[2 0 4 6 5 1 3]

Column: payment_type
[0 2 5 6 3 4 1]

Column: water_quality
[6 4 3 7 1 0 5 2]

Column: quality_group
[2 4 3 5 1 0]

Column: quantity
[1 2 0 3 4]

Column: source
[8 5 0 3 4 7 6 1 2 9]

Column: source_class
[0 1 2]

Column: waterpoint_type_group
[1 3 5 4 0 2]

Column: status_group
[0 2 1]
```

Scalling

In [23]:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler

# Identify non-numeric columns
non_numeric_cols = X_train.select_dtypes(include=['object']).columns

# Convert date columns to numerical format if applicable
for col in non_numeric_cols:
    try:
        X_train[col] = pd.to_datetime(X_train[col])
        X_test[col] = pd.to_datetime(X_test[col])

        # Convert dates to days since a reference date
        ref_date = pd.Timestamp("2000-01-01")
        X_train[col] = (X_train[col] - ref_date).dt.days
        X_test[col] = (X_test[col] - ref_date).dt.days
    except Exception:
        # If conversion fails, drop the column
        X_train = X_train.drop(columns=[col])
        X_test = X_test.drop(columns=[col])

# Ensure only numerical data remains
X_train = X_train.select_dtypes(include=[np.number])
X_test = X_test.select_dtypes(include=[np.number])

# Feature Scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [24]:

```python
# Feature scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [25]:

```python
data.construction_year.unique()
```

Out[25]:

```
array([1999, 2010, 2009, 1986,    0, 2011, 1987, 1991, 1978, 1992, 2008,
       1974, 2000, 2002, 2004, 1972, 2003, 1980, 2007, 1973, 1985, 1970,
       1995, 2006, 1962, 2005, 1997, 2012, 1996, 1977, 1983, 1984, 1990,
       1982, 1976, 1988, 1989, 1975, 1960, 1961, 1998, 1963, 1971, 1994,
       1968, 1993, 2001, 1979, 1967, 2013, 1969, 1981, 1964, 1966, 1965])
```

Modelling

In [26]:

```python
# Models Dictionary
models = {
    "Logistic Regression": LogisticRegression(),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(n_estimators=200, random_state=42),
    "K-NN": KNeighborsClassifier(),
    "SVM": SVC(),
    "Naïve Bayes": GaussianNB()
}
```

In [27]:

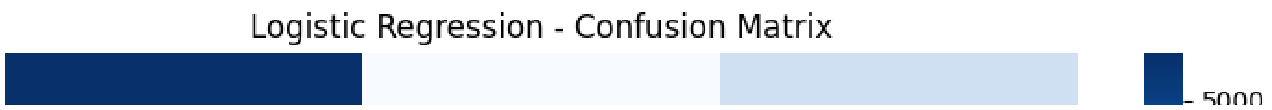
```python
# Training and Evaluating Models
results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    results[name] = acc
    print(f"{name} Accuracy: {acc:.4f}")
    print(classification_report(y_test, y_pred))
```

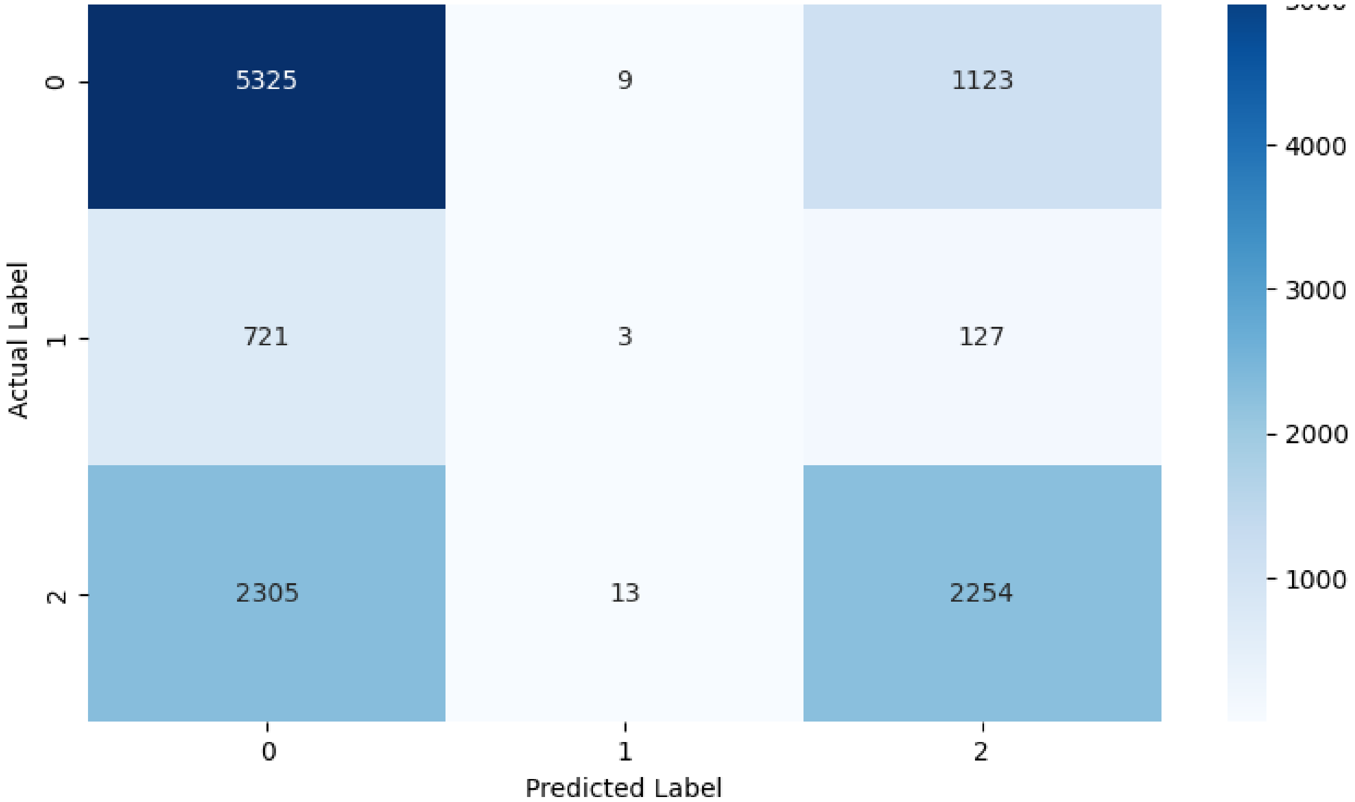
```
Logistic Regression Accuracy: 0.6382
              precision    recall  f1-score   support

           0       0.64      0.82      0.72      6457
           1       0.12      0.00      0.01       851
           2       0.64      0.49      0.56      4572

    accuracy                           0.64     11880
   macro avg       0.47      0.44      0.43     11880
weighted avg       0.60      0.64      0.61     11880

Decision Tree Accuracy: 0.7375
              precision    recall  f1-score   support

           0       0.79      0.78      0.78      6457
           1       0.32      0.34      0.33       851
           2       0.75      0.76      0.75      4572

    accuracy                           0.74     11880
   macro avg       0.62      0.63      0.62     11880
weighted avg       0.74      0.74      0.74     11880

Random Forest Accuracy: 0.8113
              precision    recall  f1-score   support

           0       0.81      0.89      0.85      6457
           1       0.57      0.33      0.42       851
```

```
           1       0.57      0.35      0.42       851
           2       0.85      0.78      0.81      4572

    accuracy                           0.81     11880
   macro avg       0.74      0.67      0.69     11880
weighted avg       0.81      0.81      0.80     11880

K-NN Accuracy: 0.7468
              precision    recall  f1-score   support

           0       0.75      0.86      0.80      6457
           1       0.44      0.27      0.34       851
           2       0.78      0.67      0.72      4572

    accuracy                           0.75     11880
   macro avg       0.66      0.60      0.62     11880
weighted avg       0.74      0.75      0.74     11880

SVM Accuracy: 0.7562
              precision    recall  f1-score   support

           0       0.73      0.92      0.81      6457
           1       0.57      0.11      0.18       851
           2       0.83      0.65      0.73      4572

    accuracy                           0.76     11880
   macro avg       0.71      0.56      0.57     11880
weighted avg       0.76      0.76      0.73     11880

Naïve Bayes Accuracy: 0.5859
              precision    recall  f1-score   support

           0       0.68      0.59      0.63      6457
           1       0.21      0.25      0.23       851
           2       0.56      0.64      0.60      4572

    accuracy                           0.59     11880
   macro avg       0.48      0.50      0.49     11880
weighted avg       0.60      0.59      0.59     11880
```

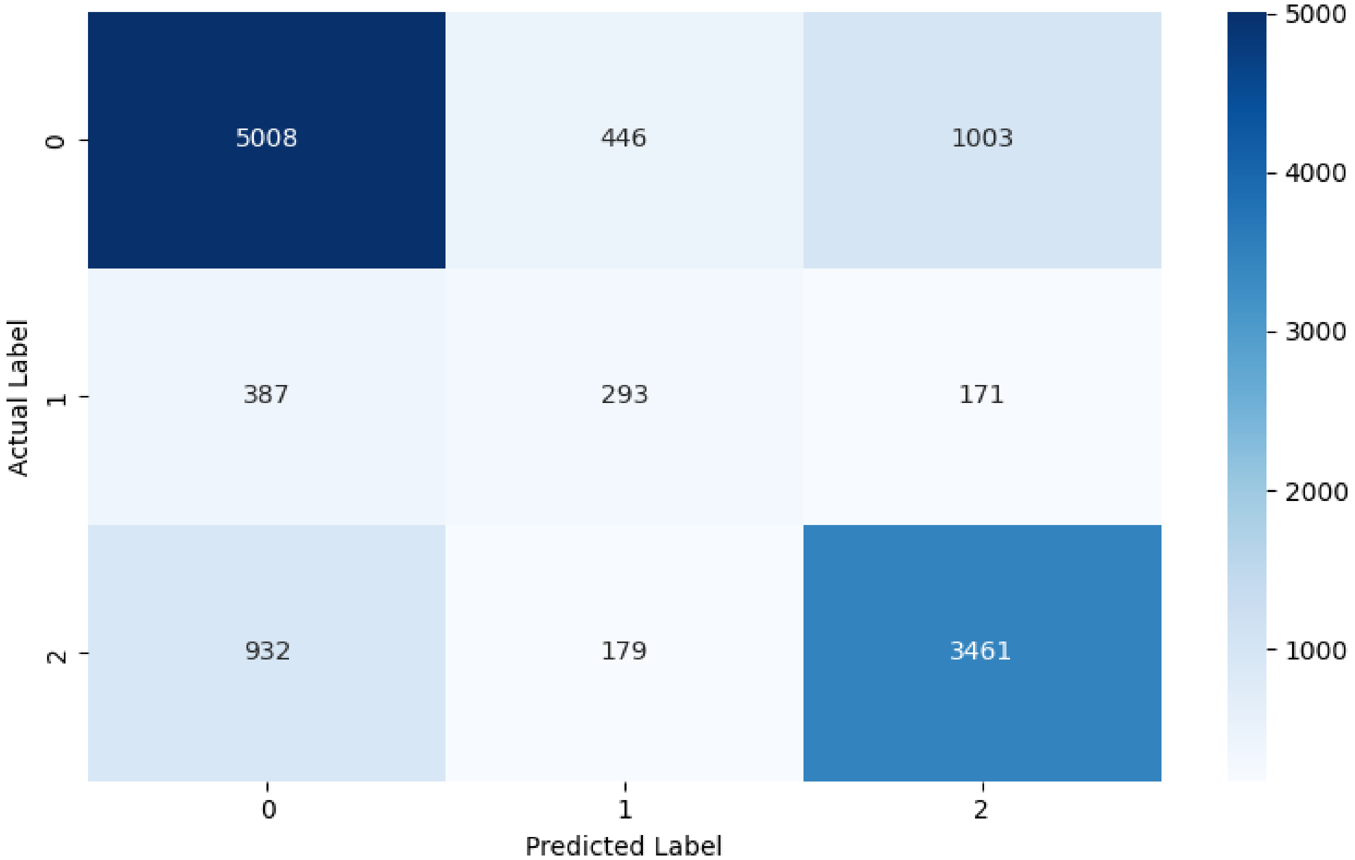
In [28]:

```python
# Create subplots for confusion matrices
fig, axes = plt.subplots(len(models), 1, figsize=(8, len(models) * 5))

for i, (name, model) in enumerate(models.items()):
    # Predict
    y_pred = model.predict(X_test)

    # Confusion Matrix
    cm = confusion_matrix(y_test, y_pred)
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", ax=axes[i])
    axes[i].set_title(f"{name} - Confusion Matrix")
    axes[i].set_xlabel("Predicted Label")
    axes[i].set_ylabel("Actual Label")

plt.tight_layout()
plt.show()

# Accuracy Bar Chart
plt.figure(figsize=(8, 5))
sns.barplot(x=list(results.keys()), y=list(results.values()), palette="viridis")
plt.xlabel("Model")
plt.ylabel("Accuracy Score")
plt.title("Model Accuracy Comparison")
plt.ylim(0, 1)  # Accuracy is between 0 and 1
plt.show()
```

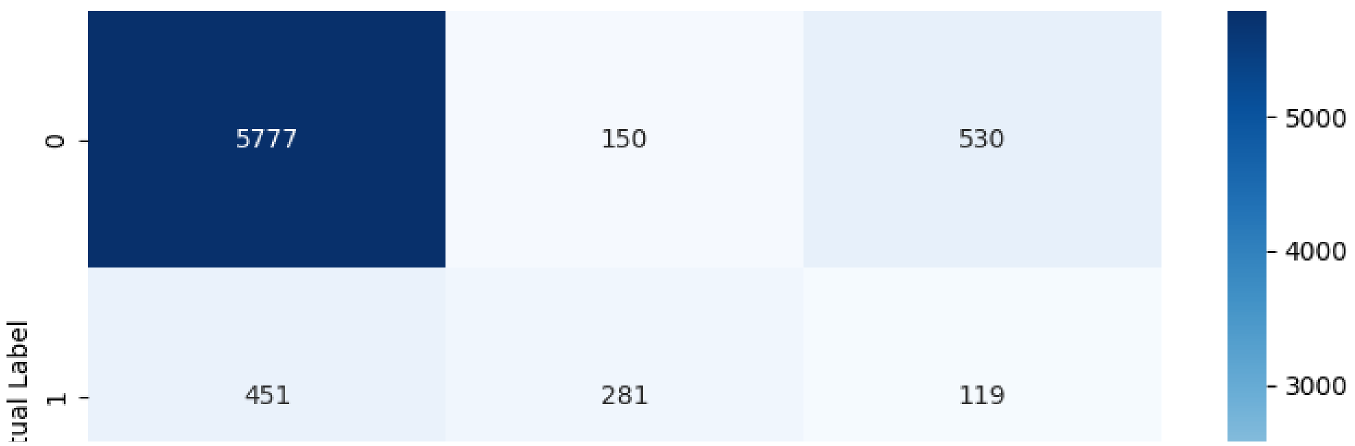


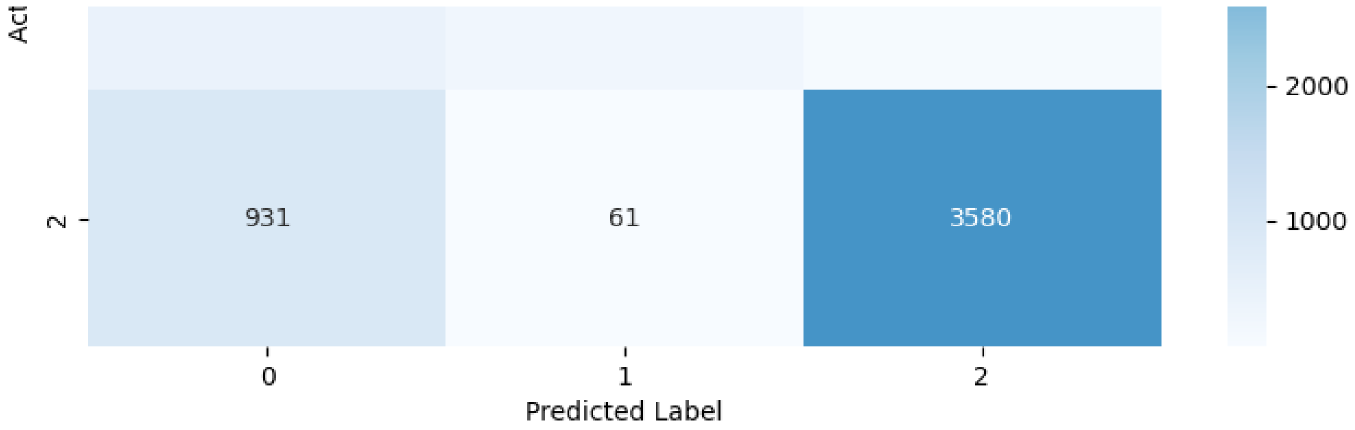


Decision Tree - Confusion Matrix

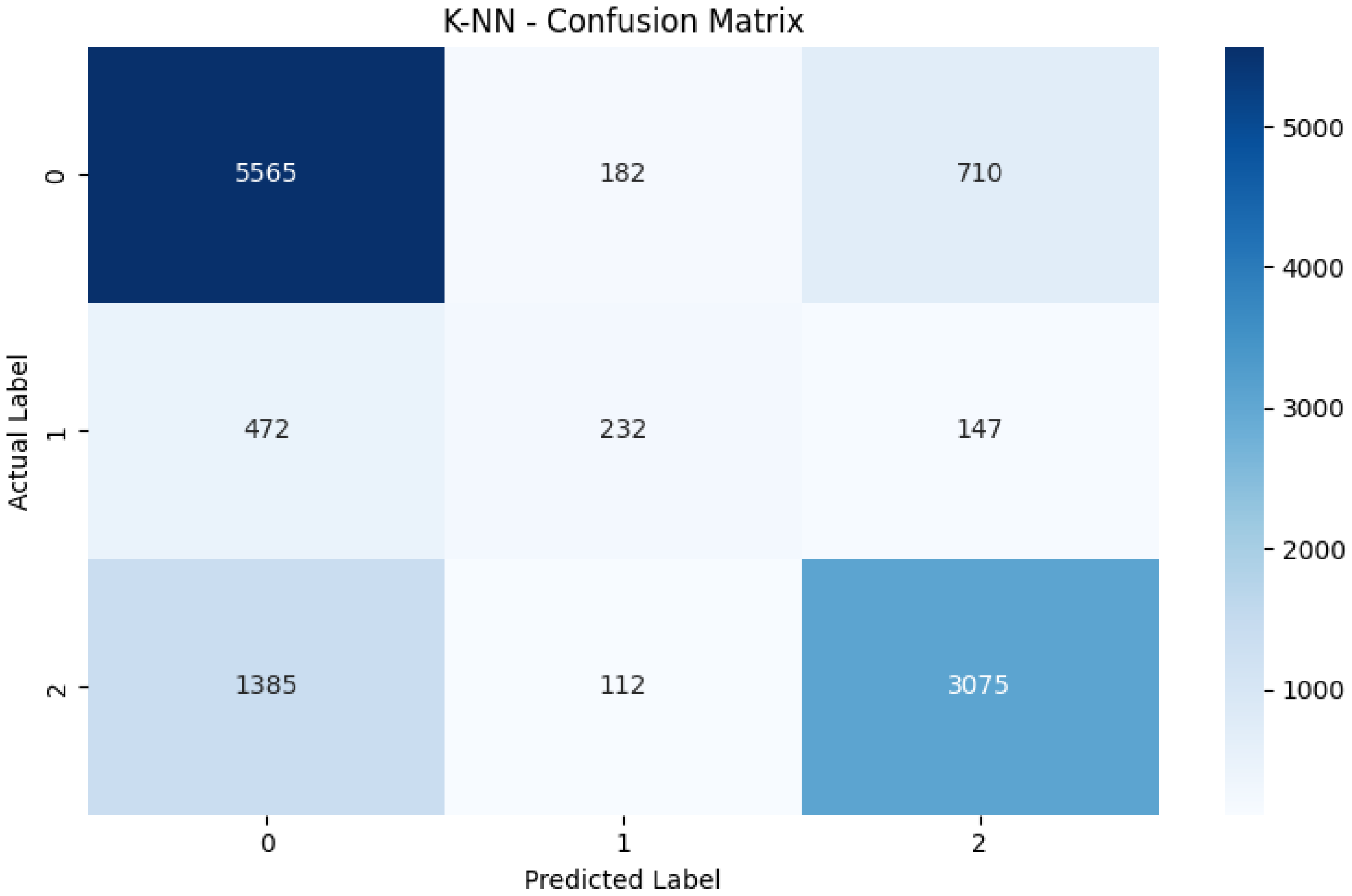


Random Forest - Confusion Matrix

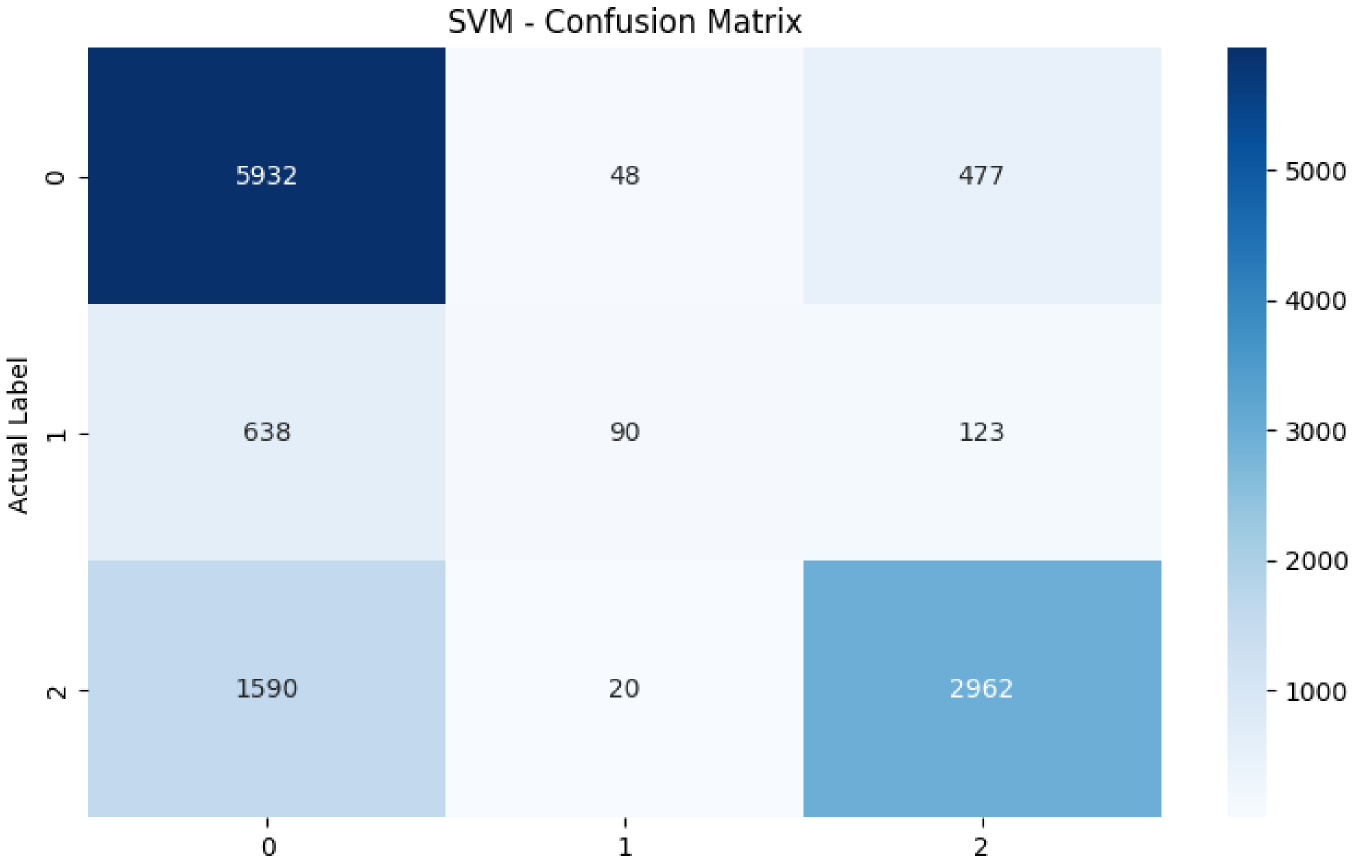




931
61
3580
2000
1000
0
1
2
Predicted Label

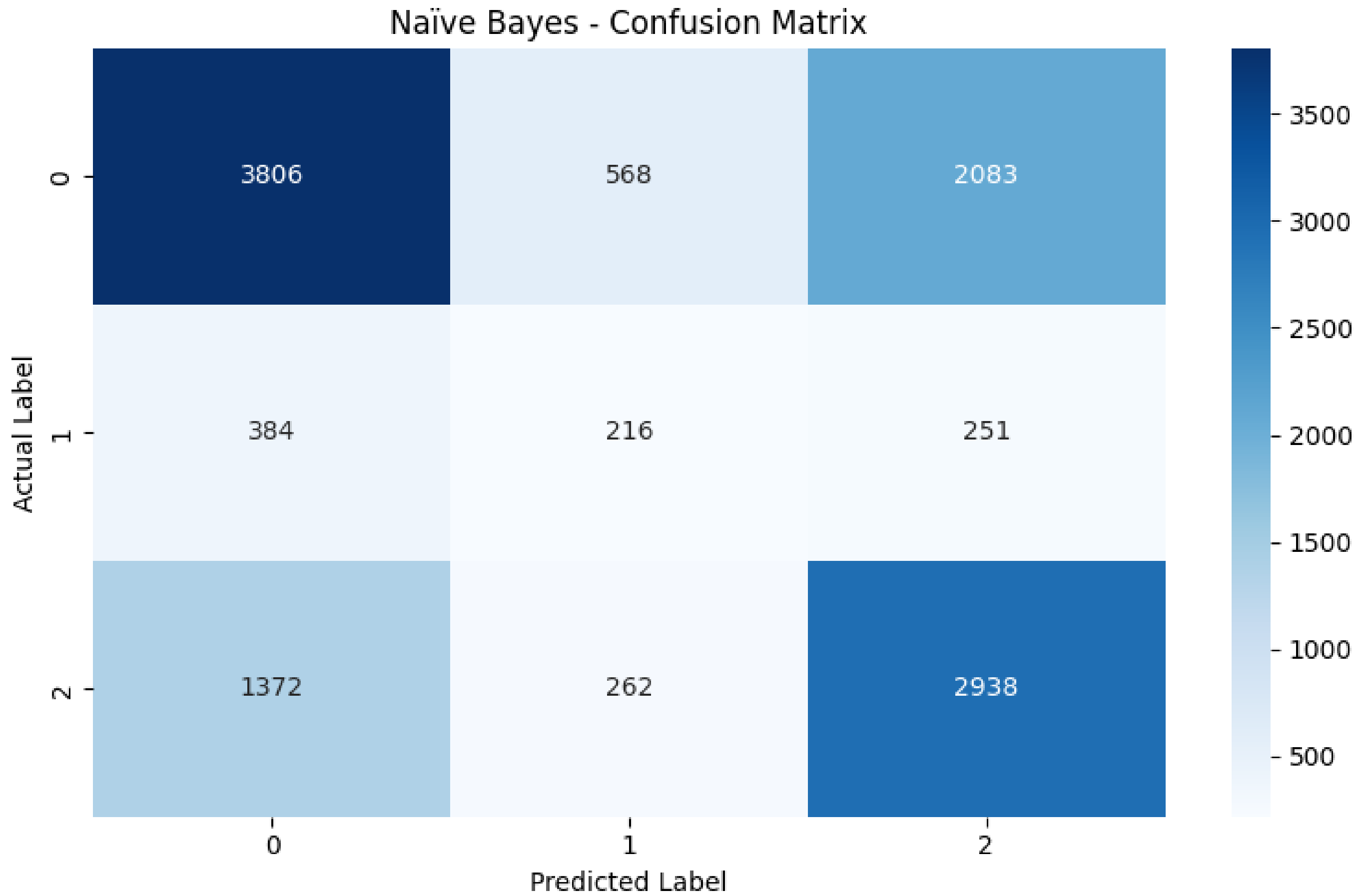


K-NN - Confusion Matrix
Actual Label
5565
182
710
472
232
147
1385
112
3075
5000
4000
3000
2000
1000
0
1
2
Predicted Label

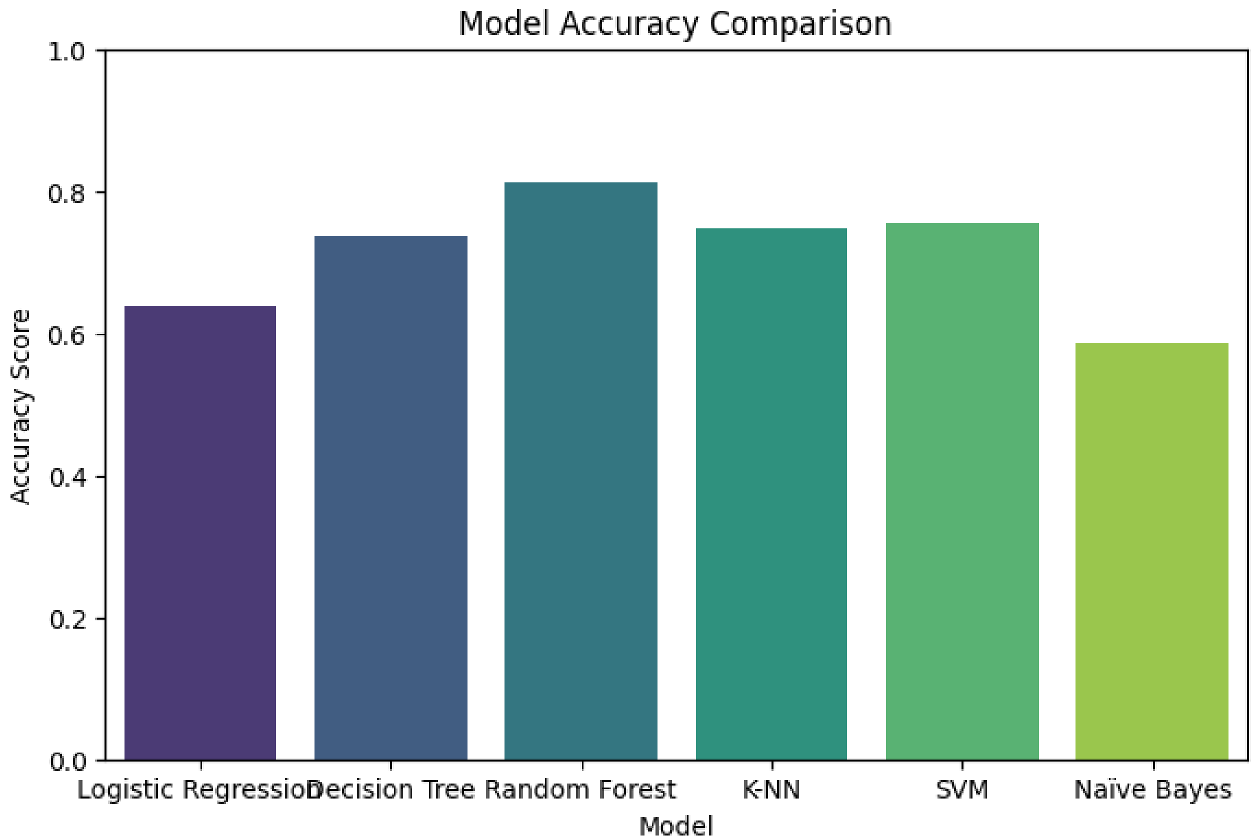


SVM - Confusion Matrix
Actual Label
5932
48
477
638
90
123
1590
20
2962
5000
4000
3000
2000
1000
0
1
2

Predicted Label




```
<ipython-input-28-f0e03e005b80>:20: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. A
ssign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=list(results.keys()), y=list(results.values()), palette="viridis")
```



Model Evaluation

Random Forest has the highest accuracy of 80%. To use the model to predict Functionality of the water wells

Hyperparameter Tuning

Hyperparameter Tuning for Decision Tree

In [29]:

```
# Hyperparameter Tuning for Decision Tree
param_grid_dt = {
    'max_depth': [5, 10, 15, 20],
    'min_samples_split': [2, 5, 10]
}
gs_dt = GridSearchCV(DecisionTreeClassifier(random_state=42), param_grid_dt, cv=3, scori
ng='accuracy')
gs_dt.fit(X_train, y_train)
print("Best Parameters for Decision Tree:", gs_dt.best_params_)
print("Best Score:", gs_dt.best_score_)
```

```
Best Parameters for Decision Tree: {'max_depth': 15, 'min_samples_split': 2}
Best Score: 0.7521675084175085
```

Hyperparameter Tuning for Naïve Bayes (var_smoothing)

In [30]:

```
# Hyperparameter Tuning for Naïve Bayes (var_smoothing)
param_grid_nb = {'var_smoothing': np.logspace(0,-9, num=100)}
gs_nb = GridSearchCV(GaussianNB(), param_grid_nb, cv=3, scoring='accuracy')
gs_nb.fit(X_train, y_train)
print("Best Parameters for Naïve Bayes:", gs_nb.best_params_)
print("Best Score:", gs_nb.best_score_)
```

```
Best Parameters for Naïve Bayes: {'var_smoothing': 1.0}
Best Score: 0.6057659932659932
```

Hyperparameter Tuning for Random Forest

In [31]:

```
# Hyperparameter Tuning for Random Forest
param_grid_rf = {
    'n_estimators': [50, 100, 100],
    'max_depth': [None, 10, 30]
}
gs_rf = GridSearchCV(RandomForestClassifier(random_state=42), param_grid_rf, cv=3, scori
ng='accuracy')
gs_rf.fit(X_train, y_train)
print("Best Parameters for Random Forest:", gs_rf.best_params_)
print("Best Score:", gs_rf.best_score_)
```

```
Best Parameters for Random Forest: {'max_depth': 30, 'n_estimators': 100}
Best Score: 0.8013257575757575
```

Conclusion

The analysis provides valuable insights into the factors influencing system functionality. The model, particularly Random Forest (80% accuracy), effectively classifies functional and non-functional cases, helping stakeholders make data-driven decisions. However, some misclassifications exist in the data, emphasizing the need for continuous model improvement and expert validation.

Recommendations

1. **Use Insights for Proactive Decision-Making – Prioritize maintenance and interventions based on model predictions to prevent failures.**
2. **Optimize Resource Allocation – Focus efforts on high-risk areas, ensuring efficient use of manpower and budget.**
3. **Regular Data Updates – Continuously update and refine the dataset to improve prediction accuracy over time.**
4. **Combine AI with Human Expertise – Use model results alongside expert knowledge for well-rounded decision-making.**
5. **Monitor Model Performance – Evaluate and adjust the model periodically to adapt to changes in data patterns**