Business Understanding

The goal of this project is to predict the condition of water wells in Tanzania to help stakeholders—such as NGOs, government bodies, and water management organizations—optimize resource allocation, maintenance efforts, and future well construction planning. This notebook presents our approach to addressing water access challenges in Tanzania through predictive modeling.

Problem Statement

Tanzania, a developing country with over 57 million people, struggles to provide clean and accessible water. Many water wells are installed across the country, but some are in need of repair or have completely failed. The classification of these wells into functional, needs repair, or non-functional helps decision-makers take action where it's needed most. I will build a classification model to identify which water wells require repairs, enabling proactive maintenance and ensuring reliable access to clean drinking water.

Objectives

1. Proactive Maintenance & Resource Allocation
2. Prioritize Repairs for High-Risk & Functional-But-Vulnerable Wells
3. Identify Key Factors Influencing Water Pump Failures
4. Strategic Planning for New Wells
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.

Import Datasets

Libraries

In [25]:

```
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
```

In [26]:

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

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

In [27]:

```
# Checking the overview of the data
def data_summary(df):
    print(df.info())


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
```

In [28]:

```
# Checking a brief summary of the data
```

```
data.describe()
```

Out[28]:

	id	amount_tsh	gps_height	longitude	latitude	num_private	region_code	district_code	
count	59400.000000	59400.000000	59400.000000	59400.000000	5.940000e+04	59400.000000	59400.000000	59400.000000	59
mean	37115.131768	317.650385	668.297239	34.077427	-5.706033e+00	0.474141	15.297003	5.629747	
std	21453.128371	2997.574558	693.116350	6.567432	2.946019e+00	12.236230	17.587406	9.633649	
min	0.000000	0.000000	-90.000000	0.000000	-1.164944e+01	0.000000	1.000000	0.000000	
25%	18519.750000	0.000000	0.000000	33.090347	-8.540621e+00	0.000000	5.000000	2.000000	
50%	37061.500000	0.000000	369.000000	34.908743	-5.021597e+00	0.000000	12.000000	3.000000	
75%	55656.500000	20.000000	1319.250000	37.178387	-3.326156e+00	0.000000	17.000000	5.000000	
max	74247.000000	350000.000000	2770.000000	40.345193	-2.000000e-08	1776.000000	99.000000	80.000000	30

In [29]:

```
# Checking any missing values
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
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

Data Cleaning

Correct formats

In [30]:

```
# Confirming the format of individual columns
print(data.info())
```

```
<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
```

Handling NAs

In [31]:

```
# Dealing with the missing values
```

```
data.fillna(method='ffill', inplace=True)
```

```
<ipython-input-31-c0aa6b171d31>:2: FutureWarning: DataFrame.fillna with 'method' is depre
cated and will raise in a future version. Use obj.ffill() or obj.bfill() instead.
  data.fillna(method='ffill', inplace=True)
<ipython-input-31-c0aa6b171d31>:2: FutureWarning: Downcasting object dtype arrays on .fil
lna, .ffill, .bfill is deprecated and will change in a future version. Call result.infer_
objects(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 [32]:

```
#Confirming whether they are sorted
data.isna().sum()
```

Out[32]:

	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

Handling duplicates

In [33]:

```
# Dropping unneccesary columns
drop_columns = ["region_code", "district_code", "quantity_group", "source_type", "num_pri
vate", "waterpoint_type"]
data = data.drop(drop_columns, axis =1)
```

In [34]:

```
#GConfirm the unique values for each column
unique_counts = data.nunique()
```

In [35]:

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 35 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  lga                    59400 non-null  object 
 13  ward                   59400 non-null  object 
 14  population             59400 non-null  int64  
 15  public_meeting         59400 non-null  bool   
 16  recorded_by            59400 non-null  object 
 17  scheme_management      59400 non-null  object 
 18  scheme_name            59400 non-null  object 
 19  permit                 59400 non-null  bool   
 20  construction_year      59400 non-null  int64  
 21  extraction_type        59400 non-null  object 
 22  extraction_type_group  59400 non-null  object 
 23  extraction_type_class  59400 non-null  object 
 24  management             59400 non-null  object 
 25  management_group       59400 non-null  object 
 26  payment                59400 non-null  object 
 27  payment_type           59400 non-null  object 
 28  water_quality          59400 non-null  object 
 29  quality_group          59400 non-null  object 
```

```
 30  quantity               59400 non-null  object
 31  source                 59400 non-null  object
 32  source_class           59400 non-null  object
 33  waterpoint_type_group  59400 non-null  object
 34  status_group           59400 non-null  object
dtypes: bool(2), float64(3), int64(4), object(26)
memory usage: 15.1+ MB
None
```

EDA

Univariate Analysis

In [36]:

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

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

Out[36]:

	count
status_group	
functional	32259
non functional	22824
functional needs repair	4317

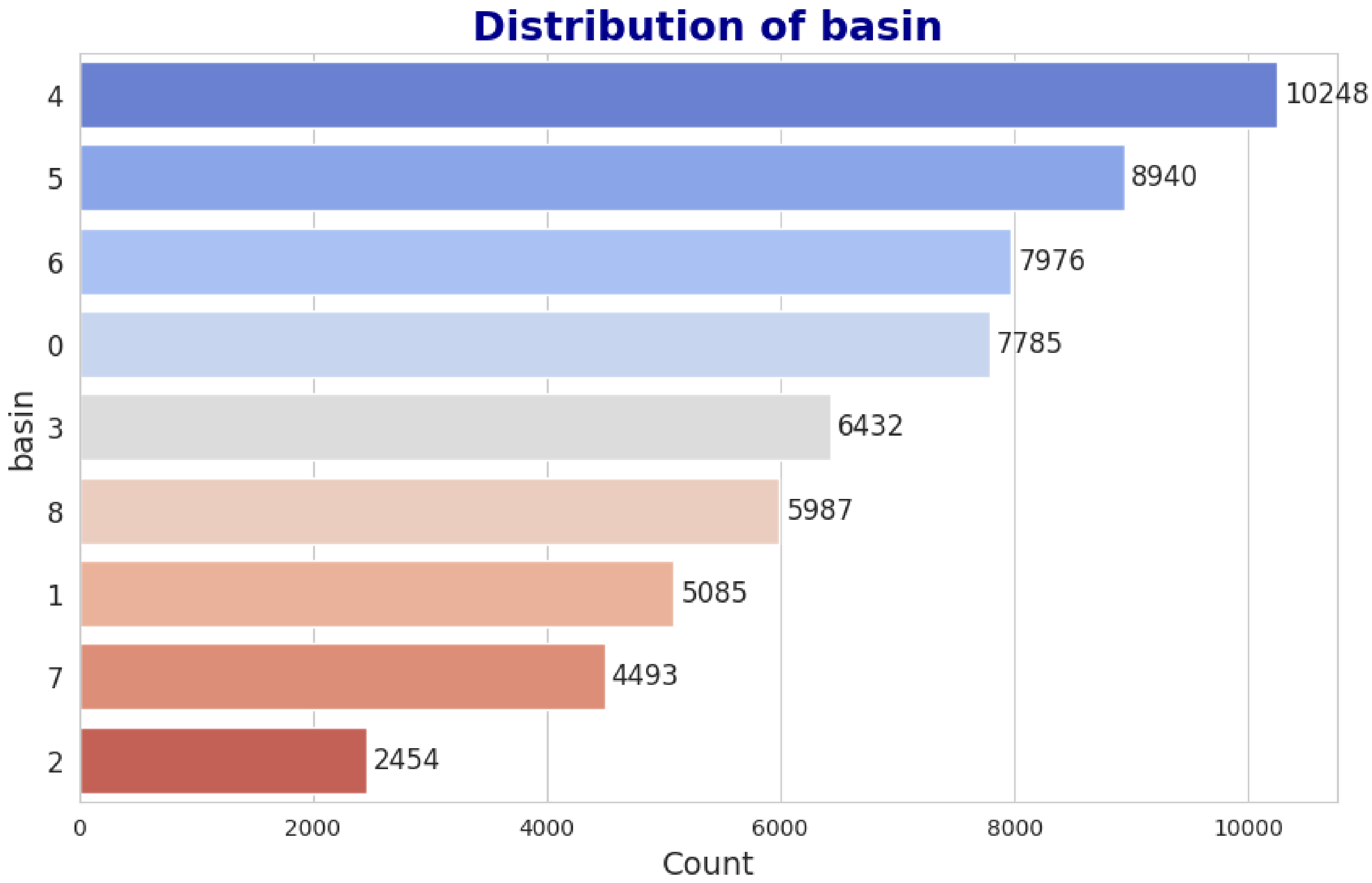
dtype: int64

In [65]:

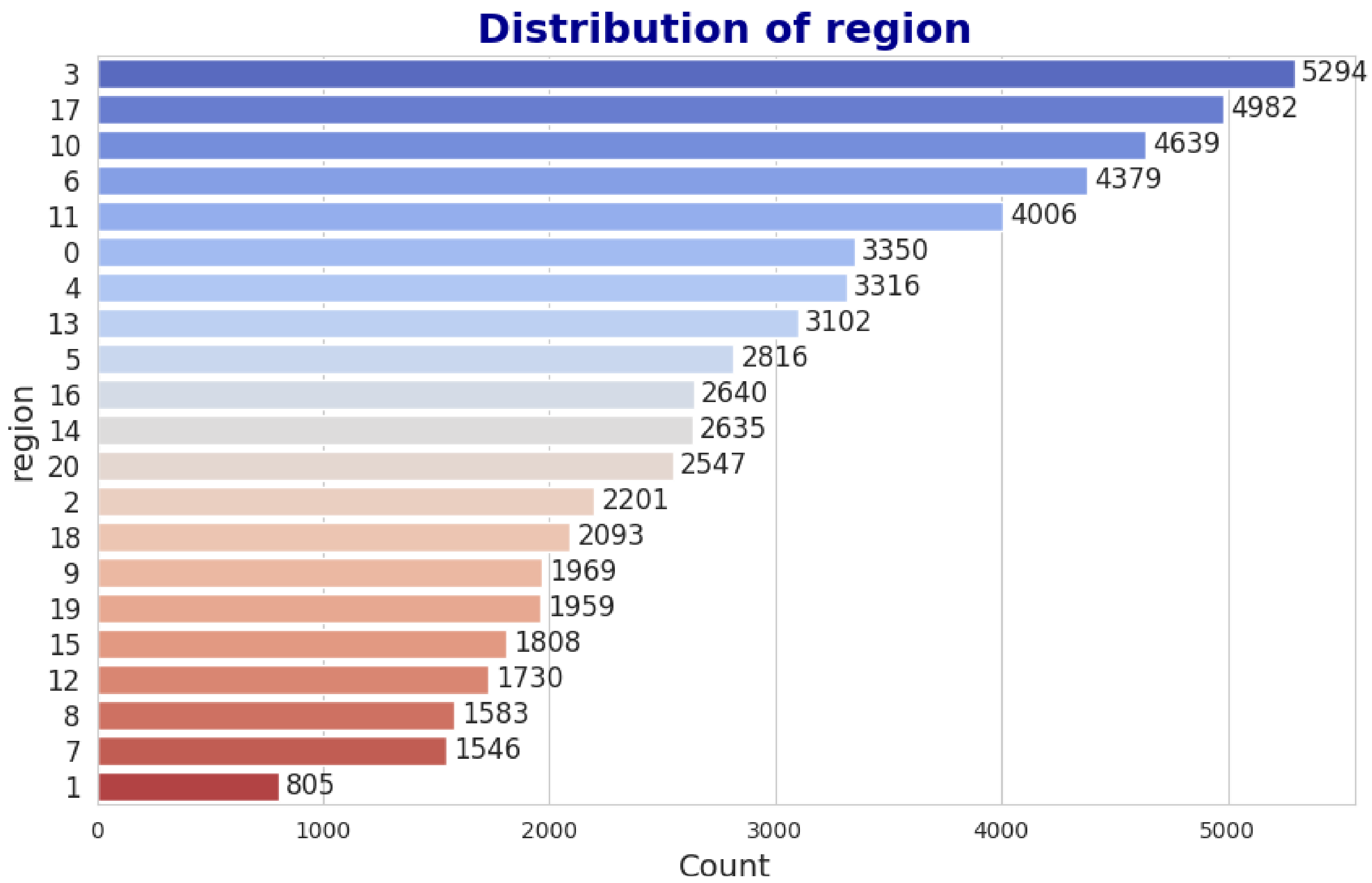
```
# checking at the distribution of object data types

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

sns.set_style("whitegrid")

for col in categorical:
    plt.figure(figsize=(10, 6))
    ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_count
s().index)
    for container in ax.containers:
        ax.bar_label(container, fmt="%d", label_type="edge", fontsize=12, padding=3)

    plt.title(f"Distribution of {col}", fontsize=18, fontweight="bold", color="darkblue"
)
    plt.xlabel("Count", fontsize=14)
    plt.ylabel(col, fontsize=14)
    plt.yticks(fontsize=12)

    plt.show()
```

```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

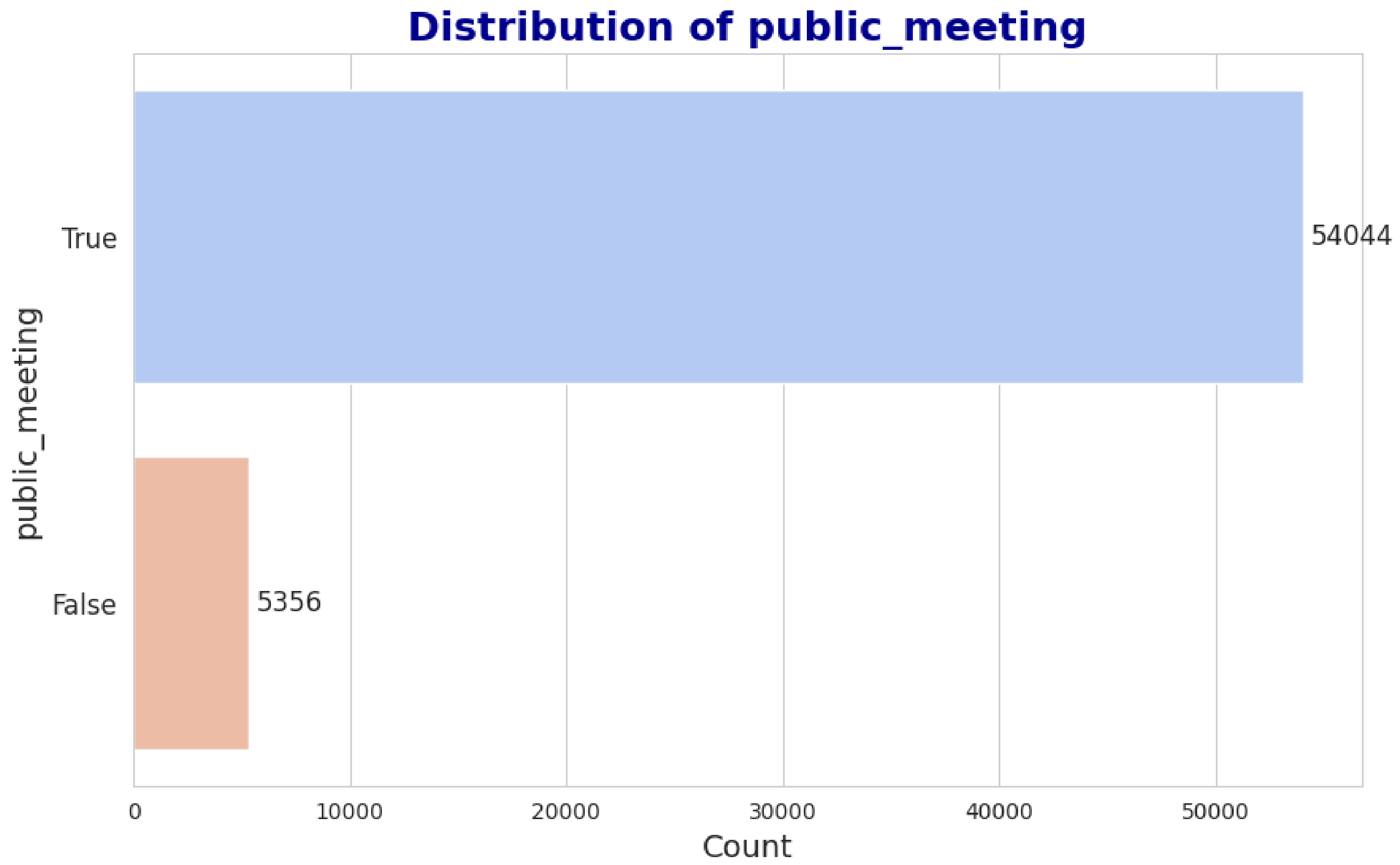
```
  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```



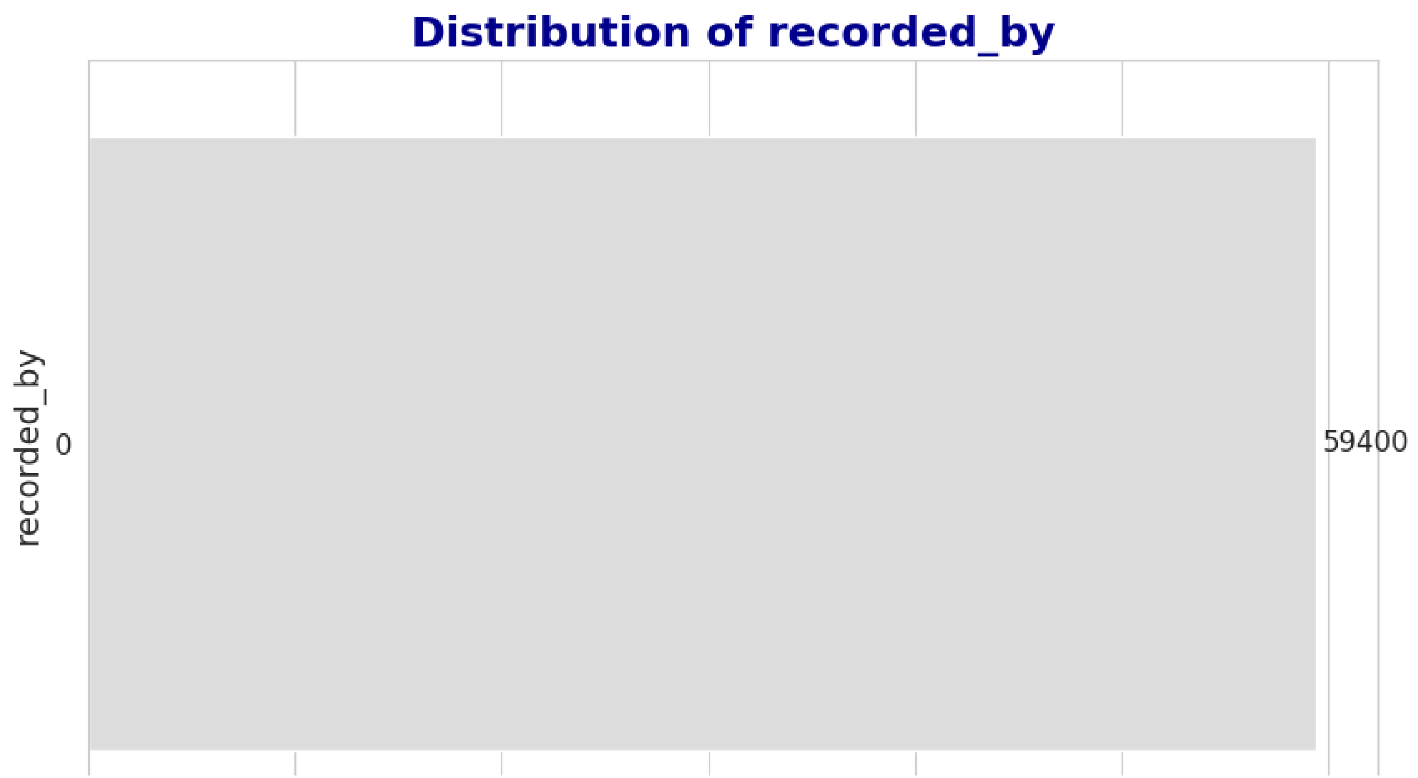

```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```

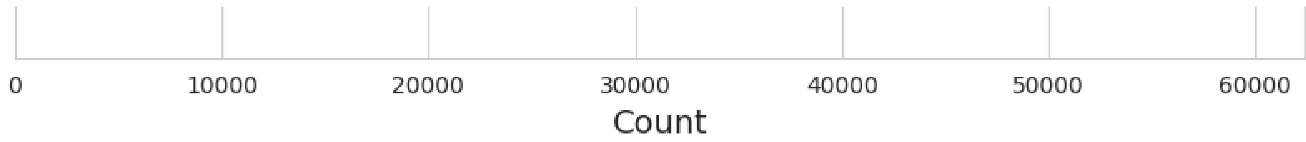


```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```



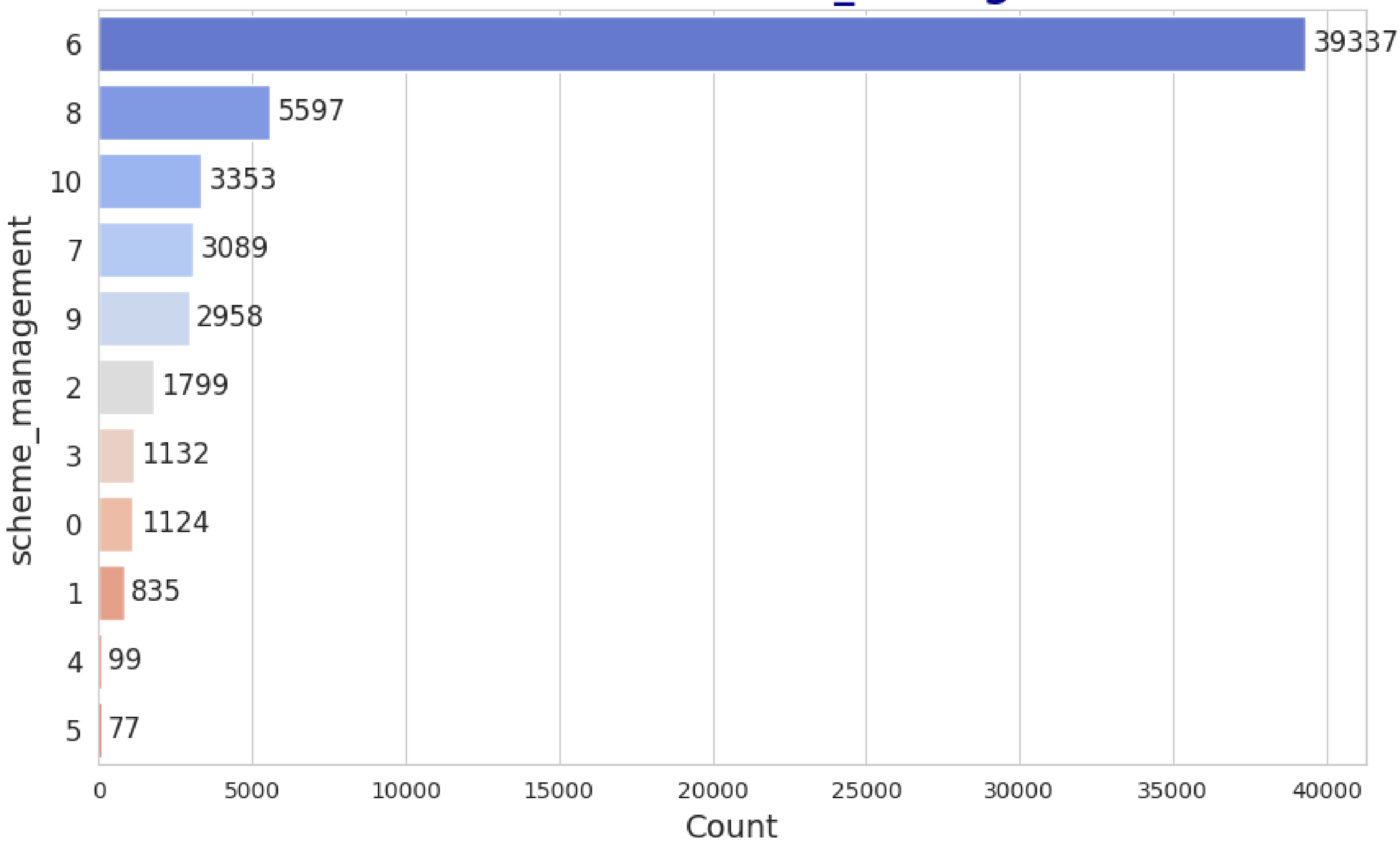

```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```





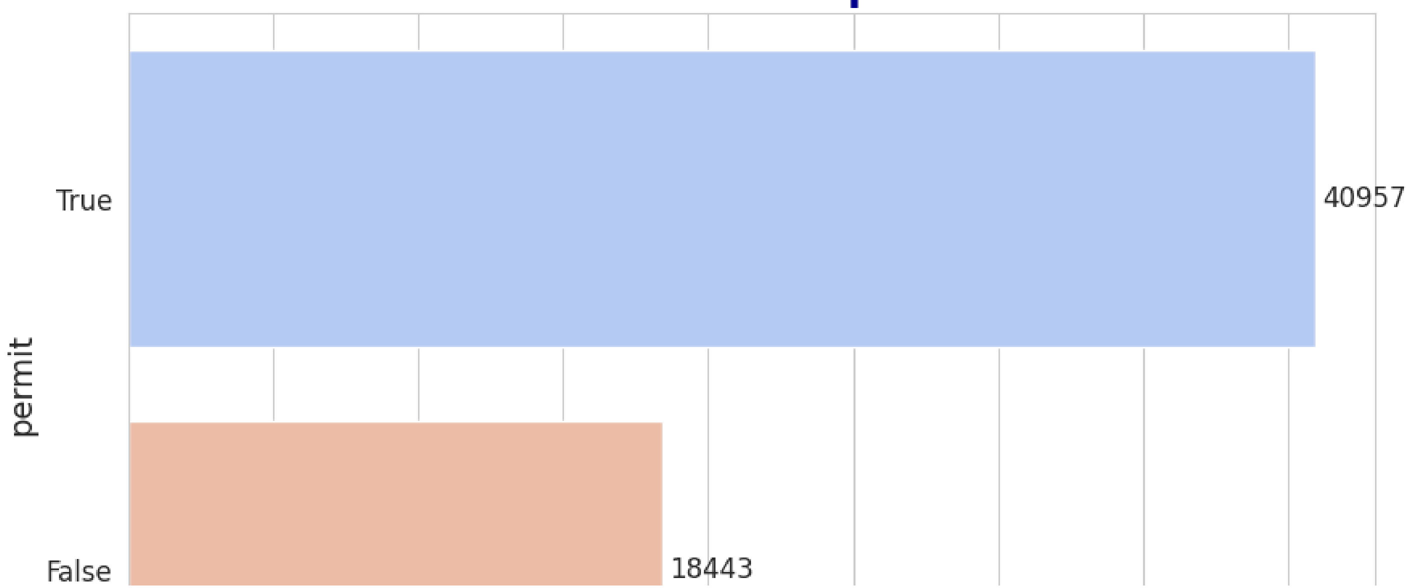

```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```

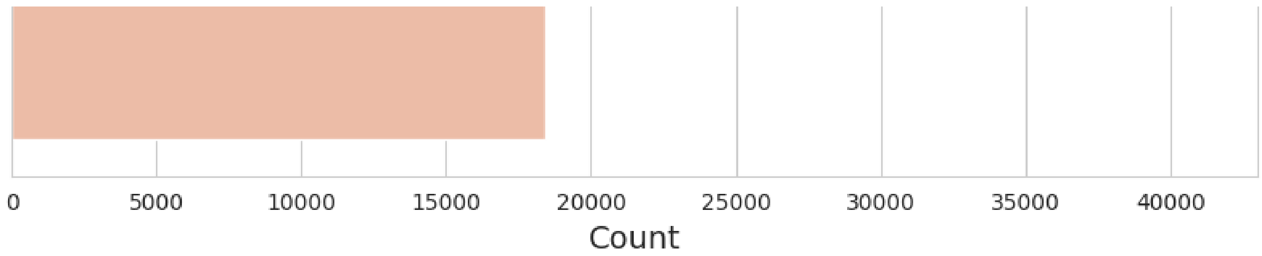
Distribution of scheme_management



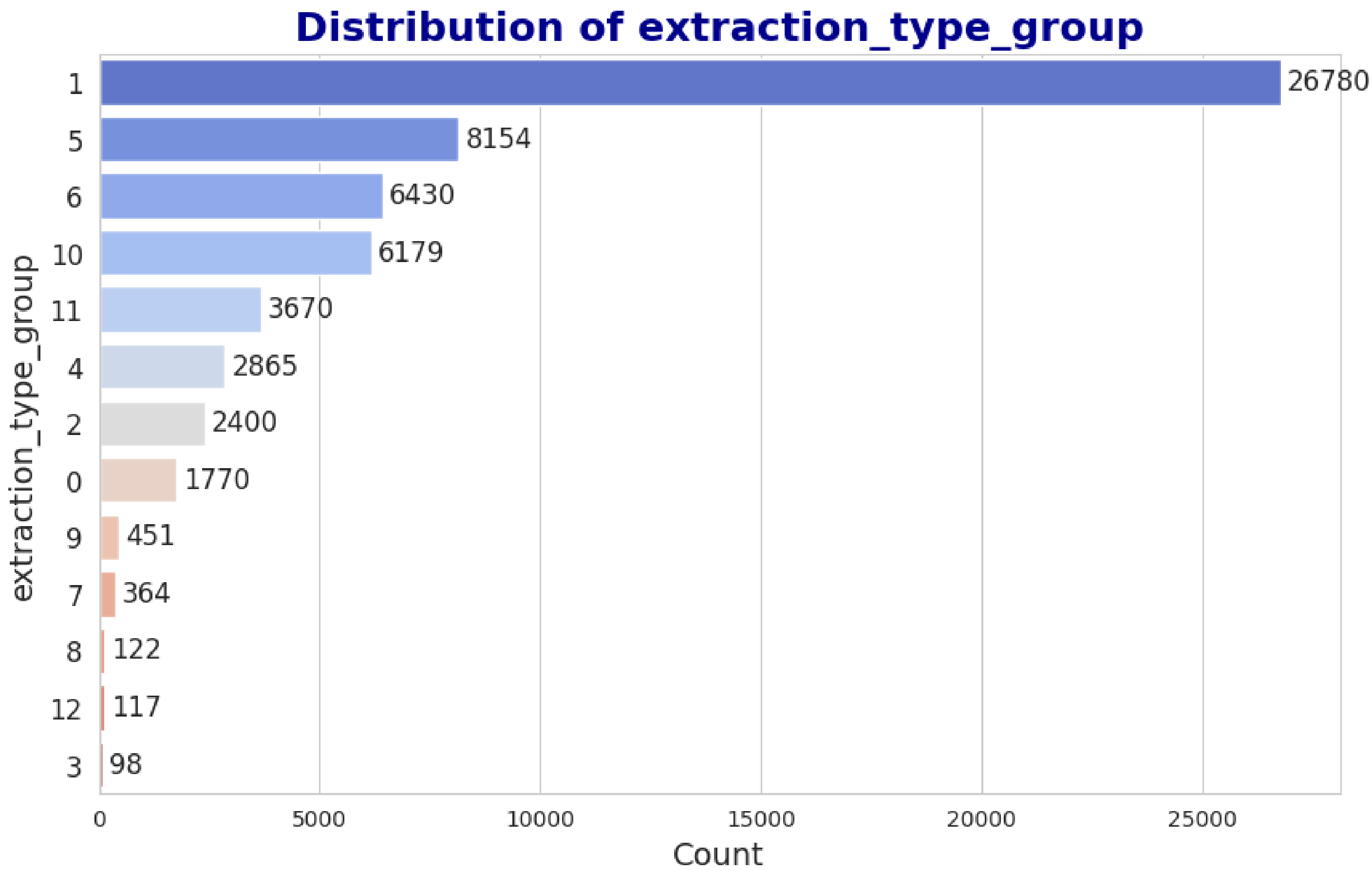

```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```

Distribution of permit

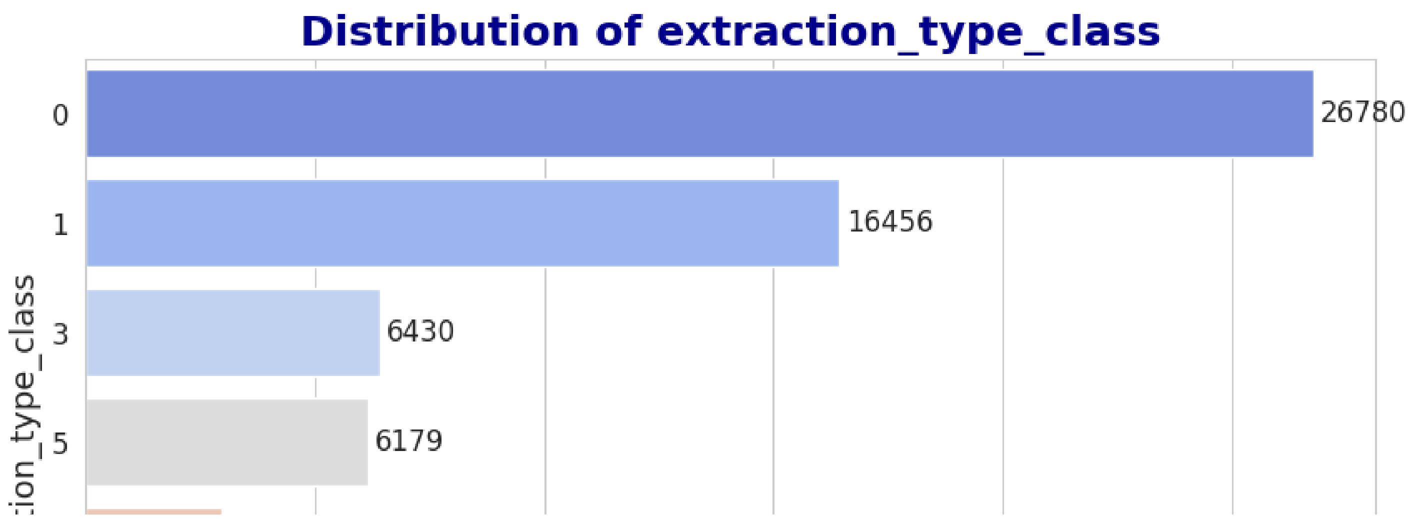


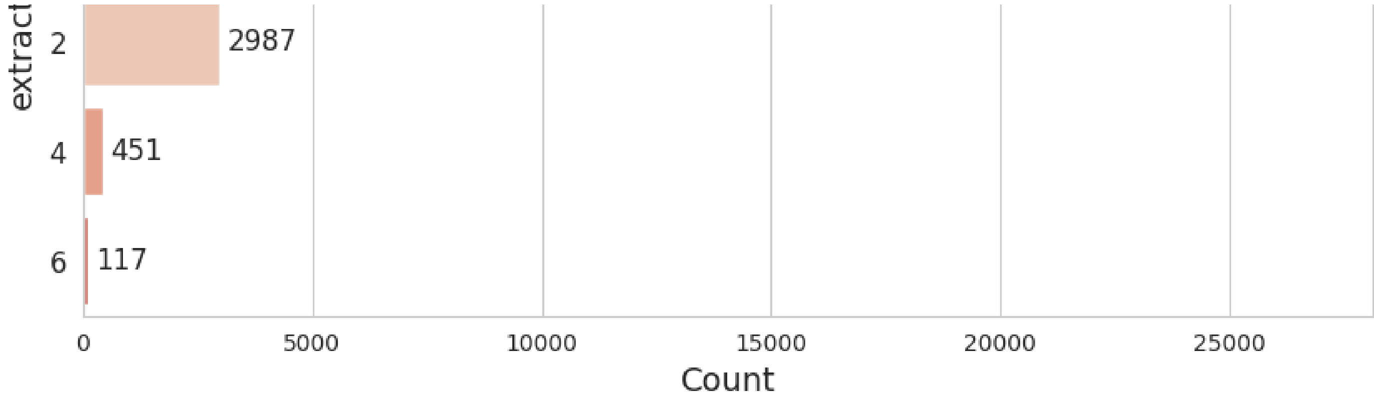



```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```

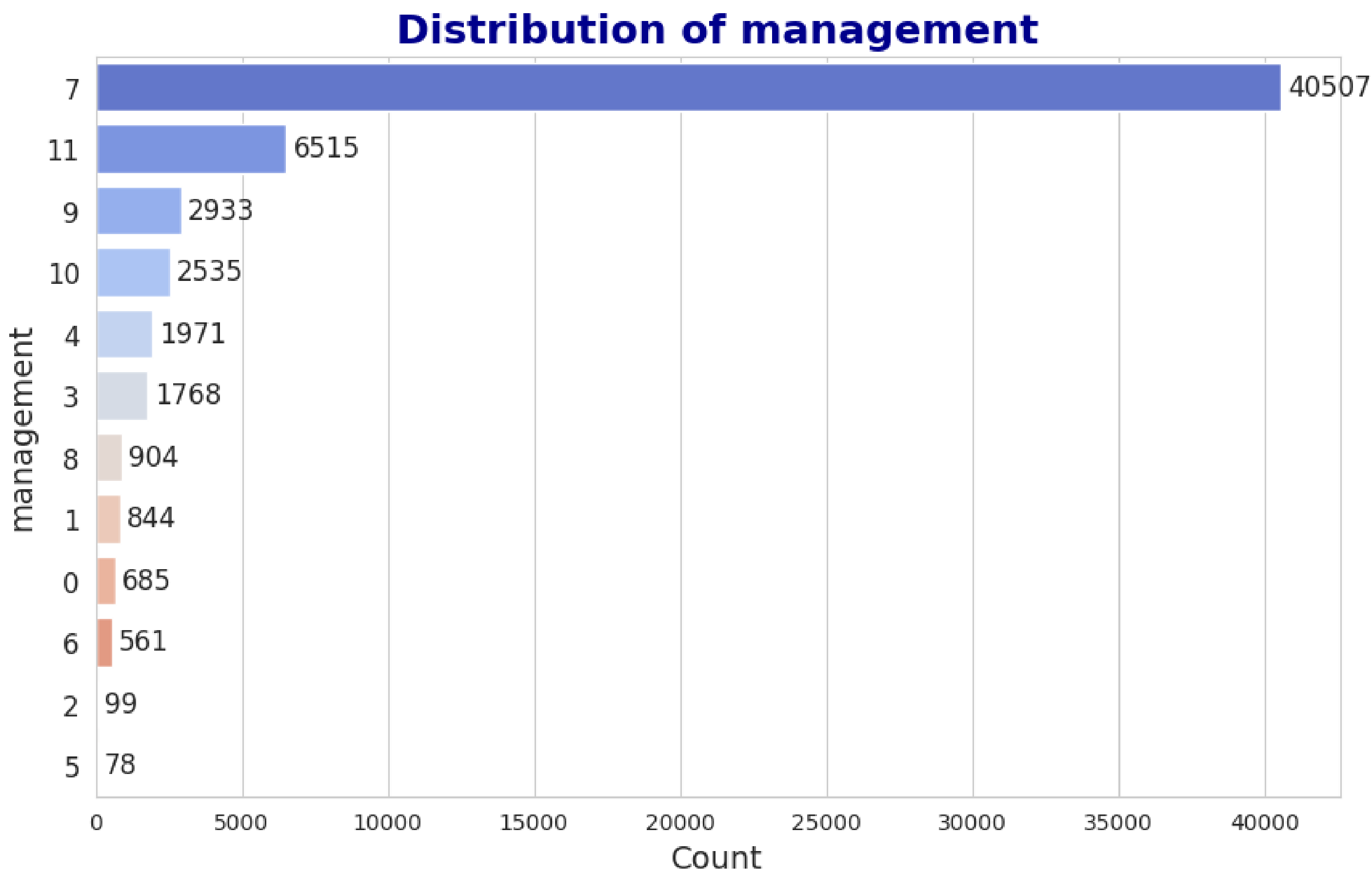



```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```

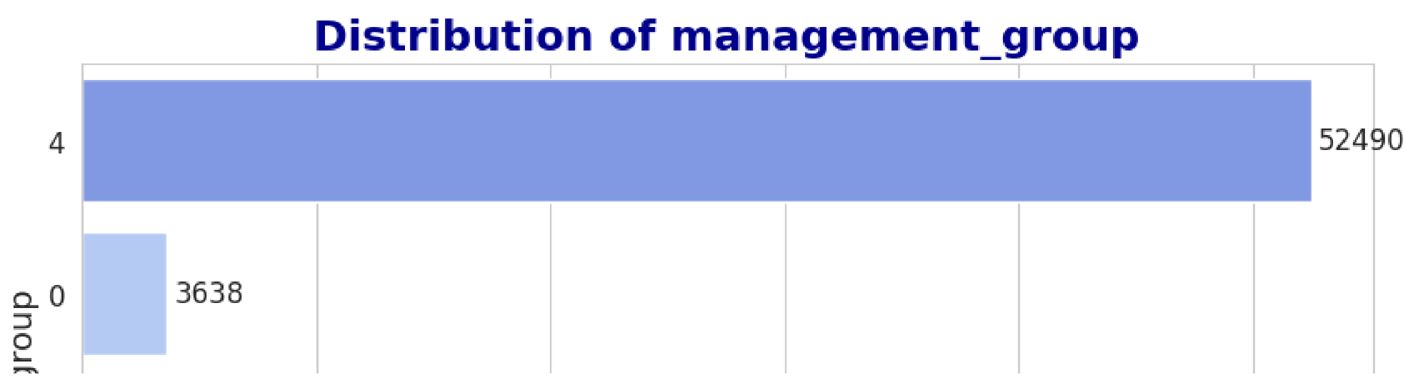


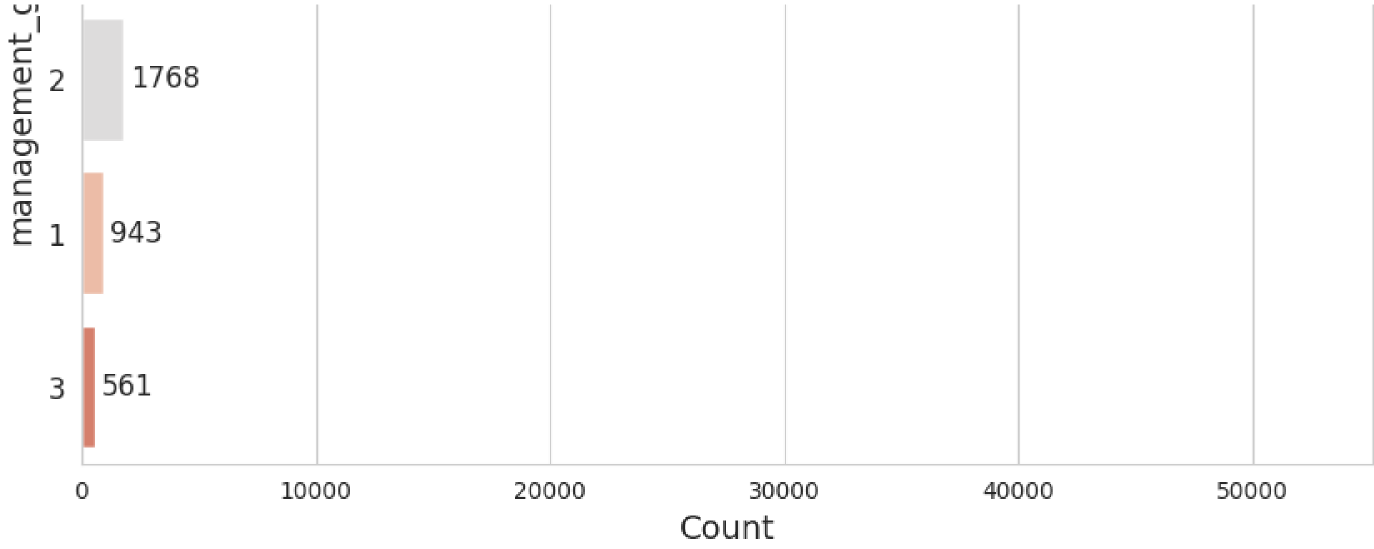



```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```



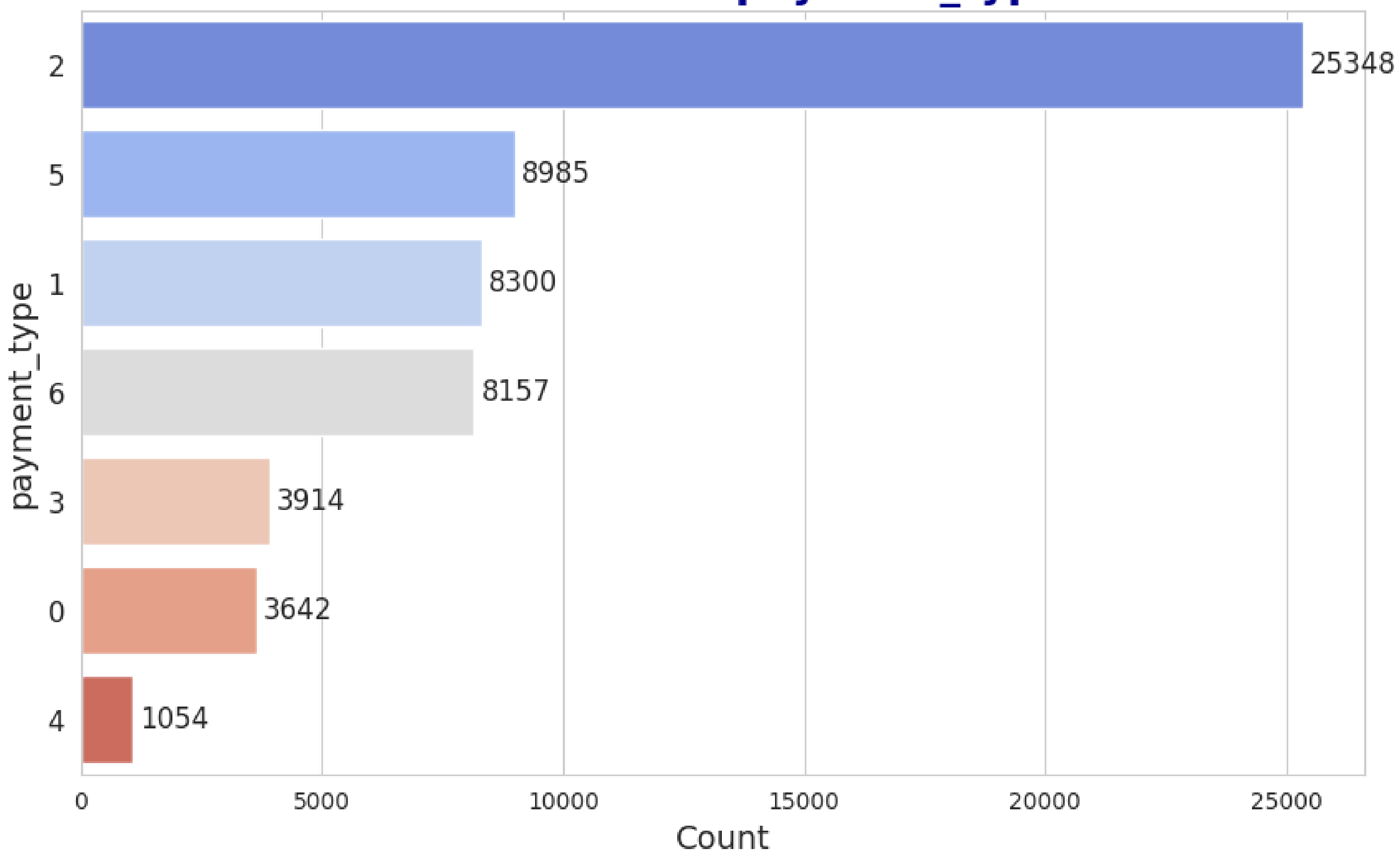

```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```





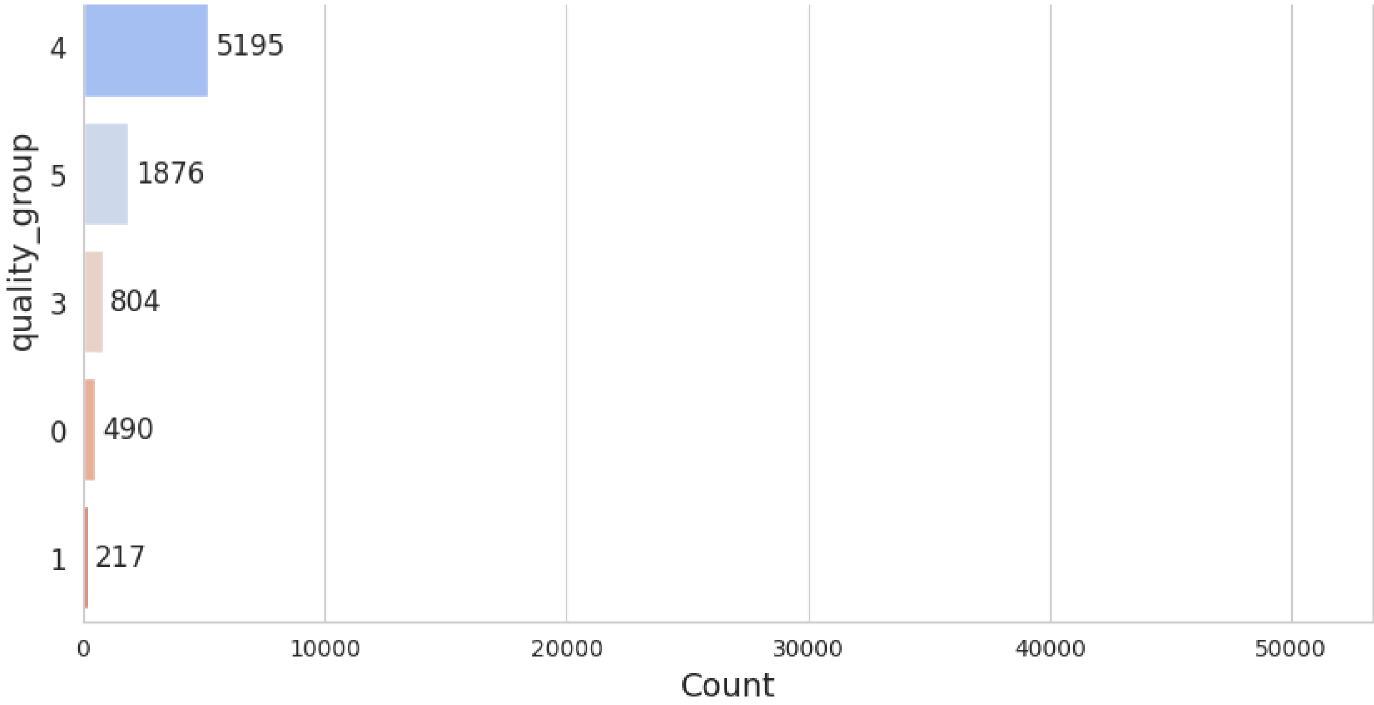

```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```

Distribution of payment_type



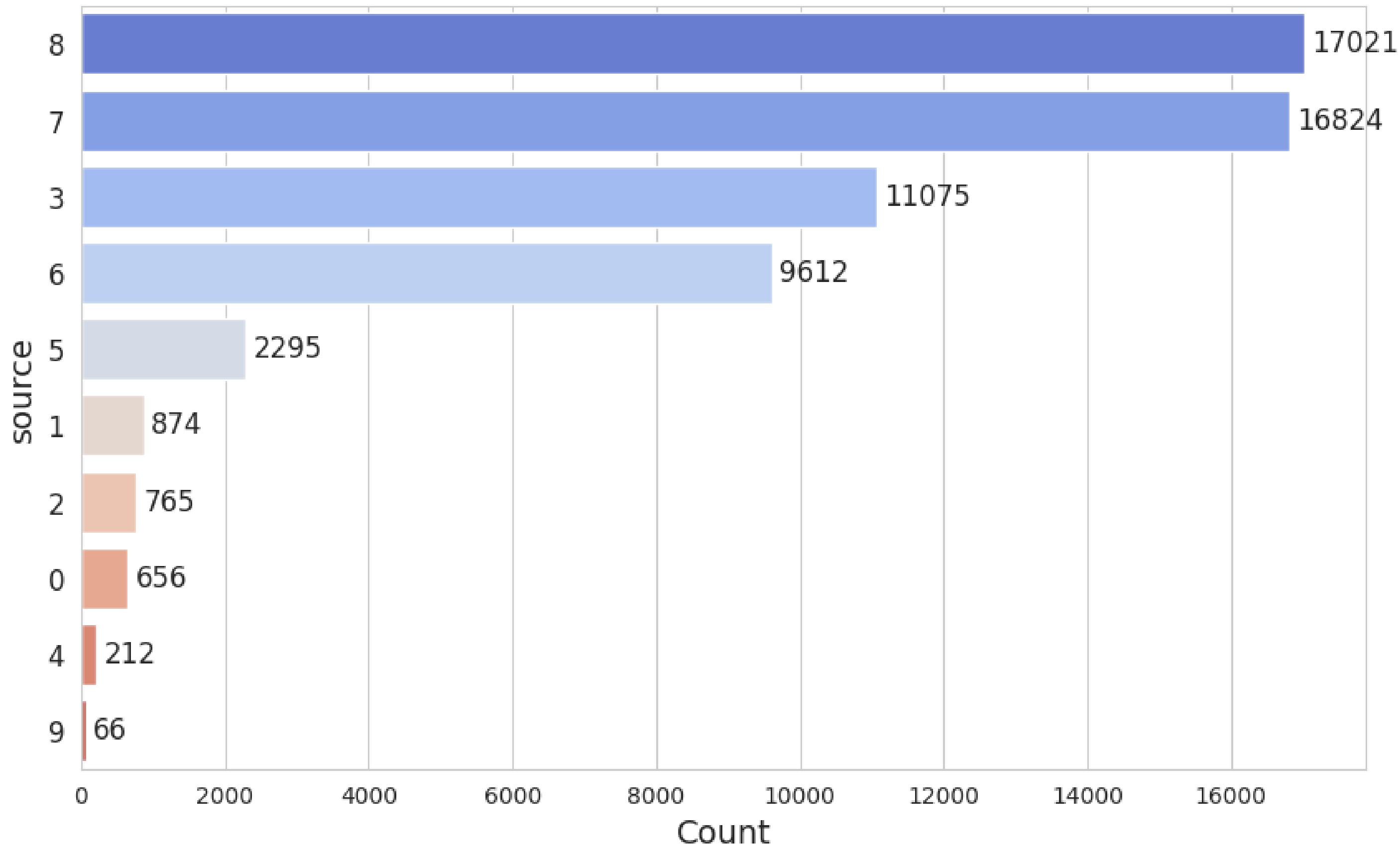

```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```

Distribution of quality_group



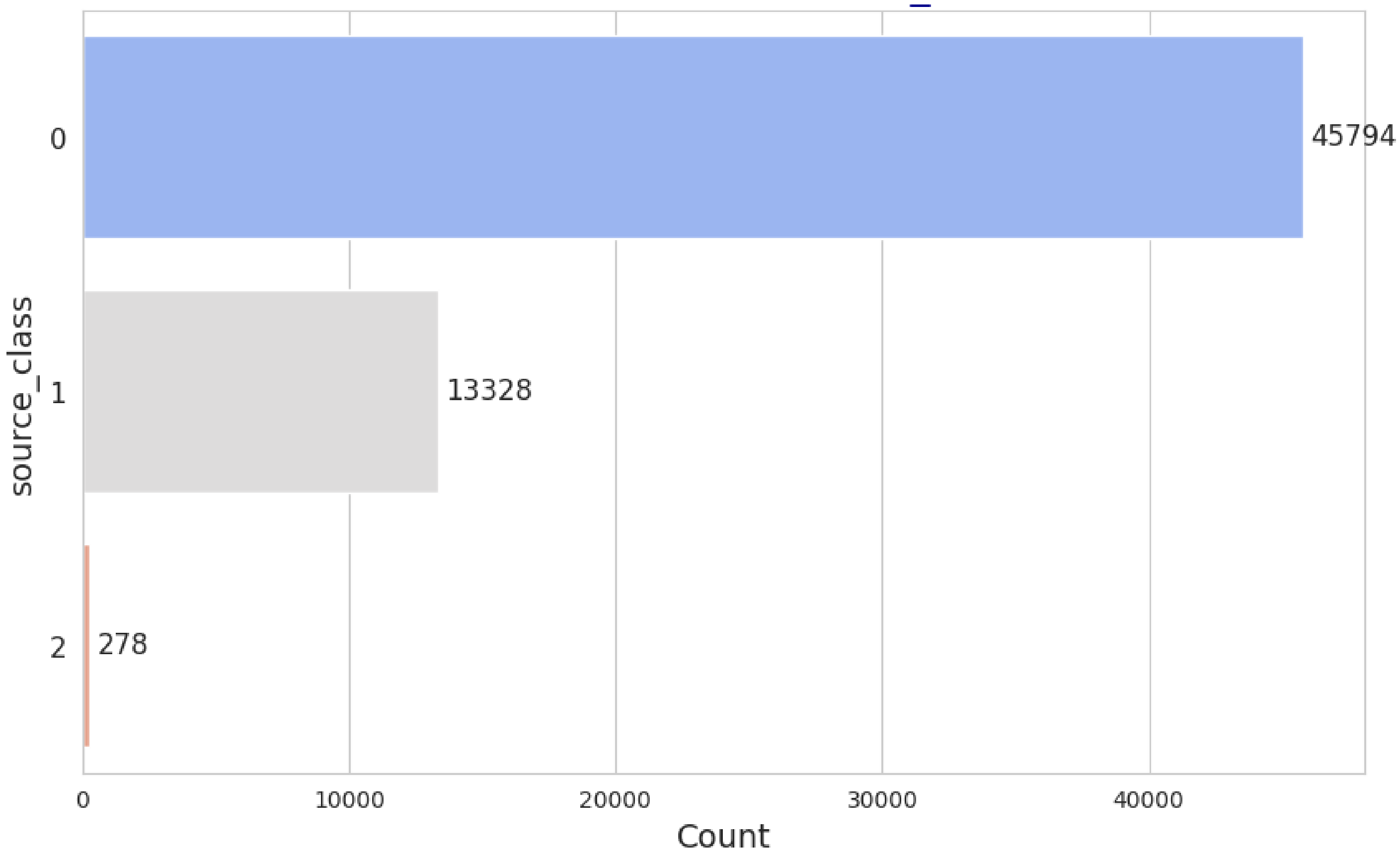

```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```

Distribution of source



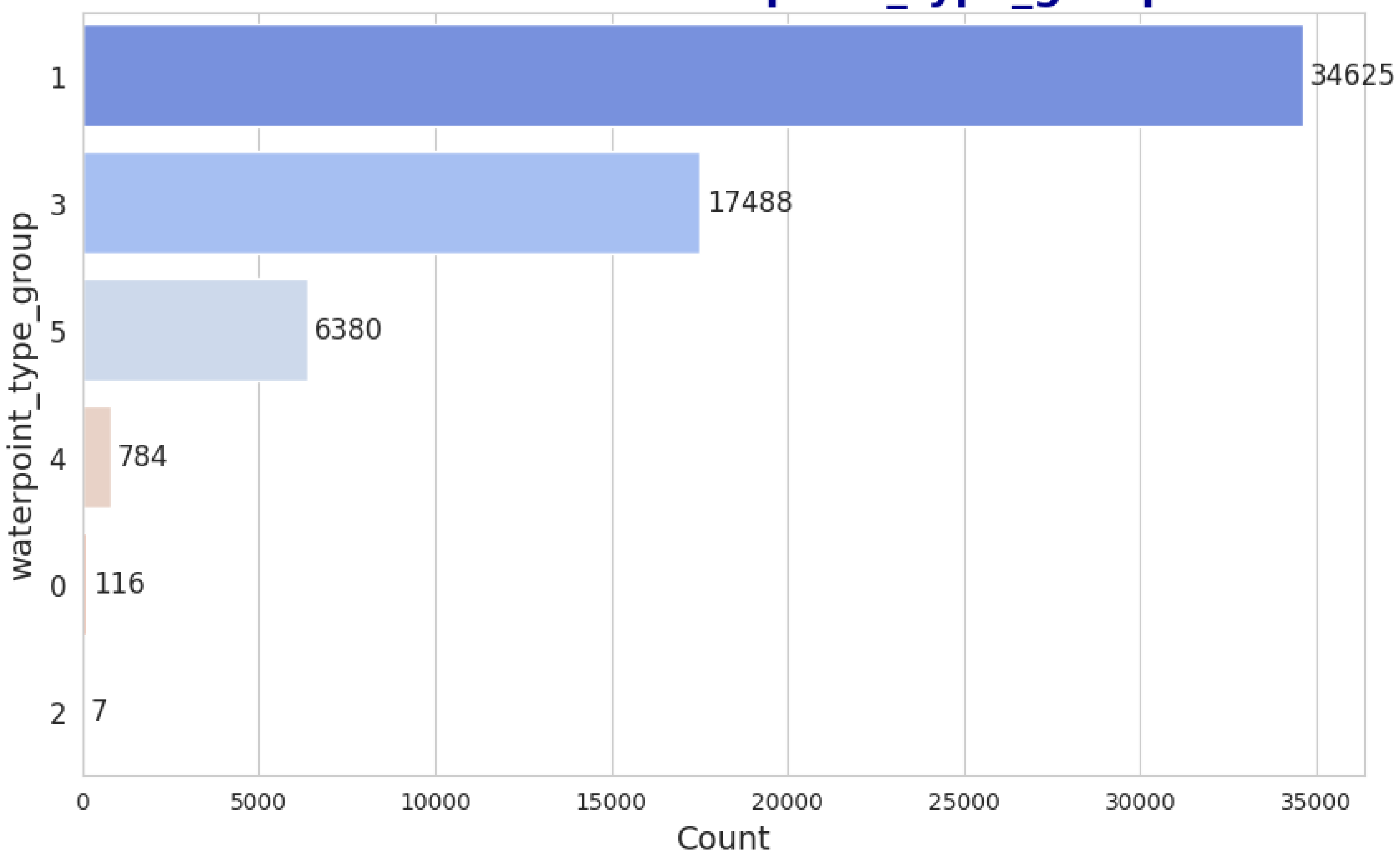

```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```

Distribution of source_class




```
<ipython-input-65-7251bd9d3019>:17: FutureWarning:

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

  ax = sns.countplot(y=col, data=data, palette="coolwarm", order=data[col].value_counts()
.index)
```

Distribution of waterpoint_type_group



Bivariate Analysis

In [39]:

```
# Getting the 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[39]:

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

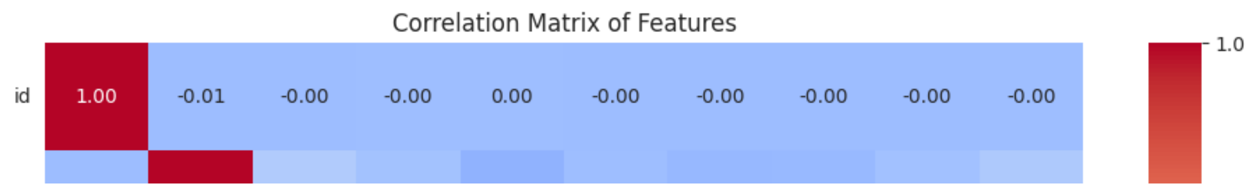
Majority of the water wells are managed by communities

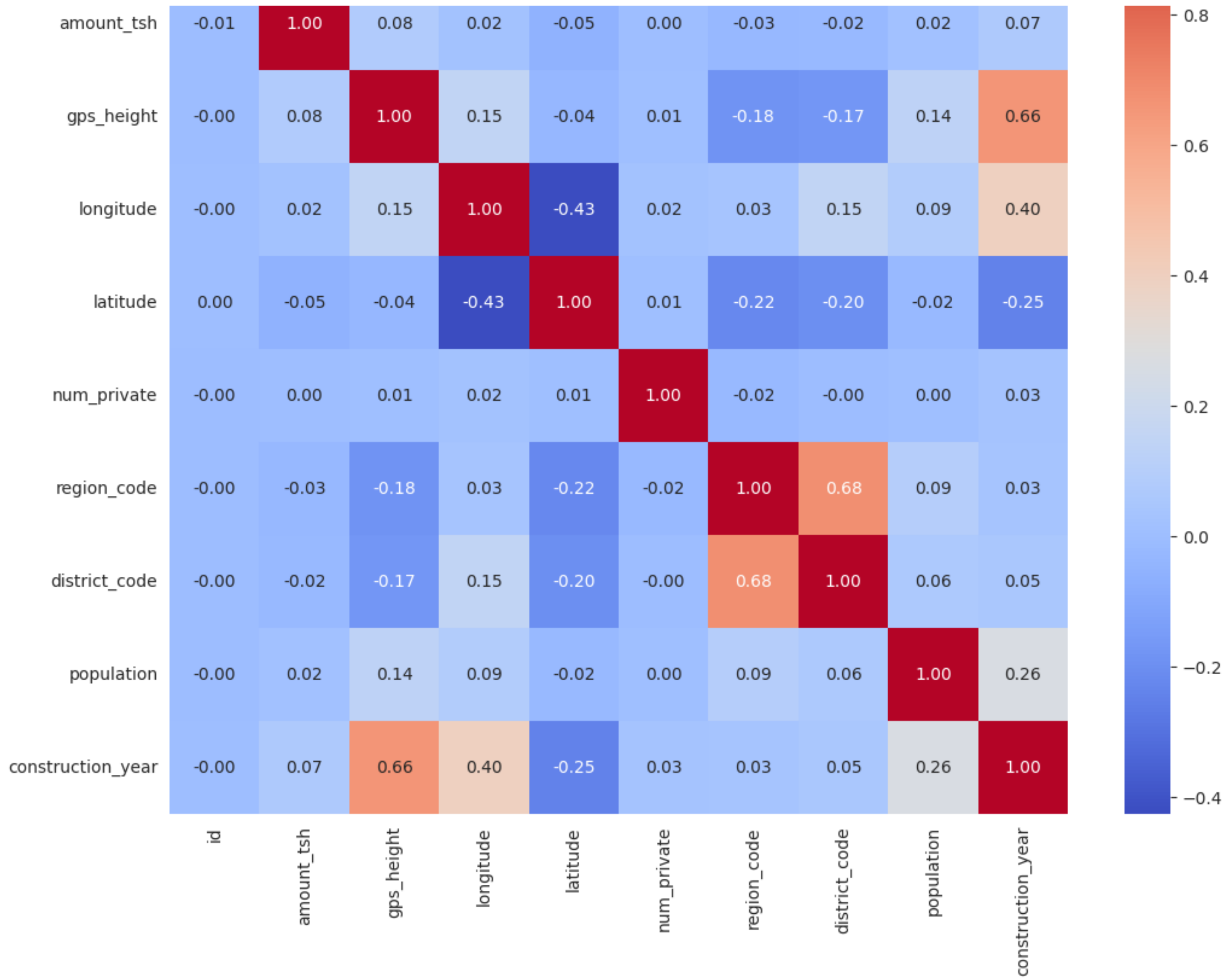
Multivariate Analysis

In [42]:

```
# Calculating the correlation matrix
correlation_matrix = train_values.select_dtypes('number').corr()
print(correlation_matrix)
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix of Features')
plt.show()
```

```
                         id  amount_tsh  gps_height  longitude  latitude  \
id                 1.000000   -0.005321   -0.004692  -0.001348  0.001718
amount_tsh        -0.005321    1.000000    0.076650   0.022134 -0.052670
gps_height        -0.004692    0.076650    1.000000   0.149155 -0.035751
longitude         -0.001348    0.022134    0.149155   1.000000 -0.425802
latitude           0.001718   -0.052670   -0.035751  -0.425802  1.000000
num_private       -0.002629    0.002944    0.007237   0.023873  0.006837
region_code       -0.003028   -0.026813   -0.183521   0.034197 -0.221018
district_code     -0.003044   -0.023599   -0.171233   0.151398 -0.201020
population        -0.002813    0.016288    0.135003   0.086590 -0.022152
construction_year -0.002082    0.067915    0.658727   0.396732 -0.245278

                   num_private  region_code  district_code  population  \
id                   -0.002629    -0.003028      -0.003044   -0.002813
amount_tsh            0.002944    -0.026813      -0.023599    0.016288
gps_height            0.007237    -0.183521      -0.171233    0.135003
longitude             0.023873     0.034197       0.151398    0.086590
latitude              0.006837    -0.221018      -0.201020   -0.022152
num_private           1.000000    -0.020377      -0.004478    0.003818
region_code          -0.020377     1.000000       0.678602    0.094088
district_code        -0.004478     0.678602       1.000000    0.061831
population            0.003818     0.094088       0.061831    1.000000
construction_year     0.026056     0.031724       0.048315    0.260910

                   construction_year
id                         -0.002082
amount_tsh                  0.067915
gps_height                  0.658727
longitude                   0.396732
latitude                   -0.245278
num_private                 0.026056
region_code                 0.031724
district_code               0.048315
population                  0.260910
construction_year           1.000000
```





Preprocessing

Encoding

In [43]:

```
# Encoding the 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 [44]:

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

In [45]:

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

In [ ]:

```

```

In [46]:

```python
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 [55]:

```
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

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])
        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:
        X_train = X_train.drop(columns=[col])
        X_test = X_test.drop(columns=[col])

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)
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-55-8574bca04012> in <cell line: 0>()
```

```
      5 # Identify non-numeric columns
      6 
----> 7 non_numeric_cols = X_train.select_dtypes(include=['object']).columns
      8 
      9 for col in non_numeric_cols:

AttributeError: 'numpy.ndarray' object has no attribute 'select_dtypes'
```

In [56]:

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

In [57]:

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

Out[57]:

```
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])
```

In [58]:

```python
data.head()
```

Out[58]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	basin	...	management_
0	69572	6000.0	171	1368	1390	1518	34.938093	-9.856322	37398	1	...	
1	8776	0.0	216	469	1399	545	34.698766	-2.147466	37194	4	...	
2	34310	25.0	144	825	686	2048	37.460664	-3.821329	14572	5	...	
3	67743	0.0	21	1740	263	1852	38.486161	-11.155298	37284	7	...	
4	19728	0.0	268	20	0	119	31.130847	-1.825359	35528	4	...	

5 rows × 35 columns

Modelling

In [59]:

```python
# Load Models Dictionary
models = {
    "Logistic Regression": LogisticRegression(),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(n_estimators=100, random_state=42),
    "K-NN": KNeighborsClassifier(),
    "SVM": SVC(),
    "Naïve Bayes": GaussianNB()
}
```

In [60]:

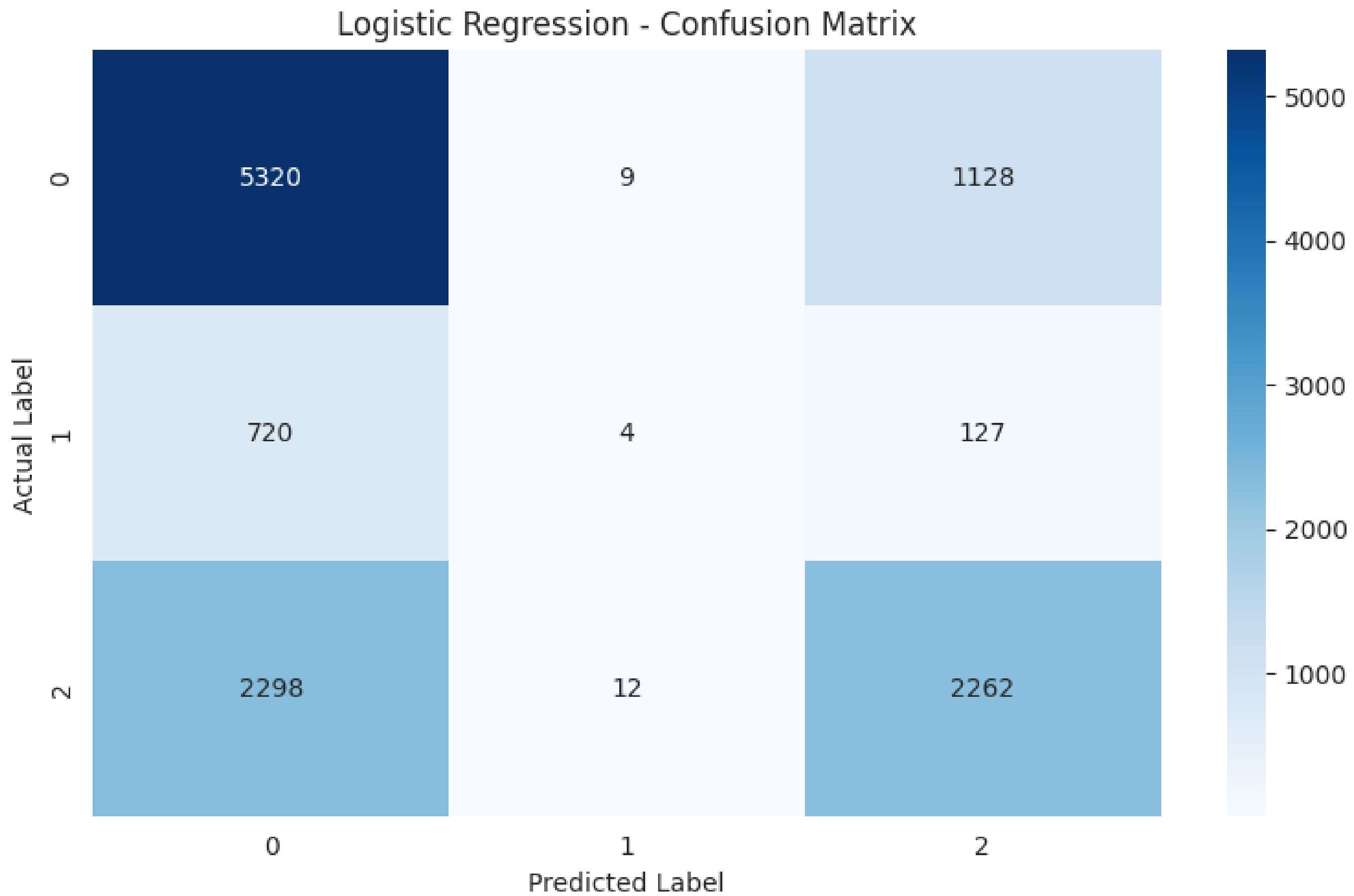
```python
# Training and Evaluating Models
results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
```

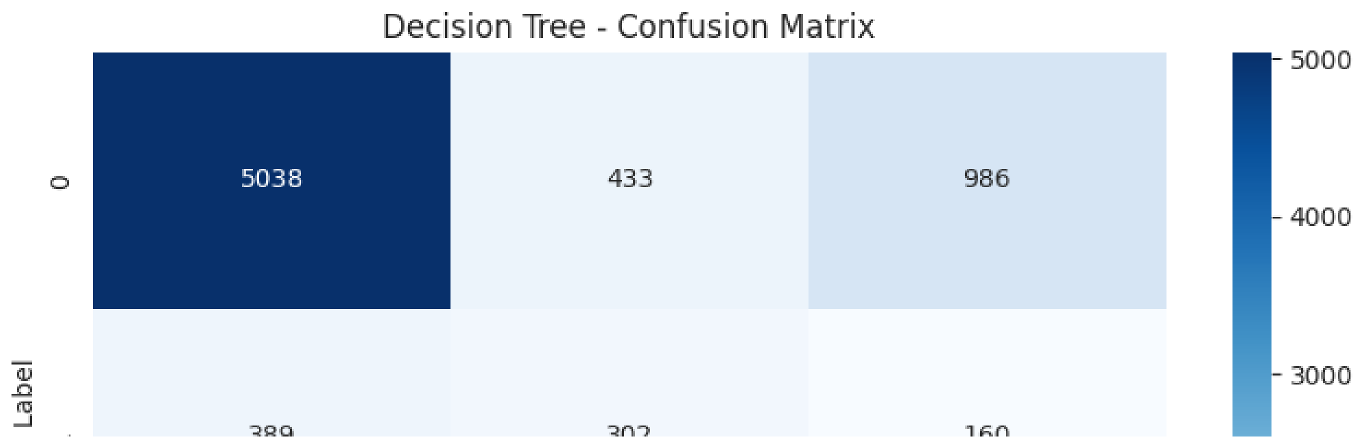
```python
    acc = accuracy_score(y_test, y_pred)
    results[name] = acc
    print(f"{name} Accuracy: {acc:.4f}")
    print(classification_report(y_test, y_pred))
```

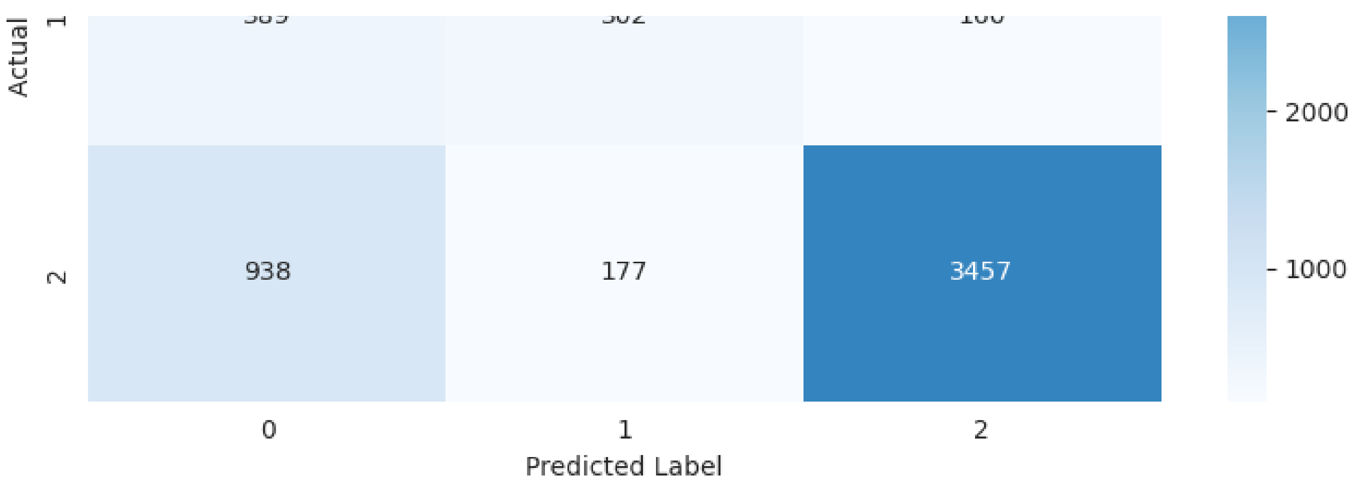
```
Logistic Regression Accuracy: 0.6386
              precision    recall  f1-score   support

           0       0.64      0.82      0.72      6457
           1       0.16      0.00      0.01       851
           2       0.64      0.49      0.56      4572

    accuracy                           0.64     11880
   macro avg       0.48      0.44      0.43     11880
weighted avg       0.61      0.64      0.61     11880

Decision Tree Accuracy: 0.7405
              precision    recall  f1-score   support

           0       0.79      0.78      0.79      6457
           1       0.33      0.35      0.34       851
           2       0.75      0.76      0.75      4572

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

Random Forest Accuracy: 0.8120
              precision    recall  f1-score   support

           0       0.81      0.90      0.85      6457
           1       0.56      0.33      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: 0.7444
              precision    recall  f1-score   support

           0       0.75      0.86      0.80      6457
           1       0.43      0.27      0.33       851
           2       0.78      0.67      0.72      4572

    accuracy                           0.74     11880
   macro avg       0.65      0.60      0.62     11880
weighted avg       0.74      0.74      0.74     11880

SVM Accuracy: 0.7551
              precision    recall  f1-score   support

           0       0.72      0.92      0.81      6457
           1       0.58      0.11      0.18       851
           2       0.84      0.64      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: 0.5657
              precision    recall  f1-score   support

           0       0.69      0.51      0.58      6457
           1       0.22      0.24      0.23       851
           2       0.52      0.71      0.60      4572

    accuracy                           0.57     11880
   macro avg       0.48      0.49      0.47     11880
weighted avg       0.59      0.57      0.57     11880
```

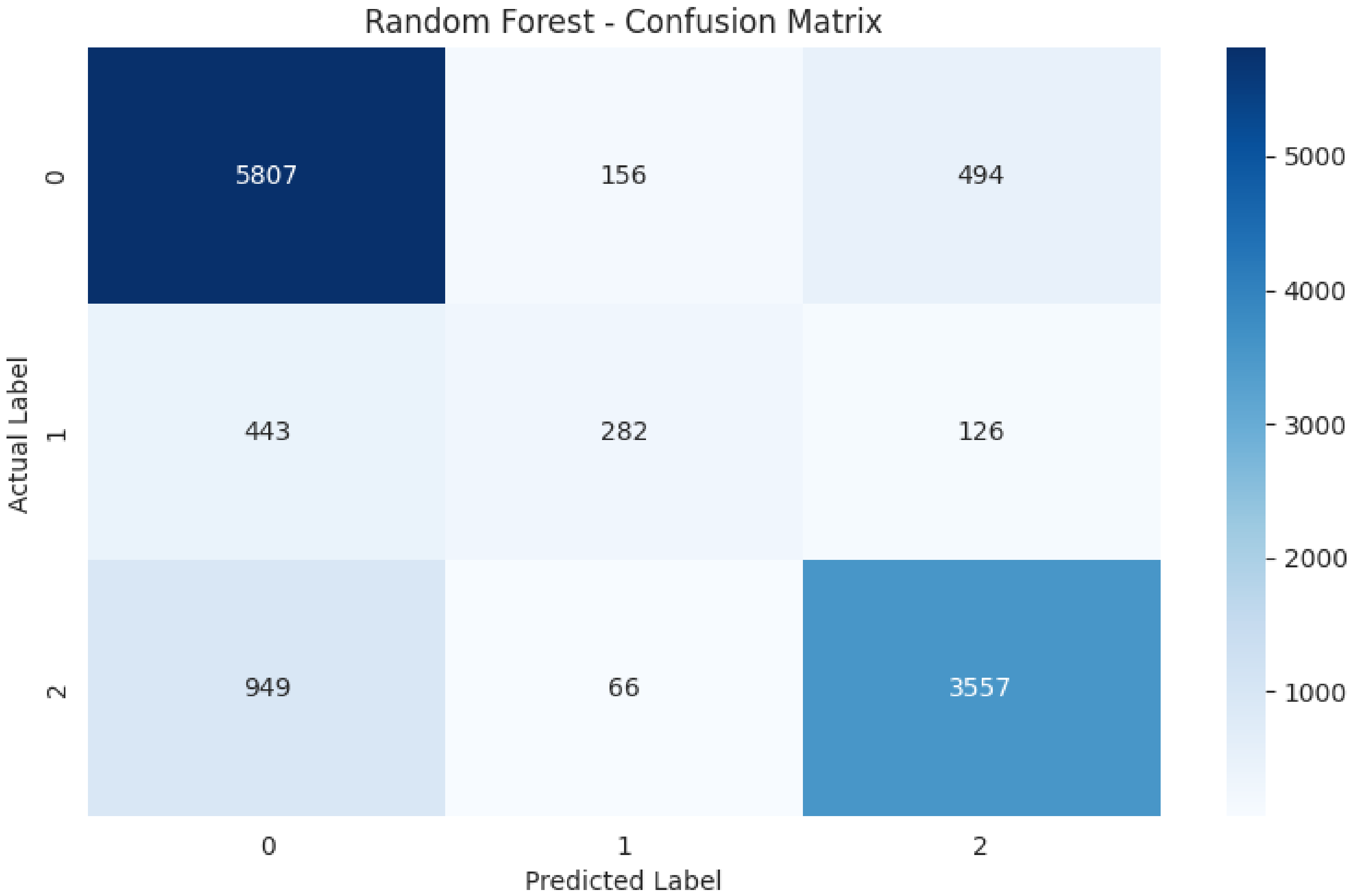
In [61]:

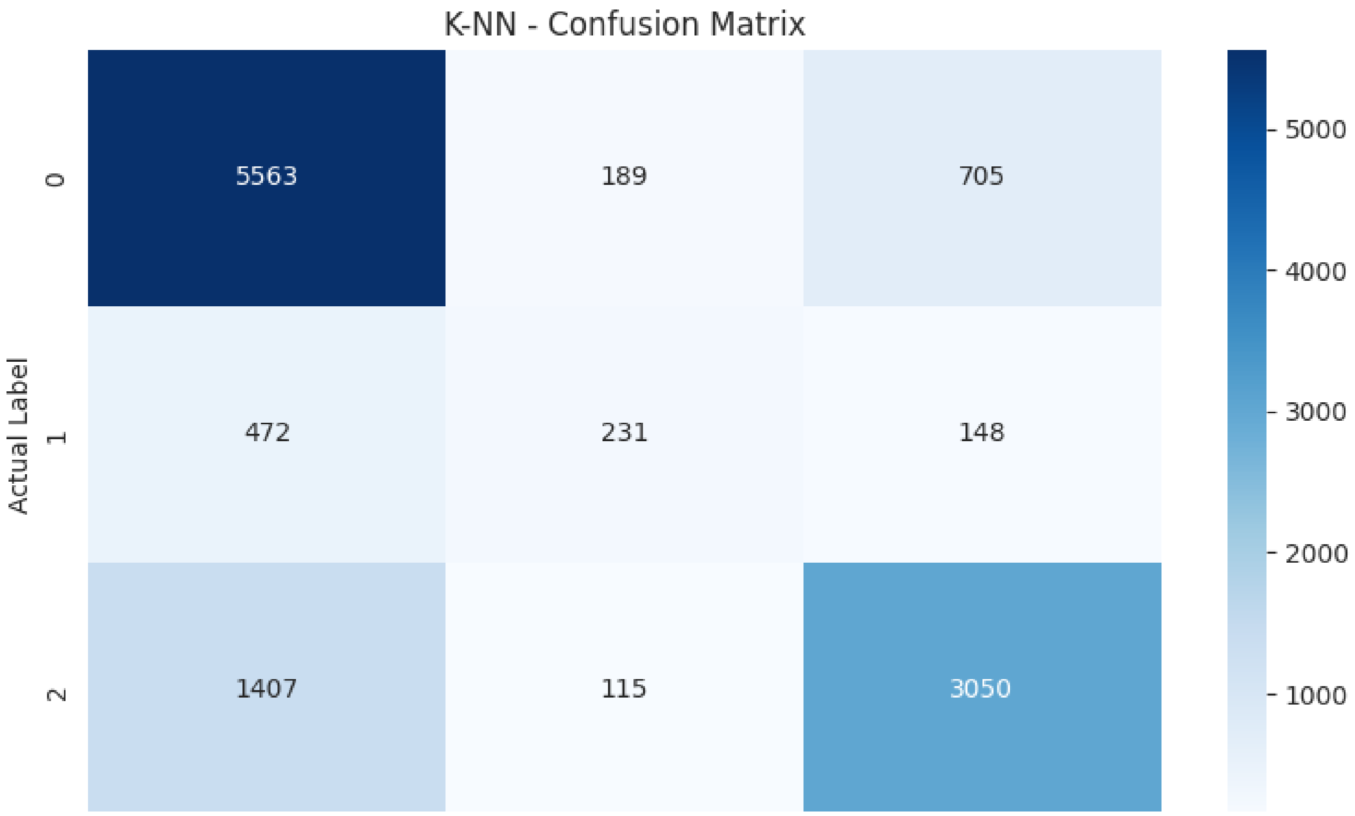
```
# Create subplots for confusion matrices
fig, axes = plt.subplots(len(models), 1, figsize=(8, len(models) * 5))

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()
```

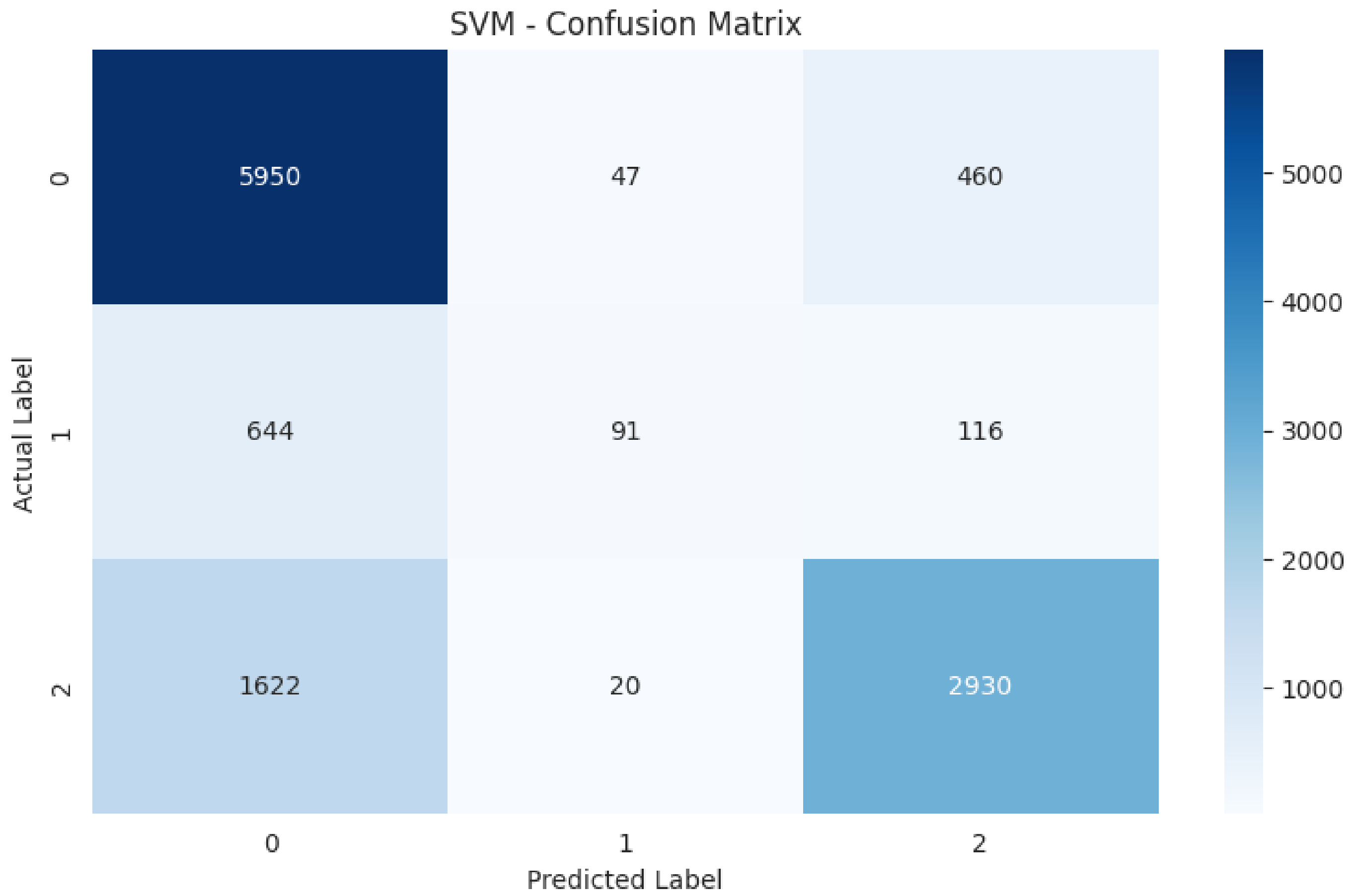


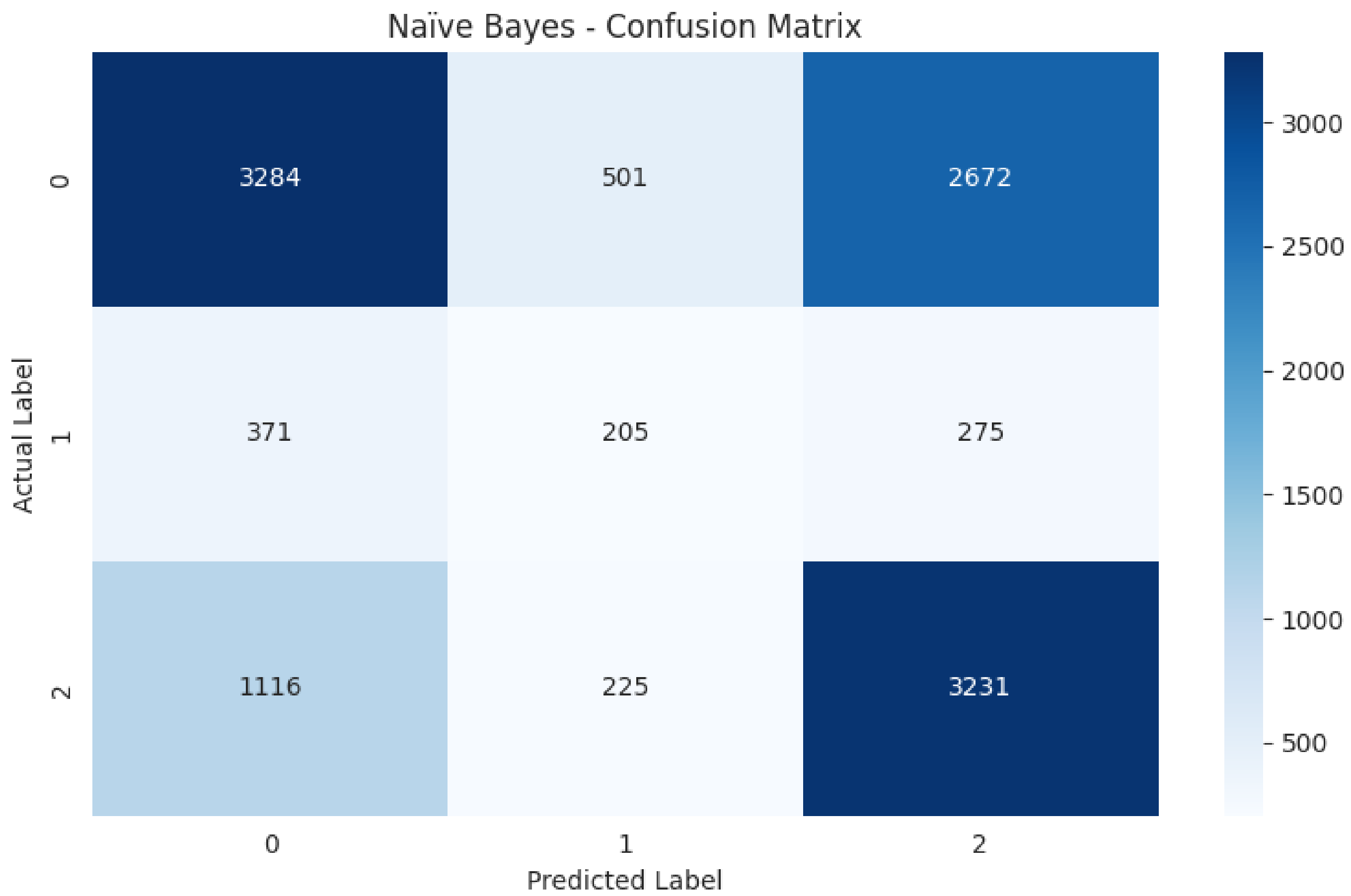



Actual
938
177
3457
2000
1000
0
1
2
Predicted Label


Random Forest - Confusion Matrix
5807
156
494
443
282
126
949
66
3557
Actual Label
0
1
2
Predicted Label
5000
4000
3000
2000
1000

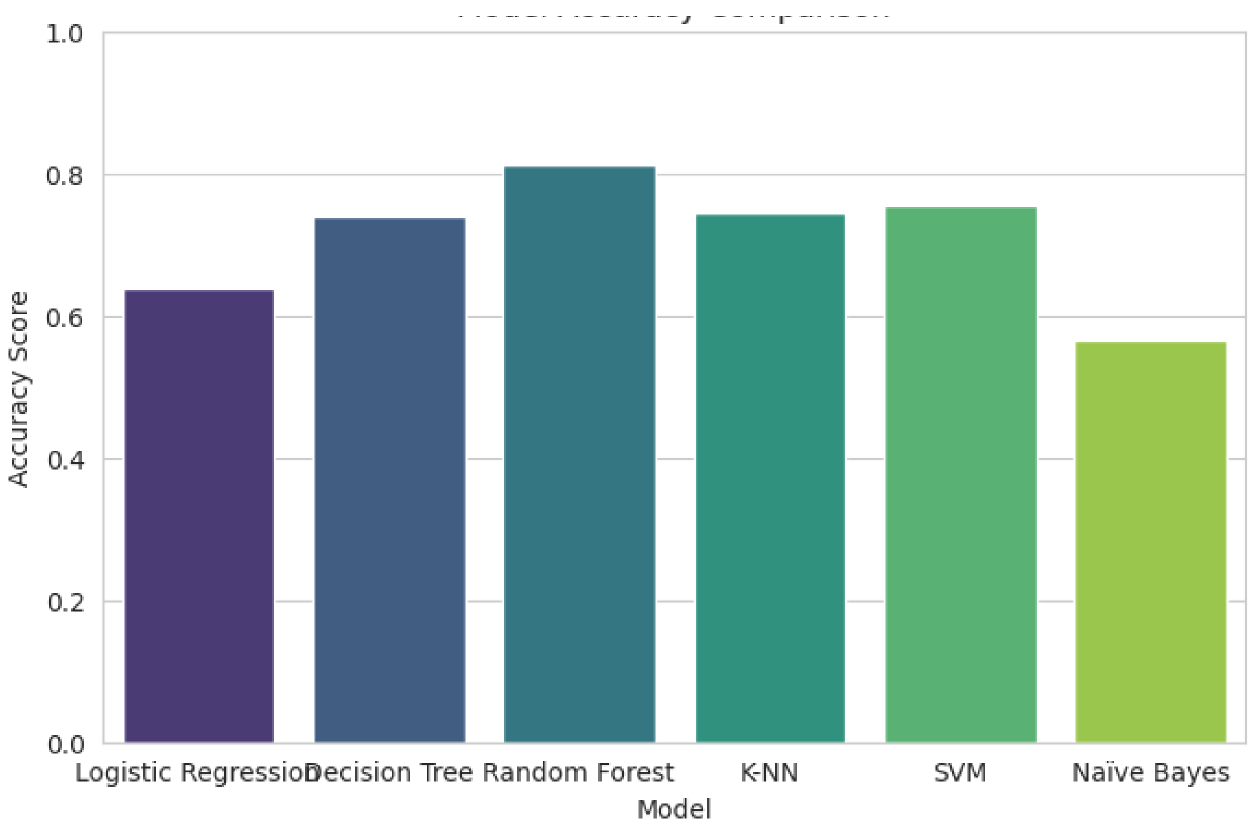

K-NN - Confusion Matrix
5563
189
705
472
231
148
1407
115
3050
Actual Label
5000
4000
3000
2000
1000






```
<ipython-input-61-326892c78896>: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 Accuracy Comparison



Model Evaluation

Random Forest performs the best overall :

- **Highest accuracy (0.8114).**
- **Highest macro-average precision (0.74), recall (0.67), and F1-score (0.69).**
- **Strong performance across all classes, especially for class 0 and class 2.**

Decision Tree and K-NN are decent alternatives :

1. **Both achieve accuracy > 0.73.**
2. **Decision Tree has better macro-average recall (0.63) compared to K-NN (0.60).**
3. **K-NN has slightly better precision (0.66) compared to Decision Tree (0.62).**

SVM performs well but struggles with class 1:

1. **High accuracy (0.7562) and precision (0.71).**
2. **Poor recall for class 1 (0.11), indicating it struggles to identify this class.**

Logistic Regression and Naïve Bayes underperform :

1. **Logistic Regression has the lowest macro-average F1-score (0.43).**
2. **Naïve Bayes has the lowest accuracy (0.5859) and struggles with precision and recall for all classes.**

Hyperparameter Tuning

Hyperparameter Tuning for Random Forest

In [62]:

```
# 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: 0.8009259259259259
```

Hyperparameter Tuning for Decision Tree

In [63]:

```
# 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': 10}
Best Score: 0.7535984848484848
```

Hyperparameter Tuning for Naïve Bayes

In [64]:

```
# 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: 0.5905934343434344
```

Conclusion & Recommendation

1) The best model evaluation:

- **Random Forest should be used as it consistently outperforms the other models across**

2) Improve the Class 1 Performance:

1. **Investigate class imbalance. If class 1 is underrepresented, consider techniques like oversampling or class weighting.**
2. **Experiment with hyperparameter tuning for better performance on this class.**

3) Alternative Models to consider:

1. **If interpretability is important, Decision Tree or Logistic Regression should be considered.**
2. **If computational efficiency is a concidered, K-NN or SVM are reasonable alternatives.**